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The Role of Financial Variables in Predicting Economic Activity in the Euro Area

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The Role of Financial Variables in Predicting Economic Activity in the Euro Area

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Abstract

The U.S. business cycle typically leads the European cycle by a few quarters and this can be used to forecast euro area GDP. We investigate whether financial variables carry additional information. We use vector autoregressions (VARs) which include the U.S. and the euro area GDPs as a minimal set of variables as well as growth in the Rest of the World (an aggregation of seven small countries) and selected combinations of financial variables. Impulse responses (in-sample) show that shocks to financial variables influence real activity. However, according to out-of-sample forecast exercises using the Root Mean Square Error (RMSE) metric, this macro-financial linkage would be weak: financial indicators do not improve short and medium term forecasts of real activity in the euro area, even when their timely availability, relative to GDP, is exploited. This result is partly due to the 'average' nature of the RMSE metric: when forecasting ability is assessed *as if* in real time (conditionally on the information available at the time of the forecast), we find that models using financial variables would have been preferred, ex ante, in several episodes, in particular between 1999 and 2002. This result suggests that one should not discard, on the basis of RMSE statistics, the use of predictive models that include financial variables if there is a theoretical prior that a financial shock is affecting growth.

JEL Classification Numbers: F30, F42, F47

Keywords: VAR, Financial Variables, International Linkages, Conditional Forecast

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I. INTRODUCTION[1]

Large bank losses and financial turbulences have been the direct consequences of the subprime mortgages crisis that erupted in the United States after July 2007. Two years later, the financial turmoil is far from being settled and, together with the global recession, has contributed to bring to the fore again the debate on the macro-linkages and the role of financial factors as amplifiers of the international transmission of real shocks.

Our goal is to study the determinants of quarterly euro area GDP in the context of financial turbulences originated in the U.S. The traditional analysis of the transmission of shocks views the trade channel as the main source of spillovers: a slowdown in the U.S. would decrease its imports, and the associated reduction of European exports would therefore lead Europe to a period of lower growth. However, this direct trade channel can hardly account for the extent of observed spillovers. Looking at the euro area, U.S. imports represent around 15% of its exports, and the euro area exports contribute for only 10% to its GDP growth. The stylized fact that the euro area lags the U.S. business cycles by a few quarters could therefore hardly be justified on account of a rather limited trade openness.

Several explanations have been put forward to rationalize the importance of the U.S.-euro area common cycle (e.g. Giannone and Reichlin, 2004, Giannone et al., 2008 and Favero and Giavazzi, 2008). First, the bilateral U.S.-euro area trade statistics could underestimate the actual trade linkages, due to third-country effects (Dees and Vansteenkiste, 2007). Second, transmission of cycles through commodity prices may explain a further amount of the observed linkages, although Bayoumi and Swiston (2007) do not find that channel to be consequential. Hence, the literature has concentrated on the financial sector as the possible missing element in the analysis of the channels of transmission. As a result of financial globalization, the financing conditions in a major economy such as the United States quickly cross the borders because of the required equalization of expected returns, a channel which may have become even more relevant as firms increased the fraction of their operations in foreign areas.[2] In fact Dees, di Mauro, Smith and Pesaran (2005) show, using a Global VAR model, that a 4 percent fall in U.S. real equity prices not only reduces U.S. output by 0.4 percent within a year, but also depresses European financial markets by around 4 percent and euro area GDP growth by

[1] We are grateful for the discussions with and the comments from participants at the conference on International Linkages (Asian Development Bank Institute, October 2008), at the GRETA conference on Credit Risk, Financial Crises and the Macroeconomy (September 2009) and at seminars at the IMF (European Department, Strategy Policy Review and Western Hemisphere Departments). We received very useful input from Tamin Bayoumi, Domenico Giannone, Michele Lenza, Bin Li, Filippo di Mauro, Martin Mühleisen, Lucrezia Reichlin, Tahsin Saadi Sedik, Silvia Sgherri, Emil Stavrev, and Song-cho Young. The views expressed in the paper belong to the authors only and should not be attributed either to the IMF, its Executive Board, or its management, the ECB or the Eurosystem.

[2] Of course due to the presence of currency, country and firm specific risk-premia, returns will not actually equalize instantaneously, but, to the extent that the investors perceive similarities between economies, risk-premia are not expected to diverge too much.

0.4 percent in the second year after the shock. Bayoumi and Swiston (2007) also argued that global financial conditions are the most relevant channel of transmission and typically swamp the impact on growth played by the trade channel or the commodity price channel.

There are at least two potential elements that can explain why developments in financial markets may precede turning points in business cycles. First, tighter financial and credit conditions limit the potential for firms' activity to expand, constraining their hiring and investment decisions (see Bloom et al., 2008). Furthermore, they prevent credit-constrained households from borrowing and hence consume during harsh times, thus restraining the possibility to smooth consumption. However, the quantification of such effects relies on the proper identification of 'structural' financial shocks, which is a very difficult task.

A second explanation is somehow less structural: asset prices are determined in markets which are fundamentally forward looking. Equity prices capture expected firms' profitability, which is linked to the future rate of growth of the economy. Hence, the correlation between depressed financial markets today and low growth in the near future could result from the forward-looking nature of financial markets, even in the absence of any causal link between financing conditions and growth. This argument is associated with an important branch of the literature analyzing the usefulness of financial data in forecasting GDP cycles. While several authors have argued that financial variables do not consistently help predicting business cycles (Stock and Watson, 2003), Ang, Piazzesi and Wei (2006) among others show that in a model that takes into account expectations for GDP and no-arbitrage conditions, yields have a non negligible role in forecasting growth.

The lack of clear-cut results may also come from the variety of asset prices available. Some authors have looked at very specific asset prices: for instance, Liew and Vassalou (2000) show that portfolios which are built as long-short positions in some stock characteristics – typically size and value – can help predict future U.S. GDP. More recently, Gilchrist et al. (2008) look at the predictive ability of credit spreads for future GDP growth and find that credit spreads based on corporate bonds with a 'median' rating convey the most useful information.

Several papers have also emphasized the role of credit quantities or lending standards as opposed to price-related information. The idea, as put forward in Carlson et al. (2008) is that deterioration in the health of a financial institution may raise the cost of intermediation and that the failure of a financial institution, leading to the loss of banking relationships, may limit firms' access to credit and hamper their ability to invest. Within this framework, Goodhart et al. (2006) find that deposit and loan rates rise and borrowing activity declines as banks' capital-asset ratios decrease towards their capital adequacy requirement. This channel of transmission completes that of the financial accelerator (Bernanke and Gertler, 1989). An empirical investigation conducted by Carlson et al. (2008) finds that the health of the financial sector indeed affects U.S. GDP, with a one standard deviation shock to an aggregate index of distance to default of financial institutions leading to a cumulative decrease in investments of about 2% over the subsequent two years. However, the above results are referred to an in-sample analysis. Similarly, Swiston (2008) recovers a financial condition index from a VAR and finds that it represents a powerful anticipator of turning points. Finally, the analysis in IMF (2008) illustrated that a large number of recent phases of slowdown and recessions took place within 6 quarters after a turbulence in the banking sector. These episodes were sharper the more leveraged were households and firms – theses results are however not based on a formal out-of-sample assessment.

Relatively few studies have concentrated on the euro area; an analysis is provided by Forni et al. (2003) who show that financial variables can help forecast inflation although they find no predictive power for industrial production.

We investigate the determinants of quarterly euro area GDP. Our analysis is related to the first set of papers insofar as we focus on various market price-related information, and we explicitly consider the international environment of the euro area and a combination of financial indicators. Specifically, we estimate the performance of a number of VAR models, constructed around the GDPs of 2 or 3 economic areas (U.S., euro area and a seven-country aggregate called Rest of the World) and extended to selected financial variables. We investigate whether considering financial variables helps tracking the observed linkages between the U.S. and the euro area. As a control we also make use of some non-price information (bank claims, financial firms' distance-to-default) as well as stock returns which do not consider the whole market but are built as differential returns between firms (the Fama and French (1993) methodology).

We look at both in-sample and out-of-sample evidence. In the former, we find that impulse responses support the existence of a relationship between financial variables and real activity both domestically and internationally. According to the forecast error variance decomposition, half of the variance of euro area GDP can be explained by U.S. and 'financial' shocks eight-quarters ahead. Further, sub-sample analysis suggests that linkages have become stronger after 1985. Counterfactual experiments reinforce this view as we show that considering financial variables in addition to GDP leads to simulated GDP values which are much closer to the actual GDP figures. We also find that the United States have had a leading role in the transmission of shocks since the 70s.

Going to the out-of-sample analysis, we consider 'unconditional' out-of-sample GDP forecasts, i.e. traditional forecasts for time $t+k$ conditional on time t as well as several types of 'conditional' forecasts in which 'future' values (next 1 or 2 quarters) of financial variables are assumed to be known (and indeed for real time forecast they are known before quarterly GDP estimates are released).

When looking at 'unconditional' forecasts, we find that a model which includes the GDPs of the two or three economic areas has the best performance in terms of forecast Root Mean Square Error (RMSE) across the eight VAR models considered. Surprisingly, adding various combinations of the financial variables leads to a *worsening* in the out-of-sample performance at short horizons while the gap tends to shrink when forecasting 2 to 3 years ahead.

Conditioning the forecasts on next period financial data (since this information is available before data on real variables is released) does not change this conclusion.

The picture differs somewhat if we use a rolling RMSE or the conditional predictive ability test proposed by Giacomini and White (2006; henceforth GW), which uses a different metric for measuring forecasting ability. Being designed to detect predictive power of econometric models conditional on current information, this test has the potential to identify periods in which models that include financial data would be predicted to outperform simpler models based on real GDP growth only. Consistently with rolling RMSE, the GW test shows that the information content provided by financial variables would have improved the forecast for the euro area GDP between 1999 and 2002.

This result suggests that one should not discard, on the basis of RMSE statistics, the use of predictive models that include financial variables if there is a theoretical prior that a financial shock is affecting growth. Indeed, the historical decomposition suggests that in that period financial shocks had a prominent role. In general, one could hypothesize that financial shocks do not occur frequently and therefore the predictive power of financial variables is marginal when evaluated on a large period. Alternatively one could think that financial prices affect real activity in a nonlinear way, which blurs their predictive power within a linear framework. The success obtained by financial prices in fitting recessionary periods in out-of-sample experiments both in the United States and in main economic areas (see Fornari and Mele, 2009, and Fornari and Lemke, 2009) as well as results based on threshold VAR models (Balke, 2000) lead some support to this view.

II. The VAR models

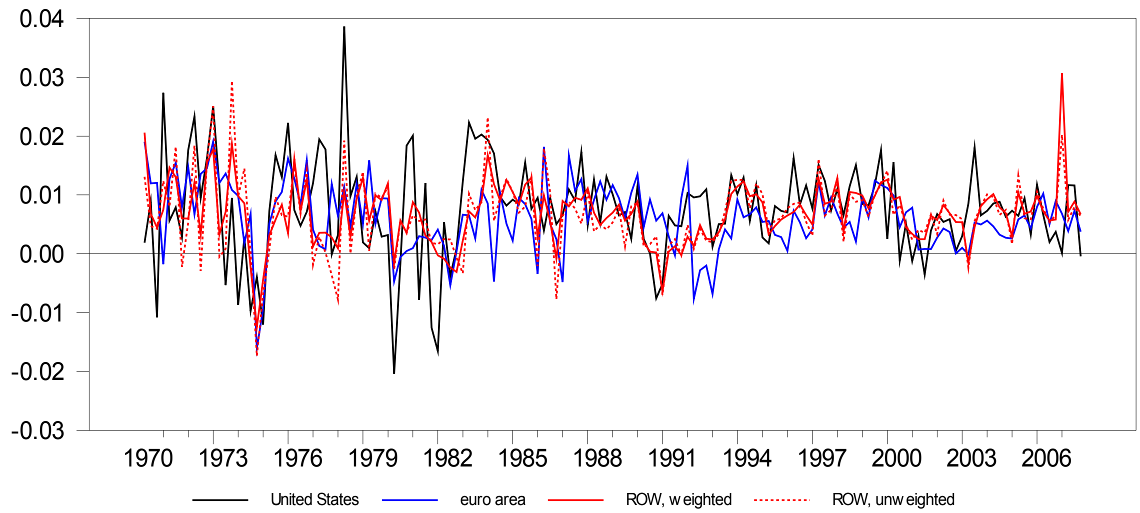
A. Data

Our measure of real activity in the three economic areas (U.S., euro area, and Rest of the World) is the seasonally adjusted quarterly real GDP observed between the first quarter of 1970 (1970q1) and the last quarter of 2007 (2007q4). The Rest of the World is an aggregation of seven countries (Australia, Canada, Denmark, Norway, New Zealand, Sweden and Switzerland) that were chosen to represent economies different enough so that a shock affecting all of them can be interpreted as 'global', following Bayoumi and Swiston (2007).[3] We build the Rest of the World as a weighted average of the seven countries (with weights being the 1995 GDP expressed in U.S. dollars – the results were similar with un-weighted

[3]The euro area GDP series is obtained from the Euro Area Wide Model (see Fagan et al., 2001), the U.S. GDP from the BEA national accounts, while the GDPs used for the Rest of the World were taken either from the IFS of the IMF, the OECD or Global Financial Data. The GDP series for Canada was taken from the BIS since the IMF and OECD data exhibited an unreasonable jump in 1995. The weights used for the construction of the Rest of the World series are the 1995 nominal GDPs in U.S. dollars. All financial data come from the Global Financial Indicators database.

averages). Notwithstanding the noise typical to quarterly GDP growth rate (see Figure 1), they evidence both the commonality in regional business cycles and episodes of clear anticipation of the United States (e.g. the U.S. leads the euro area after its 1990 recession episode).

Figure 1. Rates of Growth of Real GDP in the Three Economic Areas (quarter-on-quarter)



Note: The rest of the world aggregates seven small open economies. In one case (solid red line) the aggregation weights are based on real 1995 GDP figures expressed in dollars while in the other (dotted red line) the aggregation is based on equal weights.

We collect stock market indices and dividend yields as well as 10-year and 3-month yields for all the countries in the sample. The dividend yield is employed to construct a measure of the disequilibrium between the stock market and the bond market, obtained from the cointegrating vector between the dividend yield and the Government bond yield (this relationship is sometimes referred to as the 'Fed' model).[4]

We use stock market returns to generate time-varying stock market volatilities as 4-quarter backward-looking moving averages of their absolute values. The slope of the yield curve is the difference between the 10-year government bond and the 3-month T-Bill rate. For the euro area, the stock market is reconstructed by Global Financial Data while the slope of the yield curve relies on German data. For each country, all the financial variables have also been collected at a monthly frequency, between March 1970 and March 2008.[5]

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[4] The stock market return is calculated as the quarter on quarter logarithmic change of the stock index but we also consider a 4-quarter backward-looking moving averages of such returns, as smoother return series may help predictability by bringing financial volatility closer to the observed volatility of real GDP changes.

[5] Monthly data are transformed in the same way as quarterly data, with moving averages being based on 12-month windows, matching the choice made for quarterly data.

We use monthly financial variables to assess the information content of financial data at an intra-quarter level. To keep the size of the VAR within a reasonable limit, and thus reduce parameter uncertainty, we only include two financial variables per economic area in turn (i.e. our largest VAR has therefore 9 variables).

B. Specifications

The results in this paper are based on VAR models with four lags.[6] The VARs including GDP variables only are specified in levels with or without cointegration, while the models with financial variables are also estimated in log-difference, so as to limit the potential negative impact of the much higher volatility of financial variables relative to real GDP.[7] Based on the trace statistic (Johansen, 1988) we find evidence of at most one cointegrating vector among the three economic areas. The specifications in level are mainly aimed at checking whether imposing cointegrating restrictions actually improves or worsens forecasting ability.[8] Two VARs include measures of real activity only (GDP) while the remaining models also consider the three combinations of financial variables described before. The cointegration model is:

$$Y_t = A_0 + A_1 . Y_{t-1} + A_2 \cdot Y_{t-2} + A_3 \cdot Y_{t-3} + C \cdot \left[\lambda \cdot y_{t-4} \right] + \varepsilon_t$$

where $Y = \left[y \quad fin \right]'$ is a vector that includes the logarithm of the GDP (*y*) and the two financial variables (*fin*) selected in turn (out of three) for the different economic areas. The cointegrating vector λ links the dynamics of the two or three GDPs while ε_t is a vector of error terms (whose dimensions goes from 2×1 to 9×1) normally distributed with covariance matrix Σ.[9] The models estimated can be classified as follows:

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[6] While standard lag choice tests (AIC, SIC) suggest that one lag captures sufficiently well the dynamics of the variables, these tests are well known to underestimate the true dependence structure of the data. Based on the likelihood ratio test, and also considering that we are working with quarterly variables, we decided to fix the lag length at 4. Furthermore, the slope of the yield curve and the stock market volatility predict business cycles at rather long horizons, typically 12 to 24 months so that the choice of a short lag would automatically limit the measured predictability.

[7] We do not investigate fully-fledged Vector Error Correction models as we do not want to enter a discussion on the dimension of the cointegration space for financial variables. Furthermore, financial variables are rather synchronized across economic areas (the literature has also evidenced the presence of risks when forcing cointegration in models with nearly integrated variables, such as interest rates, see Mitchell, 2000). To all extent, the major misspecification deriving from not considering cointegration among economic variables will be for the stationary models, as all models in levels will to some extent accommodate the long run relationship among the variables.

[8] The specifications in level are not misspecified in presence of cointegration and the estimates are superconsistent.

[9] The matrices A_0, …, A_3, C are estimated through OLS, while the cointegrating vector λ is estimated in a preliminary step and the restrictions that it implies are imposed in the VAR (this is the 2-step procedure).

1. A 2-country model of the U.S. and euro area log GDP (estimated unconstrained - $BiVAR_L$ and with cointegration - $BiVAR_C$). Together with model 0 (the random walk for the GDP growth rate) this model constitutes the benchmark model against which the other specifications are tested.

2. A 3-country model of the U.S., the euro area and the Rest of the World (ROW) log GDP in levels with cointegration (TriVar model)

3. A 3-country model for the log GDP, in levels with cointegration, plus the stock market volatility and the slope ($FiVAR_{1D}$ is a model estimated in log-difference, $FiVAR_{1C}$ is a cointegrating VAR, $FiVAR_{1L}$ is a level VAR).

4. A 3-country model including the log GDP, in levels with cointegration, plus the stock market index (level) and the slope (level) ($FiVAR_{2D}$ is the log-difference model, $FiVAR_{2C}$ is a cointegrating VAR and $FiVAR_{2L}$ is the level VAR).

5. A 3-country model for the log GDP plus the dividend yield, the bond yield and the slope ($FiVAR_{3L}$).

6. A 3-country model for the log-difference of the GDP plus the stock market disequilibria and the change in the slope ($FiVAR_{3D}$).

III. Characterizing the Models

We assess in this section whether the dynamic relationships among the variables are in accordance with the results in the literature using standard orthogonalized impulse response functions, over the full sample, and in the two sub-samples 1970–1984 and 1985–2007. For identification[10], we isolate the response of slow moving variables (the real ones) from that of the fast moving variables (the financial ones) so that the impulse response associated to shocks to financial variables can be seen as a marginal impact beyond what is already accounted for by the real variables. This type of identification, which is a Choleski identification with ordering based on the 'speed' with which information is released to markets, has been employed for example in Boivin and Giannoni (2007). We also place the euro area GDP first, the rest of the world second and the U.S. last, as the United States have been typically shown to lead the other areas, so that their 'specific' shocks are those that are not shared by the other two economic areas.

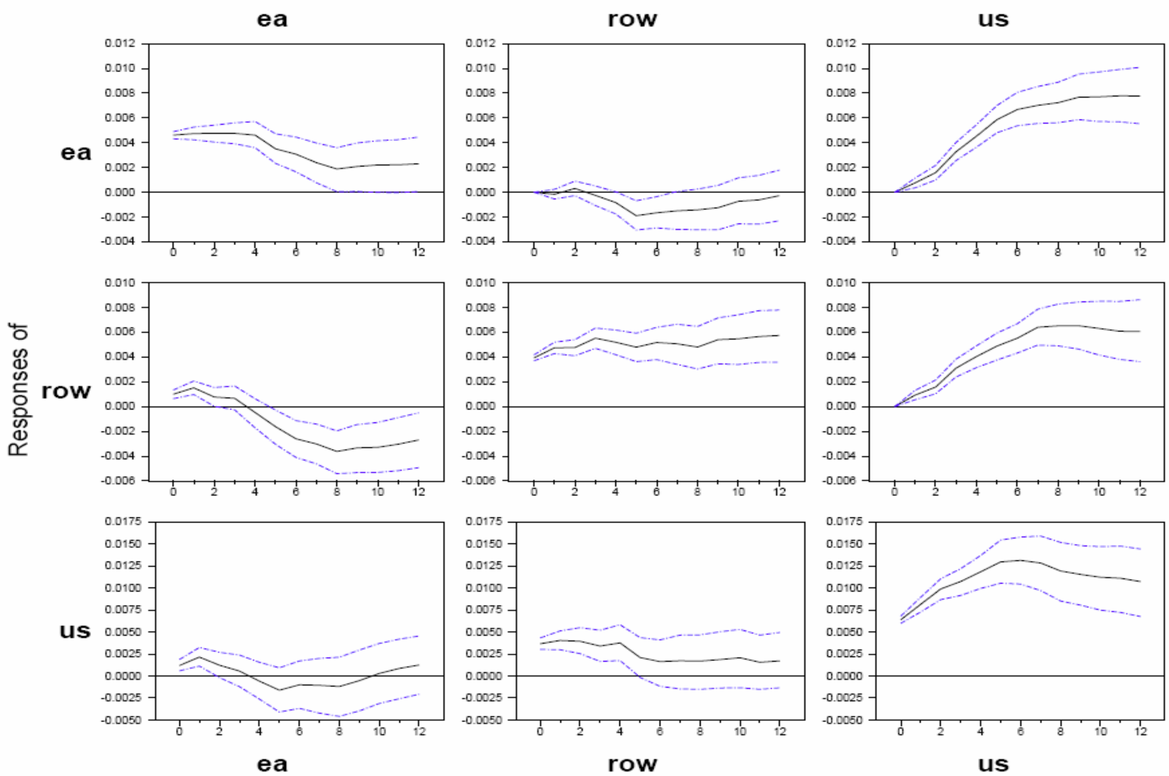
A. IRFs and Pre-1985 and Post-1985 Evidence

To simplify the presentation, the results of this subsection are based on two out of the various VAR models employed in the remainder of the paper. Figures 2 and 3 show the orthogonalized Impulse Response Functions (IRFs) coming from the model which includes the three GDP

[10] As we estimate reduced form VARs, we need to place restrictions on the A matrix and on the polynomial matrix $B(L)$ in the 'corresponding' structural VAR $y_t = A^{-1}B(L)y_{t-1} + A^{-1}u_t = A^{-1}B(L)y_{t-1} + v_t$ where $v_t = A^{-1} u_t$ are uncorrelated and orthogonal structural shocks with the identity matrix as covariance matrix.

(model 2, with the following causal ordering: euro area, ROW, U.S.) and, respectively, the IRFs coming from model 3 with cointegration ($FiVAR_{1C}$ above), where the 3 GDPs are complemented by the stock market volatility and the slope of the yield curve in each geographic area (see end of Section II). Besides some minor differences in the path towards the long-run, the two models provide very similar responses of the real variables to shocks in the real variables themselves, which may be interpreted as preliminary evidence of the fact that financial variables contribute only to a small extent to future GDP growth.

Figure 2. Impulse Response Functions from a Trivariate VAR



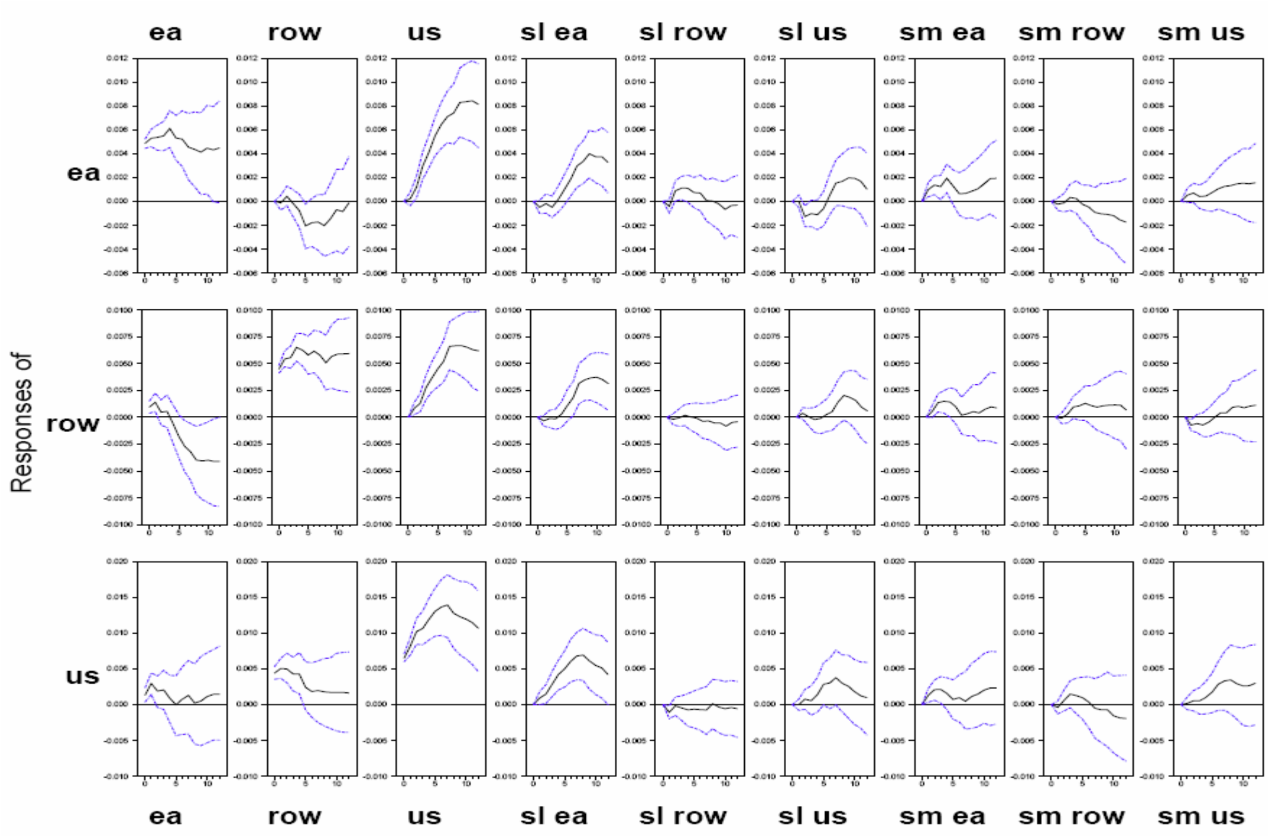
Note: The Chart reports the impulse response function and the associated 68% confidence bands from a VAR including the GDP of the United States, euro area and Rest of the World. The lines indicate the responses of the variables listed in the rows to a shock in the variables listed in the columns. The x-axis records the quarters elapsed after the shock. The VAR is estimated between 1970Q1 and 2007Q4 and has four lags.

In addition, the impulses responses confirm the findings of the literature that the U.S. GDP adjusts faster to shocks, and thereby leads other economic areas (see Giannone et al., 2008). We find some spillovers between the U.S. and the rest of the world whereas U.S. euro area spillovers are one-way only – coming from the U.S..[11] The orthogonalized IRFs from model 3 (Figure 3) suggest that the stock market index (sm) and the slope of the yield curve (sl) do affect the GDP growth. Since financial variables were ordered after real variables, the IRFs provide an estimate of the effects of a financial shock when using simple Choleski

[11] The reported error bands around the estimated impulse functions are based on 500 Monte-Carlo draws from the posterior distributions of the VAR parameters and the covariance matrix.

decompositions (i.e. financial shocks capture what 'remains' to be explained after the effects of real shocks have been accounted for).

Figure 3. Impulse Response Function from a 9-Variable VAR

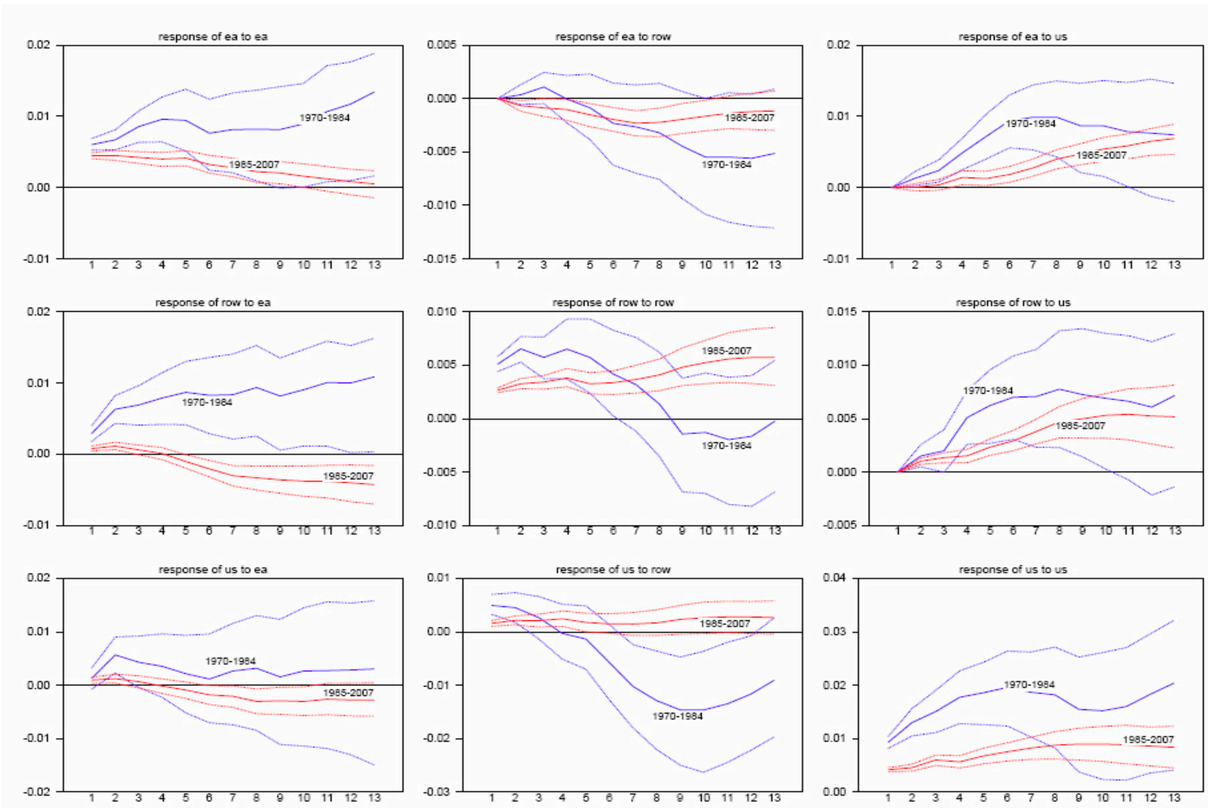


Note: The Chart reports the impulse response function and the associated 68% confidence bands from a VAR including the GDP of the United States, euro area and Rest of the World, as well as their slope of the yield curve (sl) and the stock market index (sm). The lines indicate the responses of the variables listed in the rows to a shock in the variables listed in the columns. The x-axis records the quarters elapsed after the shock. The VAR is estimated between 1970Q1 and 2007Q4 and has four lags.

Hence, the IRFs point at the presence of some influence of financial variables on real cycles, a result previously reported in the literature, e.g. in Bayoumi and Swiston (2007) and Dees et al. (2007). The latter authors, in particular, find that an 8% increase in the U.S. stock market index translates into a comparable rise in the Euro Area stock market (this impulse has not been reported given the obvious tight relationships among financial markets) and boosts U.S. and euro area activity by around 0.2% quarter-on-quarter during the first year after the shock. The significance of the effect of financial variables is however borderline in most cases and depends on the inclusion of the Great Moderation (post-1985) in the estimation sample.

The Great Moderation period has witnessed a significant drop in U.S. and worldwide macroeconomic volatility, spurring a sizeable amount of research questioning whether this lower volatility came from good luck – i.e. smaller shocks – or from a change in monetary policy or in its transmission mechanism. The recent events seem to answer the question.

Figure 4. Impulse Response Function to GDP Shocks Across Sub-Samples



Nonetheless, our VAR models allow us to investigate whether international spillovers have changed during that period (Dees and Saint-Guilhem, 2008, look at the issue in the context of a Global VAR) by re-estimating model 2 (3 GDPs) and model 3 (3 GDPs with slope of the yield curve and stock market volatility) on the sub-samples 1970–84 and 1985–2007 – see Figure 4.[12] We find that the amplitude of the IRFs has decreased and that the linkages across the variables have changed during the Great Moderation. In particular, the response of the euro area and the Rest of the World to U.S. GDP shocks has flattened significantly after 1985, although the long term effects are similar. Synchronization between the Rest of the World and the United States also strengthened though this was not observed for the euro area. Finally, the U.S. started to respond positively to a GDP shock in the Rest of the World after 1985, possibly as the impact of the latter has significantly risen in the last few years.

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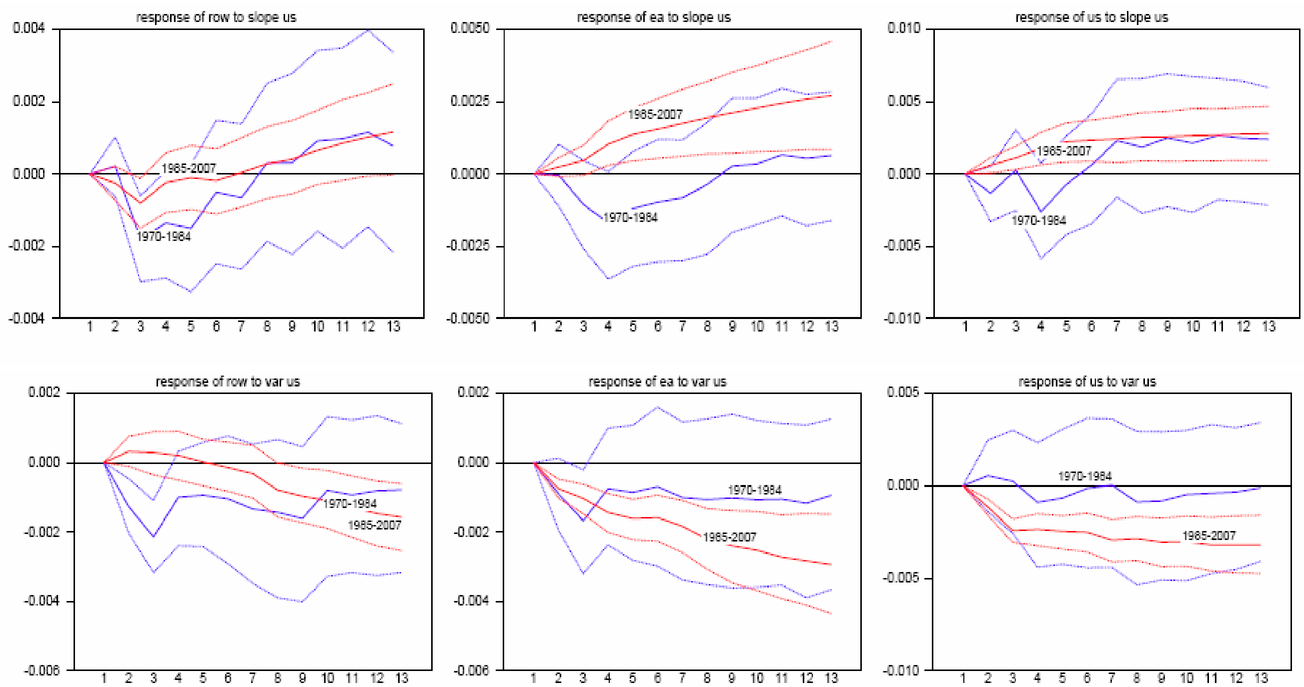
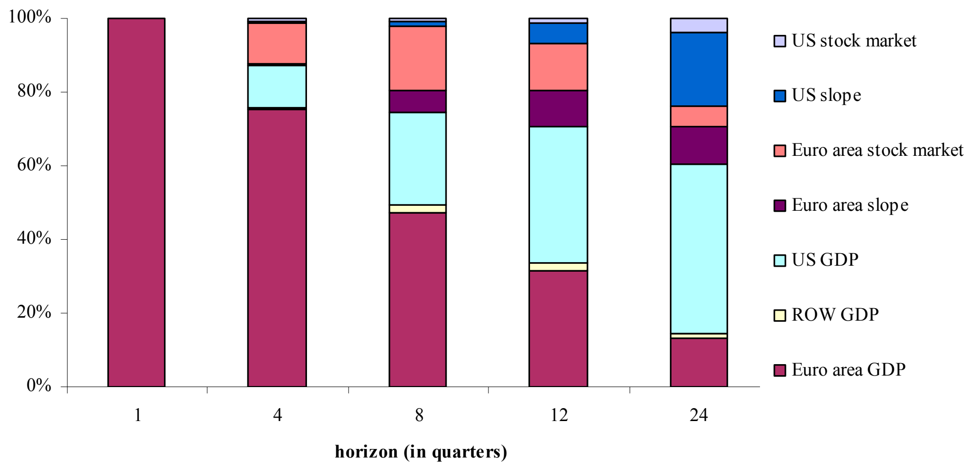
[12] Given the loss in degrees of freedom implied by the shorter sample, we estimated separately a six-variable VAR where the three GDP are complemented, in turn, by the three slopes and the three stock market volatilities, keeping as before the lags equal to four.

Figure 5. Impulse Response Functions Across Sub-Samples



Note: The Chart reports a subset of the impulse response functions and the associated 68% confidence bands from a VAR including the GDP of the United States, euro area and Rest of the World, as well as the U.S. slope of the yield curve (slope U.S.) and the volatility of the U.S. stock market index (var U.S.). The lines indicate the responses of the variables listed in the rows to a shock in the variables listed in the columns. The x-axis records the quarters elapsed after the shock. The VAR is estimated across two sub-samples, from 1970Q1 and 1984Q4 and from 1985Q1 to 2007Q4 and has four lags in both periods.

Figure 6. Forecast Error Variance Decomposition for the Euro Area GDP



The linkages between GDP and the slope of the yield curve have significantly increased and have become more stable in the latest 25 years (Figure 5). While in the first sub-sample the IRFs were negative over short horizons and estimated very imprecisely, they have become positive and significant at all horizons in the United States and in the euro area (see upper panel of Figure 5 for the reaction of GDPs to a shock in the U.S. slope). The IRF of the Rest of the World GDP to a shock in the U.S. slope is almost always insignificant until the 2-year horizon. This may reflect a very asynchronous business cycle between the United States and the rest of the world in the 80s and 90s.

The lower panel of Figure 5 highlights that the U.S. stock market volatility - perhaps providing a good proxy for business or consumer confidence (Bloom, 2008) - has started to play a very strong role on GDP growth worldwide after 1985: a 1% positive volatility shock would have lowered GDP by about 1% annualized in the U.S. and the euro area within 8 quarters. The effect for the Rest of the World is half a percentage point at the same horizon and is also significant. All in all, such in-sample evidence brings some support to the inclusion of financial variables in a VAR model aimed at forecasting economic activity worldwide.

B. Linkages and the Role of Financial Shocks

To get a deeper understanding of the amount and direction of international spillovers and the role of financial variables in the transmission of shocks we look at the forecast error variance decomposition and at simple counterfactual experiments. The forecast variance decomposition[13] of euro area GDP builds on a model with the 3 GDPs plus U.S. and euro area

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[13] The forecast error variance decomposition relies on the ordering of the variables and uses the same information needed to generate the impulses. Starting from $y_t = X_t \cdot \beta + \Sigma_{s=0}^{\infty} \Phi_s u_{t-s} = X_t \cdot \beta + \Sigma_{s=0}^{\infty} \Phi_s G v_{t-s}$, with $E(u_t u_t') = \Sigma$ and $E(v_t v_t') = I$, the covariance matrix of the K-step ahead forecast error is $\Sigma_{s=0}^{K-1} \Phi_s G G \Phi_s'$ and isolating the effect of one component of v is achieved by re-writing the sum as

(continued…)

slope and stock market index, and is computed at the 1-, 4-, 8-, 12- and 24-quarter horizons. The U.S. GDP and slope (Figure 6) explain the majority of the movements in euro area GDP at the longest horizons. At shorter horizons, domestic variables matter more. Furthermore, as already pointed out in the literature, euro area cycles have little effect on U.S. cycles (Table 1).

We obtain similar results when we consider counterfactual VARs, i.e. VARs similar to those employed for the out-of-sample predictability assessment in the next Sections but which are estimated with restrictions, so that the real and/or the financial variables of each country, in turn, are the sole drivers of the system. To provide an example, in a VAR that only includes GDP we fix to zero the coefficients of the euro area and the Rest of the World in the U.S. GDP equation, we estimate the VAR with such restrictions and last we generate 'counterfactual' series of the euro area and Rest of the World assuming that the historical values of the shocks to the European and Rest of the World GDP equations are zero. The exercise is repeated by placing each of the remaining two GDPs first in the causal ordering and keeping analogous restrictions, so that each of those countries, in turn, is the only shock propagator in the trivariate system.

Table 2, Panel A, reports the R^2 obtained by regressing the actual GDP growth rates on their 'counterfactual values'. Across the whole sample the United States would have explained about 15% of the euro area GDP growth rates and 10% of the Rest of the World GDP growth. By contrast, the euro area and the rest of the world are able to explain only a very limited fraction of the U.S. GDP growth. Looking at four sub-samples built across decades (Table 2, Panel B) shows a significant amount of time variation in this pattern. On average, shocks originating from the United States would have explained about 23% of euro area GDP growth between 1970 and 2000, a percentage that has risen to 36% since that year. Extending the exercise to include financial variables, we find that U.S. and ROW real shocks alone would have explained 12 and 8% of euro area GDP growth rates across the whole sample, percentages which rise to 18% and 16% when financial shocks are also considered.

Notwithstanding the inherent difficulty in disentangling common from country-specific shocks, our results favor the conclusion that the United States is the main source of fluctuations – although financial variables also seem to have some influence. The historical decomposition (figure 7)[14], which shows the determinants of euro area GDP, confirms that the role of euro

$\Sigma_{s=0}^{K-1}\Sigma_{i=1}^{N}\Phi_s Ge(i)e(i)G\Phi_s' = \Sigma_{i=1}^{N}\Sigma_{s=0}^{K-1}\Phi_s Ge(i)e(i)G\Phi_s'$ so that the covariance matrix of the forecast errors is decomposed into N terms, each of which is the contribution of a component of v over the K periods.

[14] The historical decomposition of the variance decomposes a time series in a projection and the accumulated effects of current and past innovations: $y_{T+j} = \Sigma_{s=0}^{j-1}\Phi_s u_{T+j-s} + \left[X_{T+j} \cdot \beta + \Sigma_{s=j}^{\infty}\Phi_s u_{T+j-s} \right]$ with the first summation being the part due to innovations from T+1 to T+j (the baseline, not reported in Figure 7) and the second term in brackets being the forecast of y_{T+j} based on information available as of time T (the contributions of the different shocks). We base the historical decomposition on a VAR where the 3 GDPs are complemented by the

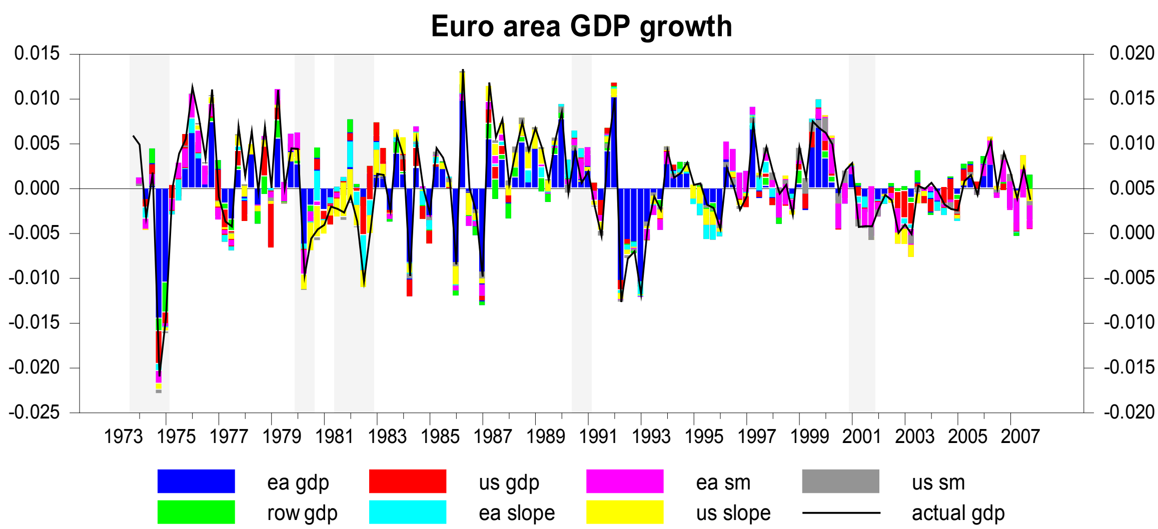
(continued…)

area financial shocks is limited, either because these shocks do not occur frequently enough or because they have a small impact on activity.

The historical decomposition is consistent with a simple picture of euro area history: the 1974 recession was worsened by negative U.S. and Rest of the World cycles. Growth was hurt in the early 80s by restrictive monetary policy, especially in the U.S. The long contraction in 1992 followed the German reunification and was not explained by international or financial factors. The latter seemed instead to matter in recent times, in particular in the 2002 recession and in the current episode.

Shocks attributed to the U.S. stock market did not play a major role throughout the U.S. recessions until 2001, when they seem to have significantly affected economic activity. The figure also shows that the role of the slope of the yield curve has been particularly sizeable between 1979 and 1983, but has since then played a rather marginal role. The same story holds for the U.S. GDP. This evidence contrasts with the results from the IRFs. However, the presence of the stock market return in the historical decomposition may to some extent limit the role of the yield curve, so that the two findings are not necessarily mutually incompatible.

Figure 7. Historical Decomposition



Note: Shaded areas correspond to U.S. recessions identified by the NBER. The decomposition comes from a VAR including the U.S., euro area and Rest of the World GDP and the U.S. and euro area slopes of the yield curve (ea slope, U.S. slope) as well as the euro area and the U.S. stock markets (ea sm and us sm), The model is estimated between 1970Q1 and 2007Q4 and has four lags.

U.S. and euro area stock market indexes and slopes.

IV. OUT-OF-SAMPLE EVIDENCE

The IRFs from the VAR models estimated across sub-samples showed that financial variables have played a stronger and more significant effect on real activity in the post-1985 period, possibly because the 2001 episode is included in the sample. In line with the 'Stock and Watson' literature (Stock and Watson, 2003), these in-sample findings need to be complemented by a full-fledged out-of-sample forecasting exercise.

Our evaluation of predictive ability is based on three main statistics: the Root Mean Square Error calculated through the out-of-sample forecast errors between 1 and 12 quarters ahead; rolling RMSEs, calculated over moving windows of 12-quarters, which allow us to examine time variation in the predictive ability of the models; and the conditional predictive ability test proposed by Giacomini and White (GW, 2006).[15] The rolling RMSE should be seen as a complement to the results of the GW test, since they can be carried out on small windows of data while the GW test requires re-estimating the VAR on windows of fixed length, which cannot be done in practice on windows shorter than 48 quarters. The comparison of the RMSE coming from the fixed estimation windows also allows us to investigate the amount of instability displayed by the data.[16]

A. 'Unconditional' Forecast Evaluation

Table 3 shows the 'unconditional predictive ability' RMSE (i.e. the RMSE for GDP growth rates between $t+j$ and $t+j+1$, for $j=1,2,\ldots,11$, coming from forecasts conditional on all information – GDP and financial data – as of time t. With the exception of the 1-step-ahead forecast, among the vast majority of the chosen forecast horizons, model 1, i.e. the VAR that includes the two GDPs only, has the best performance (see the rows in panel C in the Table) and its performance is very close to that of the VAR which includes the three GDPs as well as to the VAR where GDPs are complemented by the stock market volatility and the slope of the yield curve. Considering that these latter two models have many more parameters than the simple bivariate VAR, their performances should be taken as broadly similar. The random walk model is never a winning choice. Adding other combinations of financial variables in the VARs beyond the slope and the stock market volatility worsens the forecasts at horizons shorter than one year, while at longer horizons the forecasts tend to return near the global minimum. Either the implicit cointegration relationships between GDPs that drive comovements at longer horizons are not affected by the dynamics of financial variables or noisy information contained in financial variables is smoothed out at long horizons.

[15] While the first two tests rely on out-of-sample forecast errors coming from expanding window estimation, the third is built from fixed window recursive estimation of the VAR models.

[16] The GDP forecast which is used to rank the models' performance is the rate of growth of GDP from the beginning of the sample (1970q1) to the actual evaluation point, when using expanding windows, and the rate of growth of GDP in the last k quarters before the actual evaluation point, when a fixed window estimation is considered.

B. Conditional Forecast Evaluation

GDP numbers (even taking into account flash and preliminary estimates) are often made public with a substantial delay. As a result, the literature dedicated to short-run forecasting often makes use of financial data as leading indicators, in addition to survey data (on retail sales, labor markets and so on) to complement the flow of information used for current quarter forecasting (nowcasting) and next quarter forecasting. For instance, Giannone, Reichlin and Small (2005) analyze the information content of around 200 macroeconomic releases for the U.S. economy and find that interest rates, among a number of macroeconomic releases, improve the nowcasting of GDP.

In this section, we put ourselves in the position of a short-term forecaster. We use our VAR models to forecast period *t*+1 and beyond using financial data up to period *t*+1, but the most recent GDP release 'known' by the model refers to period *t* only. The forecasts are generated as conditional forecasts, i.e. we condition the VAR forecasts between *t*+1 and *t*+12 on financial data as of time *t*+1 and GDP as of time *t*.[17]

The results are presented in Table 4, panels A and B. The third-to-last row in each panel reports the minimum RMSE achieved by the models in Table 3, i.e. the lowest RMSE of the unconditional forecasting exercise. Conditional forecasts are worth being employed if this RMSE is lowered, i.e. if information dated *t* and *t*+1 is richer than information dated *t* only. Looking at panel A, up to the 8th step ahead, forecasting performance deteriorates for all models with financial variables, by between 15 and 35%. Between the 2- and the 3-year ahead horizon, the RMSE gets close to the overall minimum in Table 3. Panel B reports the same information when knowledge about GDP is further restricted to time *t*-1 while financial variables are known as of times *t* and *t*+1. The picture does not change too much with respect to panel A. This result is surprising since it implies that the optimal forecast need not use the most recent quarterly financial data.

Relying on the most recent monthly financial data would not help either. We present in the three panels of Table 5 the results obtained from a similar exercise, conditioning on GDP as of time *t* and monthly financial variables dated *t*+1/3, *t*+2/3 and *t*+3/3 of a quarter[18]. For models m_4 to m_6, including financial data drastically deteriorates forecasting ability. For model 3 (the

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[17] Conditional forecasts amount to placing restrictions on the forecast errors of the VAR model $\Sigma_{s=0}^{K-1}\Theta_s u_{t-s}$. The errors are orthogonalized so that the forecast errors becomes $\Sigma_{s=0}^{K-1}\Theta_s G v_{t-s}$, where G is a factor of the covariance matrix. Stacking the orthogonalized innovations in the forecast period, the constraints can now be written as RV = r, where R holds the restriction in V. In this way one first computes the vector which minimizes $V'V$ subject to the constraint, i.e. $V = R'(RR')^{-1}R$. The shocks are then translated into non-orthogonalized shocks and the model is used with these added shocks.

[18] Notice that the financial variables in *t*+3/3 differ from the quarterly variables in *t*+1 as rates of changes have a month-on-month reference period, rather than a quarter-on-quarter reference period.

three GDPs plus stock market volatility and slope) 'unconditional forecast' and conditional forecast errors are similar at long horizons. The main improvements are for model 7 at horizons h=8, 9, 10 (conditioning on first month and second month data) and at h=9 (conditioning on third month data).

As a whole our forecasting exercise shows that the more general 'GDP models' consistently beat the random walk over all the considered horizons for the euro area. In particular, models with 2 or 3 GDPs, also including stock market volatility and the slope of the yield curve, consistently improve the forecasts. Adding other combinations of financial variables tends to worsen predictions (a result in line with the U.S. literature, e.g. Stock and Watson, 2003) but the losses are small especially at very long horizons (between 1.5 and 3 years ahead) despite the increased uncertainty brought by the larger number of parameters to be estimated. However, it is rather surprising that predictions worsen significantly in our conditional forecast exercise.[19] The 2-GDP model performs the best, although the performance of the model with 3 GDP is only slightly worse, which suggests that there are indeed gains to take into account the activity of the small open economies, in order to capture global shocks in addition to idiosyncratic U.S. shocks.[20]

The monthly information on financial variables in the next one and two quarters does not seem to provide a boost to models' predictive ability, which nonetheless remains around the value associated to the unconditional forecasts given by the models which include only real variables. However (not reported to save space), the forecast paths from both model 1 (the two GDPs) and model 2 (the three GDPs) are extremely flat throughout the sample, somewhat intuitively in contrast with the superior forecasting ability that they have displayed. On the contrary, the GDP forecasts from the models that include financial variables are much more time varying and, in particular periods of time, they visually track very well the true values of the GDP growth. So, is the predictive ability of models with financial variables superior in particular periods of time and worse in others, so that the overall result is that they have low forecasting power?

C. Additional Explanatory Factors

Before moving to conditional predictive ability, we consider briefly whether non-price financial information or price related information associated with specific characteristics of the firms have the potential of changing the picture which has emerged so far. According to recent

[19] The worsening occurs especially at short horizons and therefore does not seem to be due to a poor forecasting of the financial variables, which for 3 quarters ahead mostly coincide with actual data.

[20] The situation changes somewhat when one considers models that are specified in levels rather than in cointegration, always keeping the models in difference in the forecasting exercise. As in previous exercise, 4 lags are allowed for the variables. In this case, however, model 7 has 12 variables, as we have to leave unrestricted the relations between the dividend yield and the long rate (valuation of the stock market relative to the bond market) and the relationship between the long rate and the short rate (slope of the yield curve).

research (see Liew and Vassalou, 2000, Gilchrist et al., 2008, and Carlson et al., 2008) some less broad price information or non-price information seems to improve predictions.

We repeated the same forecasting exercise envisaged before using the Fama and French (1993) factors (hml, smb), the distance to default measure employed in Carlson et al. (2008) together with its cross-sectional dispersion, measured by the interquartile range, the Consumer and Industrial bank loans alone and together with consumer credit loans and real estate loans.[21]

The RMSE from these models are reported in Panel C of Tables 4 to 6 and overall show that while these measures lead to some improvement in out-of-sample forecasting ability relative to models with financial prices-related information, they lead nonetheless to a worsening of predictions relative to VAR models which consider only the 2 or the 3 GDPs as endogenous variables.

V. Conditional evaluation

A. Rolling RMSEs

The conditional predictive ability of the models described in the previous subsection is assessed via rolling RMSE over 12-quarter periods and thanks to the Giacomini and White (2006) test. The rolling RMSEs calculated over 12-quarter windows are reported for classes of models, at 4- and 8-quarters-ahead horizons in Figure 8 and in Figure 9 for some selected individual models. They seem to contradict to some extent the picture given by the unconditional and conditional RMSEs calculated for the whole sample and reported in Tables 3 to 5. Between March 1996 and March 1999 and between 2002 and 2005 monthly information improved the forecasting performance over the ‘unconditional’ forecast. Figure 8 and Figure 9 suggest that overall there is a dramatic loss in forecasting ability when one uses quarterly information while a substantial gain emerges when one uses monthly releases, with particular reference to the second months of the quarter. In particular, improvement in forecasting ability derives from the second month of the quarter at a 4-step ahead horizon and from the first month at 8-step ahead (Figure 8).

Looking at the specific models that produce the gain in predictive ability (Figure 9) the VARs which include the slope of the yield curve and the stock market volatility, as well as the distance to default (itself a function of the volatility of a number of equity volatilities) seem to be particularly successful.

[21] The Fama and French factors are stationary variables (they are yields). The distance to default and interquartile range have been found to be stationary using a Dickey and Fuller augmented test with 4 lags. The same test suggests that the three types of bank loans are of order one and they have therefore been considered in first differences. As all the financial variables have been transformed to be stationary - or were already stationary -, we only employed VARs where GDPs are considered in first logarithmic differences.

B. Conditional Predictive Ability Test

We complement the informal findings obtained using rolling RMSEs with results of the GW test, which allows us to analyze out-of-sample predictive ability in realistic situations. The test generalizes the widely employed Diebold and Mariano (1995) test along two dimensions, namely the limiting properties and the conditional evaluation of the predictive ability. This latter feature allows us to answer the question "can we predict whether two forecasts will be different and if so which model should be chosen at a given point in time?"[22]

For horizons $\tau = 1$, 4 and 8 quarters we test the null hypothesis that the expectation, at time t, of the difference in forecast performance (using the loss function L) for the two competing models '*ma*' and '*mb*' is zero

$$H_0 \ : \ E\left[\left|GDP_{t+\tau} - G\hat{D}P^{\tau}_{t,ma}\right| - \left|GDP_{t+\tau} - G\hat{D}P^{\tau}_{t,mb}\right| \mid G_t\right] = E[\Delta L_{t+\tau} \mid G_t] = 0,$$

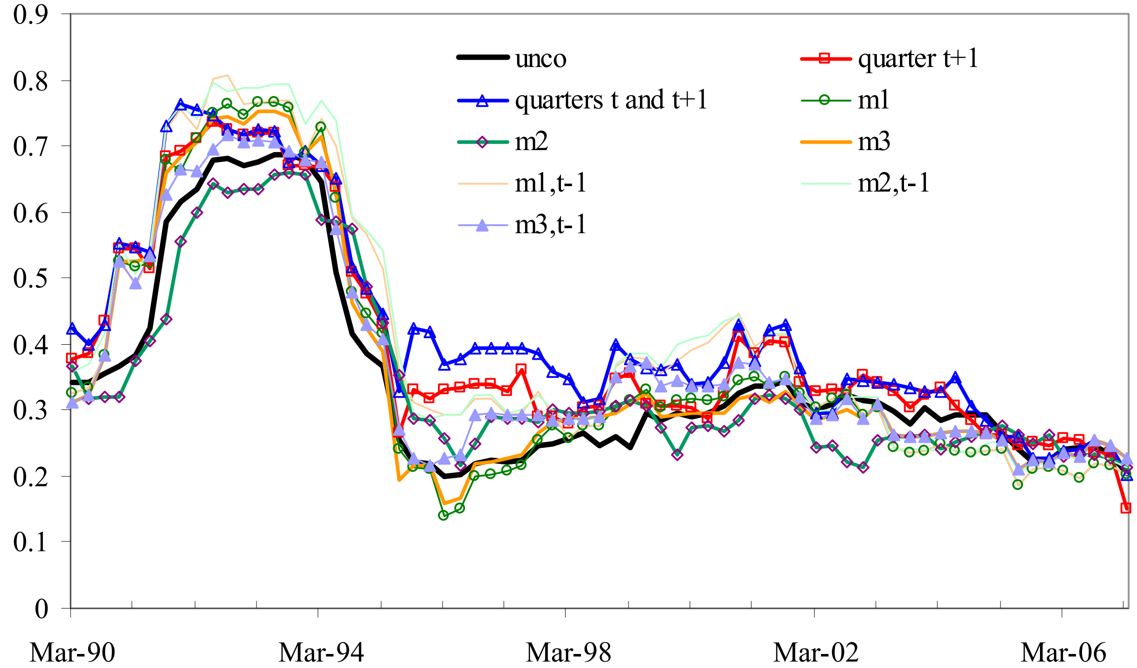
Giacomini and White (2006) show that the test can be computed from the R^2 of a regression of the difference in the absolute forecast performance on its lag and a constant.[23] Broadly speaking, this corresponds to testing whether past differences in forecasting performance (between model *ma* and model *mb*) explain τ -steps ahead differences in forecasting performance. If past performance helps predict future performance, the fitted value of the regression indicates which model should be preferred (the choice function). The forecast performance is estimated on fixed length windows by rolling estimations. When the information set upon which the test is built is such that $G_t = F_t$, the test that two forecasts are different is a conditional test, whereas when G_t includes the full sample ($[0,\infty[$) it is an unconditional test (the equivalent of the Diebold-Mariano test). The conditional test is a powerful tool in fine-tuning the choice of a predictive model depending on the underlying environment.

[22] The test is valid for both nested and non-nested models. For the computation of the GW test all the models are re-estimated over fixed intervals of 60 quarters since the test applies to rolling windows of fixed size only

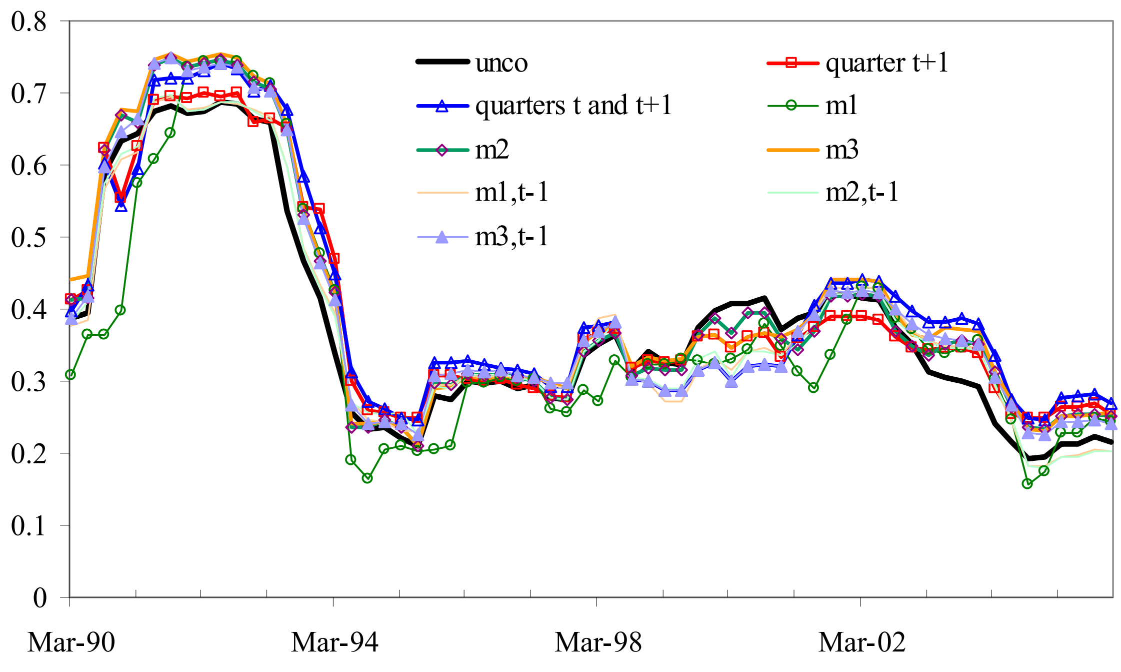
[23] The test statistics can be computed as n·R2m where R2 is the uncentered squared multiple correlation coefficient for the artificial regression of the constant unity on (ht.ΔLm,t+1) where ht = (1, ΔLm,t). In addition, if ΔLm,t is assumed to be homoskedastic the test can be based on the n·R2 of the regression of ΔLm,t+1 on ht.

Figure 8. RMSE from Competing Classes of Models

Panel A: 4-Step Ahead



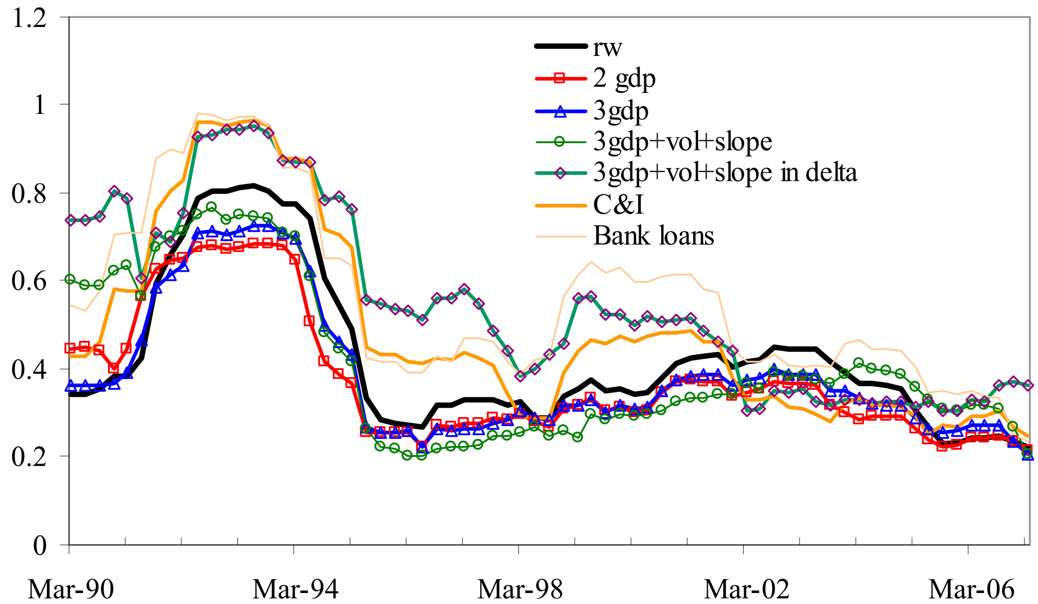
Panel B: 8-step ahead



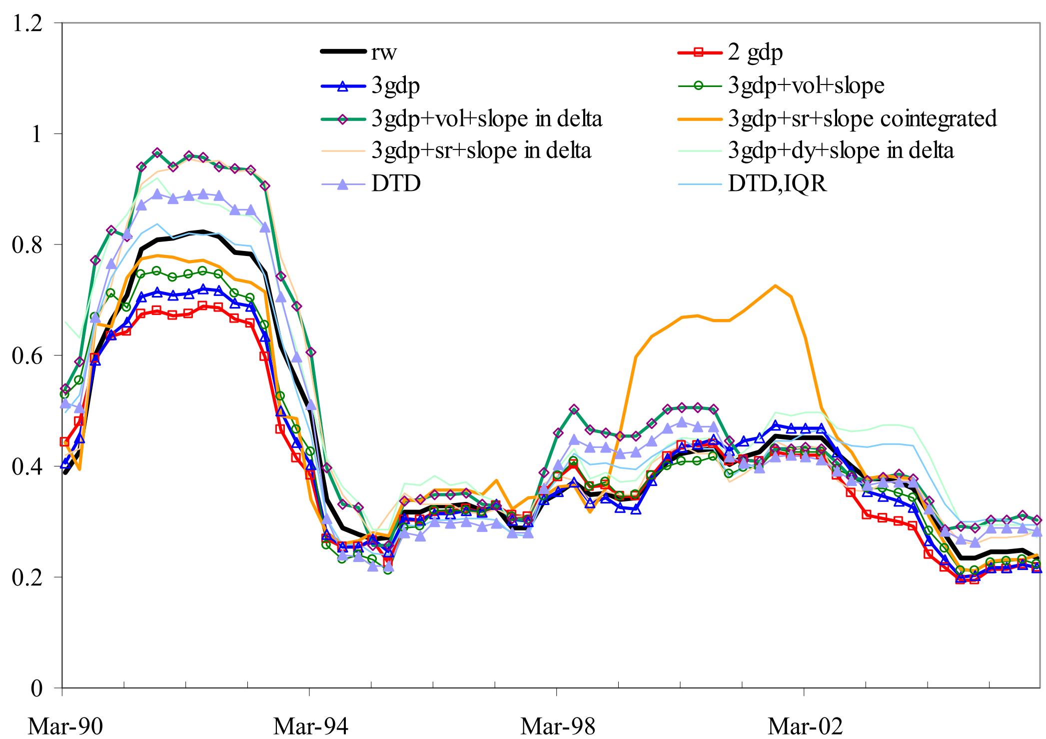
Note: “unco” refers to the model with financial variables, with forecast estimated without any conditioning. “quarters t and t+1” refers to the model estimated up to t-1, and the forecast is conditional on financial data at time t and t+1. “quarter t+1” refers to a model estimated up to t, with the forecast conditional on financial variables at time t+1. “m1”, “m2” and “m3” refer to the model forecast when conditioning on current GDP and 1.2 and 3 months ahead financial data. “m1,t-1”, “m2,t-1” and “m3,t-1” refer to the model forecast when conditioning on last quarter GDP and 1, 2 and 3 months ahead financial data.

Figure 9. RMSE from Competing Classes of Models (continued)

Panel A: 4-Step Ahead



Panel B: 8-step ahead



The first three columns in Table 6 report the results for the Giacomini – White test. The test shows that in many cases the difference between the two forecasting performances of a financial model and a random walk or a 'real model' (with only GDP variables) can be predicted (the p-values are lower than 0.05 Figures for the FiVar1D, FiVar2D, the model including the Fama-French factors, the model including C&I loans)

Figures 10–12 report the choice functions for selected models.[24] A choice function is set to one when the second model in the pairwise comparison would have been preferred over the first model.[25] The number of quarters each model would have been chosen is reported in the last 9 columns of Table 6.

The random walk model would have been preferred in a significant fraction of the quarters only to model 1 (the two GDPs) and less frequently to model 2 (the 3 GDPs) but it would have been by far surpassed by nearly all the models with financial variables, both price- and non-price related (Figure 10). The model with the 2 GDPs only, which performs extremely well based on the in-sample and out-of-sample RMSE criterion, would have instead been frequently over-performed by a VAR which includes the stock market volatility and the yield curve slope beyond the 3 GDPs.

The same occurs for the model with 3 GDPs only against this richer VAR model with stock market volatility and yield curve slope. It is interesting to note that models with financial variables performed best in 1999 and between 2001 and 2003, periods in which the historical decomposition attributed the largest revisions to the baseline forecast to shocks in financial variables.

In a nutshell, although on average financial variables may not contribute to improving forecasts according to the RMSE metric, they seem to have conveyed useful information for the euro area GDP forecast in several episodes in the past. This result suggests that one should not discard, on the basis of a poor long-term average RMSE performance, the use of predictive models that include financial variables if there is a theoretical prior that a financial shock is affecting growth.

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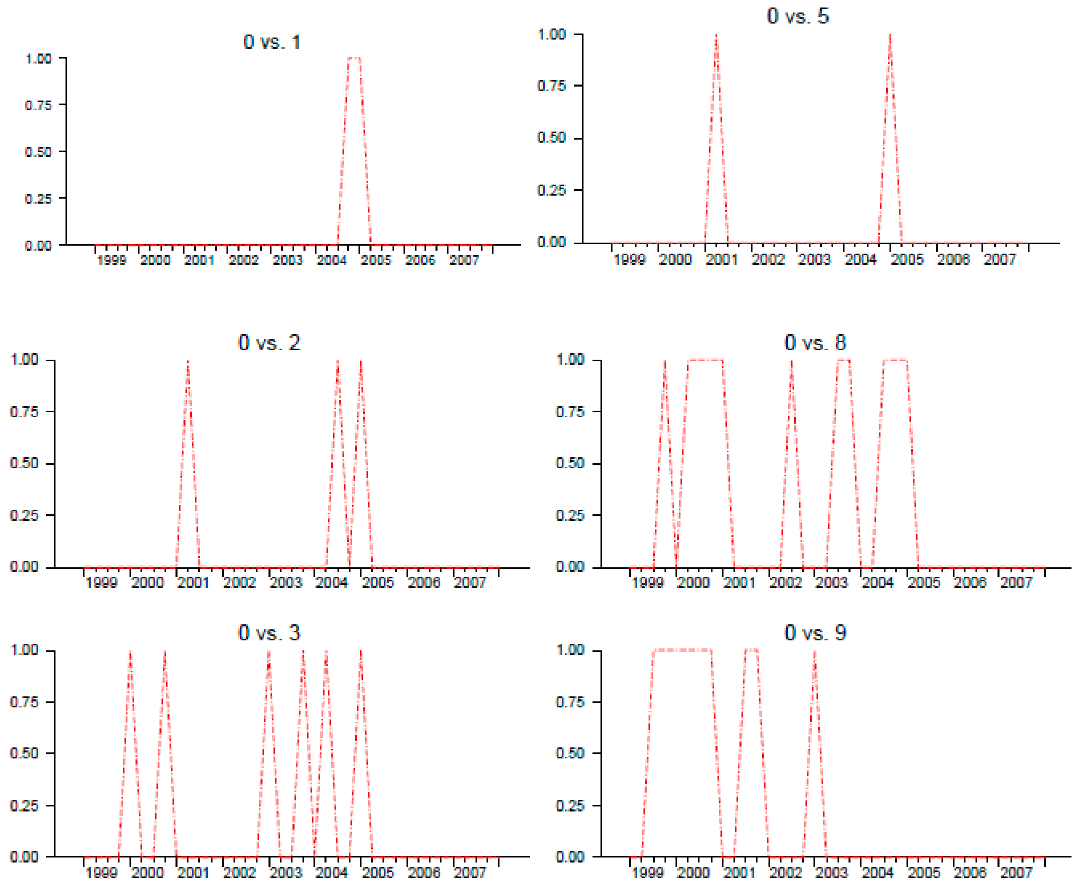
[24] The figures show the time series of the pairwise conditional GW test applied, respectively, to the random walk model and to the VAR with 2 and 3 GDPs against all the remaining VARs which embody information from financial variables. All pairwise comparisons refer to the 4-step ahead predictive ability only, for the period 1999–2007, but results are common to the other horizons, and to further preserve space, results are only presented for the 'unconditional' forecasts, i.e. forecast from the VARs as of time t conditional on the knowledge of all variables as of time t.

[25] The test is based on the information set spanning [0,t-k] where k is the horizon over which the predictive ability is tested (k=4 in Figure 12).

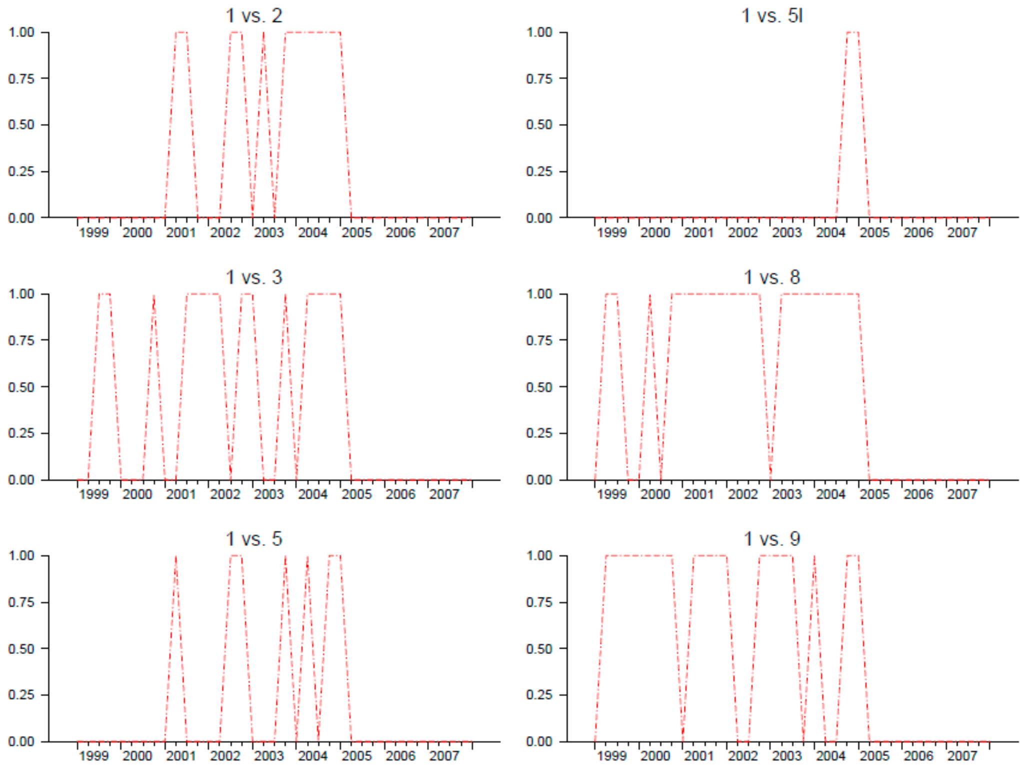
Figure 10. GW Test for Conditional Predictive - Random Walk Model
Conditional choice: model 0 (random walk) vs. selected competing models (4-step ahead)



Note: The panels in the Figure show the results of the conditional test of predictive ability proposed by Giacomini and White (2006). The test is presented as a series of zeros and ones, with one indicating that model 0 (the random walk assumption for GDP growth) would be chosen over the alternative model. The test builds on a regression of the historical differences between absolute forecast errors 4 quarteres ahead on their first four lags. Model 1 is a bivariate VAR for U.S. and euro area GDPs, Model 2 adds the GDP of the Rest of the World, Model 3, Model 4 and Model 3l add the stock market volatility and the slope of the yield curve, Model 5, Model 5l and Model 6 add instead the stock market return and the slope of the yield curve, Model 7 and Model 7l add the dividend yield, the long term nominal rate and the slope of the yield curve. Models 8 to 12 add to the three GDPs respectively: the slope and the distance to default of a set of financial firms, the slope, the distance to default and its interquartile range for a set of financial firms, the Fama and French factors, the C&I loans, and consumer credit bank loans.

Figure 11. GW Test for Conditional Predictive Ability - 2 GDP VAR

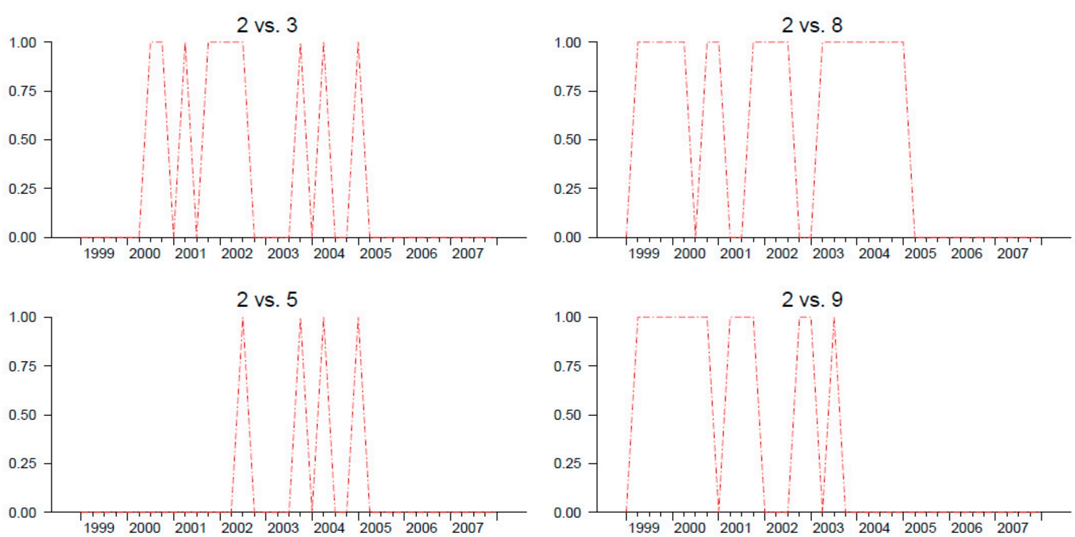
Conditional Choice of Mode 1 vs. Selected Competing Models (4-step ahead)



Note: see Figure 10.

Figure 12. GW Test for Conditional Predictive Ability - 3 GDP VAR

Conditional Choice of Model 2 (3GDPs) vs. Selected Competing Models (4-step ahead)



Note: see Figure 10.

VI. CONCLUSIONS

Against the background of the financial turmoil and global recession originated by a declining U.S. housing market, this paper attempts to shed further light on the role of financial variables in predicting economic growth. In-sample evidence suggests that 'financial shocks' matter for euro area real activity. However, when out-of-sample forecasts are judged under a RMSE metric, we share the Stock and Watson (2003) conclusion that financial variables do not help forecasting real activity, even when taking into account their timeliness. The picture changes when conditional predictive ability tests are considered, with financial variables playing a role in the prediction of the euro area GDP especially in 1999 and between 2001 and 2003, in agreement with our results based on historical decomposition.

A caveat which also entails some directions for future research relates to the linear framework we have employed throughout the paper. Indeed, our results are devised in the setting of linear models, and therefore our findings and statements about the forecasting power of financial variables should be interpreted within that framework. As a consequence, it could indeed be the case that financial variables have a nonlinear impact on macroeconomic variables. For example, Fornari and Lemke (2009), in the setting of a Markov-Switching model, show that financial variables do help in forecasting turning points of the GDP. There are many other ways in which financial developments can affect nonlinearly the predictability of GDP. For example, one can envisage that the forecasting power of financial variables may indeed be larger whenever broadband negative movements in financial indicators take place. This is certainly an interesting avenue for future research.

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Table 1. Variance Decomposition of the GDP in the Three Areas

	Euro area GDP	ROW GDP	U.S. GDP	Euro area slope	Euro area stock market	U.S. slope	U.S. stock market
horizon							
1	100.0	0.0	0.0	0.0	0.00	0.0	0.0
4	75.14	0.55	11.66	0.23	11.05	0.35	1.00
8	47.36	2.11	25.19	5.73	17.66	1.19	0.76
12	31.42	2.21	37.02	9.77	12.72	5.78	1.10
24	13.39	1.16	45.82	10.12	5.52	20.29	3.68
Row GDP							
horizon							
1	5.63	94.38	0.00	0.00	0.00	0.00	0.00
4	3.65	79.91	12.83	0.55	2.35	0.24	0.47
8	1.68	58.28	30.27	1.19	2.86	2.91	2.81
12	2.19	43.83	36.26	2.54	1.79	7.47	5.93
24	3.80	30.82	33.25	3.34	2.97	13.62	12.21
U.S. GDP							
horizon							
1	2.19	8.34	89.47	0.00	0.00	0.00	0.00
4	3.48	5.57	80.88	1.97	4.18	2.62	1.29
8	1.50	2.24	66.91	8.56	2.30	12.23	6.27
12	1.20	1.56	57.71	9.71	2.59	18.53	8.69
24	0.79	2.81	50.11	9.25	2.19	22.94	11.92

Note: The Table reports the percentage of the total variance of the three GDP attributable to the different variables at various horizons. The VAR model includes 7 variables in the following order: euro area GDP, Row GDP, U.S. GDP, euro area slope and stock market, U.S. slope and stock market.

Table 2. R^2 of a Regression of Δlog GDP on its Counterfactual

Counterfactual R2			
PANEL A: (full sample)			
	U.S.	euro area	R.o.W
U.S.	0.9	0.14	0.21
euro area	0.04	0.8	0.14
row	0.01	0.1	0.61
PANEL B: (across decades)			
	U.S.	euro area	R.o.W
U.S. 1970s	0.7	0.23	0.27
U.S. 1980s	0.81	0.21	0.42
U.S. 1990s	0.87	0.25	0.46
U.S. 2000s	0.89	0.36	0.29
	U.S.	euro area	R.o.W
euro area 1970s	0.03	0.45	0.01
euro area 1980s	0	0.86	0
euro area 1990s	0.23	0.89	0.6
euro area 2000s	0.18	0.95	0.31
	U.S.	euro area	R.o.W
row 1970s	0	0.1	0.55
row 1980s	0	0.21	0.22
row 1990s	0.23	0.12	0.51
row 2000s	0.08	0.25	0.8

Note: The VARs are estimated in levels without imposed cointegration between 1970q1 and 2007q4, with four lags. Taking the standpoint of the United States, the three R^2 come from the regression $\Delta\log \text{GDP} = \alpha+\beta \Delta\log \hat{GDP}$ where the superscript denotes the counterfactual values of the GDP in each of the three areas coming from a VAR where shocks other than the U.S. shocks are restricted to zero and the U.S. is therefore the common factor for the other two countries.

Table 3. Unconditional Out-of-Sample RMSE

Abbv.	Forecast horizon	1	2	3	4	5	6	7	8	9	10	11	12
	Panel A												
RW	Random walk	0.45	0.44	0.45	0.46	0.46	0.46	0.46	0.47	0.47	0.47	0.47	0.47
BiVARC	2 gdp coint.	0.43	0.41	0.41	0.40	0.40	0.40	0.40	0.41	0.42	0.42	0.43	0.43
BiVARL	2 gdp level	0.43	0.41	0.41	0.40	0.40	0.40	0.40	0.41	0.42	0.43	0.44	0.44
TriVARC	3 gdp coint.	0.42	0.42	0.43	0.42	0.41	0.42	0.43	0.44	0.44	0.45	0.45	0.45
TriVARL	3 gdp level	0.44	0.42	0.44	0.44	0.43	0.44	0.45	0.46	0.47	0.48	0.48	0.49
FIVAR1C	var slope cointegrated	0.49	0.43	0.48	0.47	0.45	0.44	0.45	0.45	0.43	0.44	0.44	0.44
FIVAR1L	var slope level	0.56	0.51	0.58	0.60	0.58	0.58	0.56	0.56	0.53	0.53	0.55	0.52
FIVARD	var slope in delta	0.63	0.56	0.53	0.60	0.58	0.54	0.53	0.53	0.43	0.51	0.50	0.45
FIVAR2C	sm slope coint.	0.56	0.55	0.49	0.49	0.52	0.49	0.48	0.50	0.46	0.50	0.50	0.48
FIVAR2L	sm slope level	0.73	0.73	0.65	0.73	0.72	0.72	0.79	0.81	0.77	0.85	0.80	0.82
FIVAR2D	sm slope in delta	0.47	0.48	0.52	0.56	0.55	0.54	0.52	0.50	0.48	0.47	0.47	0.47
FIVAR3D	dy slope in level	0.61	0.58	0.68	0.69	0.73	0.72	0.67	0.64	0.62	0.64	0.65	0.64
FIVAR3L	dy slope in delta	0.58	0.48	0.49	0.55	0.59	0.59	0.56	0.53	0.50	0.50	0.50	0.50
	Panel B												
MDS	median dist, slope	0.50	0.44	0.49	0.54	0.50	0.51	0.52	0.50	0.47	0.46	0.46	0.45
MDIS	median dist, iqr, slope	0.55	0.48	0.51	0.56	0.53	0.52	0.52	0.49	0.46	0.44	0.45	0.44
FF	Fama French factors	0.51	0.52	0.54	0.55	0.52	0.52	0.52	0.51	0.46	0.44	0.45	0.44
C&I	C&I Loans	0.47	0.45	0.48	0.53	0.53	0.54	0.54	0.52	0.49	0.47	0.47	0.46
BL	Bank loans	0.54	0.48	0.52	0.59	0.58	0.61	0.61	0.64	0.60	0.57	0.53	0.49
	Panel C												
	minimum all	*0.42*	*0.41*	*0.41*	*0.40*	*0.40*	*0.40*	*0.40*	*0.41*	*0.42*	*0.42*	*0.43*	*0.43*
	minimum fin	*0.47*	*0.43*	*0.48*	*0.47*	*0.45*	*0.44*	*0.45*	*0.45*	*0.43*	*0.44*	*0.44*	*0.44*
	relative gap	*0.05*	*0.02*	*0.07*	*0.07*	*0.05*	*0.04*	*0.05*	*0.04*	*0.01*	*0.02*	*0.02*	*0.01*
	% gap	*12.43*	*4.34*	*16.66*	*16.86*	*11.88*	*11.18*	*12.75*	*8.87*	*2.48*	*3.73*	*3.67*	*2.32*

Note: The Table shows the out-of-sample RMSE for a number of models between 1 and 12 quarters ahead. The forecast are made as of time *t* conditional on the values of all the variables as of time *t*. Shaded areas identify classes of models. The RMSE are obtained by estimating the models on expanding windows the first of which starts in 1970Q1 and ends in 1986Q4. One observation at the time is included in the rolling procedure. The last four lines of the Table report the minimum RMSE across all models, the minimum RMSE across all models that include also variables other than just GDP, the relative gap between such two minima and the percentage gap. 'MDS' and 'MDIS' are the models including the slope as well as, respectively, the median and the interquartile range of the distance to default for a set of financial firms (see Carlson et al., 2008), 'C&I' are the U.S. Commercial and Industrial Loans, 'BL' include Commercial and Industrial Loans, Real Estate Loans and Consumer Credit Loans.

Table 4. Out-of-Sample RMSE

Abbv.	Forecast horizon	1	2	3	4	5	6	7	8	9	10	11	12
	Panel A: estimation up to *t*, forecasts conditional on time *t*+1 information												
FIVAR1C	var slope coint.	0.51	0.49	0.54	0.61	0.70	0.68	0.63	0.64	0.57	0.60	0.60	0.57
FIVAR1L	var slope in level	0.62	0.54	0.54	0.62	0.59	0.61	0.60	0.55	0.55	0.53	0.55	0.57
FIVARD	var slope in delta	0.58	0.51	0.57	0.58	0.53	0.53	0.52	0.52	0.54	0.48	0.50	0.46
FIVAR2C	sm slope coint.	0.60	0.59	0.57	0.55	0.53	0.52	0.50	0.49	0.47	0.45	0.48	0.47
FIVAR2L	sm slope in level	0.81	0.77	0.72	0.84	0.72	0.76	0.77	0.82	0.78	0.79	0.82	0.78
FIVAR2D	sm slope in delta	0.51	0.47	0.47	0.57	0.59	0.55	0.55	0.53	0.49	0.47	0.48	0.47
FIVAR3D	dy slope in level	0.72	0.61	0.60	0.75	0.78	0.80	0.67	0.72	0.63	0.68	0.71	0.68
FIVAR3L	dy slope in delta	0.60	0.50	0.48	0.53	0.58	0.57	0.56	0.55	0.51	0.50	0.49	0.51
MDS	median dist, slope	0.54	0.49	0.45	0.53	0.53	0.51	0.51	0.52	0.49	0.47	0.46	0.45
MDIS	median dist, iqr,slope	0.60	0.54	0.49	0.57	0.58	0.55	0.51	0.52	0.47	0.44	0.45	0.44
FF	Fama French factors	0.55	0.53	0.52	0.58	0.55	0.52	0.52	0.51	0.48	0.45	0.44	0.44
C&I	C&I Loans	0.49	0.47	0.46	0.53	0.53	0.53	0.53	0.54	0.51	0.48	0.47	0.46
BL	Bank loans	0.57	0.54	0.49	0.56	0.60	0.61	0.60	0.62	0.61	0.57	0.56	0.51
	minimum	*0.49*	*0.47*	*0.45*	*0.53*	*0.53*	*0.51*	*0.50*	*0.49*	*0.47*	*0.44*	*0.44*	*0.44*
	gain/loss over unco	*0.07*	*0.05*	*0.05*	*0.13*	*0.13*	*0.11*	*0.10*	*0.07*	*0.05*	*0.02*	*0.01*	*0.00*
	% gap	*17.1*	*13.2*	*11.6*	*32.2*	*33.1*	*28.0*	*25.4*	*18.0*	*12.9*	*4.9*	*1.6*	*1.1*
	Panel B: estimation up to *t*-1, forecasts conditional on time *t* and *t*+1 information												
FIVAR1C	var slope coint.	0.81	0.80	0.89	0.93	1.08	1.15	1.11	1.11	1.10	1.12	1.14	1.04
FIVAR1L	var slope in level	1.00	0.58	0.62	0.62	0.66	0.60	0.59	0.54	0.55	0.55	0.59	0.64
FIVARD	var slope in delta	0.61	0.60	0.59	0.59	0.58	0.53	0.52	0.54	0.50	0.51	0.46	0.45
FIVAR2C	sm slope coint.	0.96	0.62	0.65	0.58	0.59	0.53	0.53	0.50	0.44	0.48	0.44	0.46
FIVAR2L	sm slope in level	1.33	0.81	0.92	0.90	0.78	0.79	0.85	0.83	0.85	0.83	0.78	0.80
FIVAR2D	sm slope in delta	0.52	0.48	0.53	0.60	0.59	0.55	0.55	0.52	0.49	0.48	0.48	0.47
FIVAR3L	dy slope in level	1.09	0.67	0.69	0.88	0.86	0.75	0.80	0.82	0.69	0.77	0.79	0.72
FIVAR3D	dy slope in delta	0.54	0.49	0.54	0.55	0.57	0.56	0.56	0.53	0.50	0.49	0.50	0.52
MDS	median dist, slope	0.54	0.51	0.50	0.54	0.55	0.51	0.51	0.52	0.48	0.47	0.45	0.46
MDIS	median dist, iqr,slope	0.61	0.55	0.56	0.59	0.60	0.54	0.52	0.50	0.47	0.46	0.43	0.44
FF	Fama French factors	0.58	0.54	0.58	0.58	0.56	0.51	0.52	0.50	0.47	0.44	0.43	0.44
C&I	C&I Loans	0.50	0.49	0.50	0.55	0.55	0.53	0.54	0.54	0.50	0.48	0.47	0.46
BL	Bank loans	0.57	0.54	0.53	0.58	0.63	0.61	0.60	0.62	0.59	0.58	0.58	0.49
	minimum	*0.50*	*0.48*	*0.50*	*0.54*	*0.55*	*0.51*	*0.51*	*0.50*	*0.44*	*0.44*	*0.43*	*0.44*
	gain/loss over unco	*0.07*	*0.07*	*0.09*	*0.14*	*0.15*	*0.11*	*0.11*	*0.09*	*0.03*	*0.02*	*0.00*	*0.00*
	% gap	*17.6*	*17.4*	*23.0*	*34.2*	*37.5*	*27.9*	*27.4*	*21.5*	*6.5*	*5.3*	*0.6*	*1.1*

Note: The two panels of the Table show the out-of-sample RMSE for a number of models between 1 and 12 quarters ahead. In Panel A, the forecast are made as of time *t* conditional on the values of the GDP as of time *t* and on the financial variables as of *t*+1. In Panel B, the forecast are made as of time *t*-1 conditional on the values of the GDP as of time *t*-1 and on the financial variables as of *t* and *t*+1. Shaded areas identify classes of models. The RMSE are obtained by estimating the models on expanding windows the first of which starts in 1970Q1 and ends in 1986Q4. One observation at the time is included in the rolling procedure. The last four lines of the Table report the minimum RMSE across all models, the minimum RMSE across all models that include also variables other than just GDP, the relative gap between such two minima and their percentage gap. 'MDS' and 'MDIS' are the models including the slope as well as, respectively, the median and the interquartile range of the distance to default for a set of financial firms (see Carlson et al., 2008), 'C&I' are the U.S. Commercial and Industrial Loans, 'BL' include Commercial and Industrial Loans, Real Estate Loans and Consumer Credit Loans.

Table 5. Out of Sample RMSE

	Forecast horizon	1	2	3	4	5	6	7	8	9	10	11	12
	Panel A: estimation up to *t*, forecasts conditional on month *t*+1/3 information												
FIVAR1C	var slope coint.	0.52	0.50	0.47	0.47	0.45	0.42	0.43	0.45	0.42	0.43	0.44	0.44
FIVAR1L	var slope in level	0.61	0.55	0.55	0.63	0.57	0.61	0.59	0.57	0.54	0.53	0.55	0.59
FIVARD	var slope in delta	0.62	0.53	0.52	0.56	0.55	0.53	0.51	0.52	0.53	0.51	0.51	0.46
FIVAR2C	sm slope coint.	1.07	0.71	0.60	1.02	0.85	0.81	0.83	0.74	0.89	0.53	0.61	0.50
FIVAR2L	sm slope in level	1.60	0.88	0.76	1.90	1.15	1.04	1.12	1.08	1.14	0.96	1.13	0.93
FIVAR2D	sm slope in delta	0.51	0.46	0.47	0.57	0.56	0.54	0.51	0.51	0.47	0.46	0.47	0.47
FIVAR3D	dy slope in level	0.73	0.59	0.61	0.75	0.76	0.76	0.65	0.65	0.62	0.64	0.70	0.68
FIVAR3L	dy slope in delta	0.60	0.52	0.52	0.54	0.57	0.56	0.53	0.52	0.49	0.49	0.49	0.50
MDS	median dist, slope	0.55	0.46	0.47	0.52	0.52	0.51	0.50	0.51	0.48	0.47	0.46	0.45
MDIS	median dist, iqr, slope	0.60	0.50	0.51	0.58	0.56	0.54	0.51	0.51	0.46	0.44	0.45	0.44
FF	Fama French factors	0.60	0.50	0.51	0.58	0.56	0.54	0.51	0.51	0.46	0.44	0.45	0.44
C&I	C&I Loans	0.50	0.46	0.48	0.53	0.52	0.53	0.51	0.52	0.50	0.48	0.47	0.46
BL	Bank loans	0.59	0.51	0.50	0.56	0.60	0.60	0.56	0.59	0.57	0.54	0.53	0.49
	minimum	*0.50*	*0.46*	*0.47*	*0.47*	*0.45*	*0.42*	*0.43*	*0.45*	*0.42*	*0.43*	*0.44*	*0.44*
	gain/loss over unco	*0.08*	*0.05*	*0.06*	*0.07*	*0.05*	*0.02*	*0.03*	*0.03*	*0.00*	*0.01*	*0.01*	*0.01*
	% gap	*18.2*	*11.2*	*14.8*	*17.3*	*12.5*	*5.6*	*8.2*	*8.0*	*1.2*	*2.4*	*3.0*	*2.3*
	Panel B: estimation up to *t*, forecasts conditional on month *t*+2/3 information												
FIVAR1C	var slope coint.	0.50	0.50	0.46	0.48	0.45	0.42	0.43	0.44	0.42	0.43	0.44	0.44
FIVAR1L	var slope level	0.61	0.55	0.56	0.64	0.57	0.61	0.61	0.56	0.55	0.53	0.55	0.59
FIVARD	var slope in delta	0.50	0.50	0.46	0.48	0.45	0.42	0.43	0.44	0.42	0.43	0.44	0.44
FIVAR2C	sm slope coint.	1.07	0.74	0.69	1.05	0.86	0.81	0.84	0.74	0.89	0.53	0.60	0.50
FIVAR2L	sm slope level	1.60	0.93	0.82	1.95	1.17	1.09	1.15	1.09	1.13	0.96	1.12	0.92
FIVAR2D	sm slope in delta	0.50	0.47	0.47	0.56	0.57	0.54	0.53	0.51	0.47	0.47	0.47	0.47
FIVAR3D	dy slope in level	0.71	0.61	0.60	0.75	0.78	0.78	0.67	0.68	0.62	0.67	0.70	0.68
FIVAR3L	dy slope in delta	0.56	0.54	0.51	0.54	0.55	0.56	0.53	0.53	0.49	0.48	0.49	0.51
MDS	median dist, slope	0.52	0.49	0.47	0.52	0.51	0.51	0.50	0.51	0.48	0.46	0.45	0.45
MDIS	median dist, iqr, slope	0.58	0.52	0.51	0.57	0.55	0.54	0.51	0.51	0.46	0.44	0.44	0.44
FF	Fama French factors	0.58	0.52	0.51	0.57	0.55	0.54	0.51	0.51	0.46	0.44	0.44	0.44
C&I	C&I Loans	0.47	0.46	0.46	0.53	0.52	0.53	0.51	0.52	0.50	0.47	0.47	0.46
BL	Bank loans	0.58	0.52	0.48	0.57	0.60	0.59	0.56	0.58	0.57	0.53	0.53	0.49
	minimum	*0.47*	*0.46*	*0.46*	*0.48*	*0.45*	*0.42*	*0.43*	*0.44*	*0.42*	*0.43*	*0.44*	*0.44*
	gain/loss over cond Q	*0.05*	*0.05*	*0.05*	*0.08*	*0.05*	*0.02*	*0.03*	*0.03*	*0.01*	*0.01*	*0.01*	*0.01*
	% gap	*11.9*	*12.5*	*12.7*	*19.5*	*13.7*	*4.7*	*8.0*	*7.0*	*1.7*	*2.8*	*3.1*	*1.7*
	Panel C: estimation up to *t*, forecasts conditional on month *t*+3/3 information												
FIVAR1C	var slope coint.	0.51	0.51	0.44	0.48	0.46	0.42	0.44	0.44	0.43	0.43	0.44	0.44
FIVAR1L	var slope level	0.62	0.56	0.54	0.64	0.57	0.62	0.62	0.57	0.55	0.53	0.55	0.59
FIVARD	var slope in delta	0.59	0.54	0.51	0.56	0.55	0.54	0.53	0.52	0.53	0.52	0.51	0.47
FIVAR2C	sm slope coint.	1.07	0.72	0.70	1.10	0.87	0.82	0.87	0.75	0.90	0.53	0.60	0.51
FIVAR2L	sm slope level	1.58	0.93	0.82	2.01	1.15	1.09	1.18	1.10	1.15	0.94	1.15	0.94
FIVAR2D	sm slope in delta	0.51	0.47	0.46	0.57	0.56	0.54	0.52	0.52	0.48	0.47	0.47	0.47
FIVAR3D	dy slope in level	0.72	0.61	0.60	0.75	0.78	0.80	0.67	0.72	0.63	0.68	0.71	0.68
FIVAR3L	dy slope in delta	0.57	0.53	0.49	0.54	0.55	0.56	0.54	0.54	0.50	0.49	0.49	0.50
MDS	median dist, slope	0.52	0.48	0.44	0.52	0.52	0.51	0.50	0.52	0.49	0.46	0.45	0.45
MDIS	median dist, iqr, slope	0.58	0.53	0.48	0.57	0.56	0.54	0.52	0.52	0.47	0.44	0.45	0.43
FF	Fama French factors	0.58	0.53	0.48	0.57	0.56	0.54	0.52	0.52	0.47	0.44	0.45	0.43
C&I	C&I Loans	0.47	0.45	0.44	0.52	0.53	0.53	0.52	0.54	0.51	0.48	0.47	0.46
BL	Bank loans	0.59	0.50	0.47	0.57	0.60	0.59	0.57	0.60	0.58	0.53	0.53	0.49
	minimum	*0.47*	*0.45*	*0.44*	*0.48*	*0.46*	*0.42*	*0.44*	*0.44*	*0.43*	*0.43*	*0.44*	*0.43*
	gain/loss over cond Q	*0.05*	*0.04*	*0.03*	*0.08*	*0.06*	*0.02*	*0.04*	*0.03*	*0.01*	*0.01*	*0.01*	*0.00*
	% gap	*12.6*	*10.0*	*8.1*	*20.4*	*15.2*	*5.3*	*8.8*	*7.9*	*2.7*	*1.9*	*2.6*	*0.5*

Note: The panels show the RMSE estimated on expanding windows 1 to 12 quarters ahead. The forecasts are made as of time *t* conditional on the values of the GDP as of time *t* and on the financial variables as of, respectively, quarter *t* + 1 month, 2 months and 3 months. Shaded areas identify classes of models. The last lines report the minimum RMSE and the minimum RMSE across models that include financial variables.

Table 6. Conditional Choice Between Models at Selected Horizons

	Conditional GW Test, h=∞			Choices, h=4			Choices, h=8			Choices, h=12		
	RW vs.	BiVarC vs.	TriVarC vs.	RW vs.	BiVarC vs.	TriVarC vs.	RW vs.	BiVarC vs.	TriVarC vs.	RW vs.	BiVarC vs.	TriVarC vs.
BiVarC	0.34			20			9			1		
BiVarL	0.11	0.53		20	4		10	24		16	15	
TriVarC	0.05	0.06		7	6		11	14		3	9	
TriVarL	0.14	0.23	0.18	11	6	31	13	22	26	17	18	19
FiVar1C	0.05	0.07	0.07	6	10	9	13	16	22	6	12	10
FiVar1L	0.12	0.06	0.11	4	12	14	26	26	25	17	18	18
FiVar1D	0.00	0.00	0.00	2	21	21	10	17	15	5	8	6
FiVar2C	0.53	0.16	0.07	3	14	10	2	5	5	2	5	4
FiVar2L	0.36	0.48	1.00	2	4	2	0	2	0	0	0	0
FiVar2D	0.00	0.00	0.00	3	25	29	4	6	3	15	17	18
FiVar3D	0.17	0.48	0.24	3	27	29	22	23	22	20	22	19
MDS	0.11	0.07	0.10	2	28	23	13	21	21	11	19	19
MDIS	0.03	0.09	0.16	2	26	26	17	22	26	9	16	20
FF	0.00	0.00	0.01	2	15	21	12	17	18	20	19	13
C&I	0.01	0.01	0.02	2	13	17	6	11	8	14	21	17
BL	0.46	0.45	0.46	2	10	10	12	16	14	14	16	15
Cases				**38**	**38**	**36**	**30**	**30**	**28**	**24**	**24**	**24**

Note: The first three columns of the Table report the all-sample conditional predictive ability test, proposed by Giacomini and White (2006). In its unconditional version, the test would be equivalent to the Diebold-Mariano (1996) test and is expressed as a *p*-value which in our cases refers to a chi-square with 2 degrees of freedom. For the conditional test reported in this Table, values larger than 0.05 indicate that the model in the first row would not be surpassed by the model in the first column. The other columns, under the headings $h = 4$, $h = 8$ and $h = 12$ show the conditional model choice test, i.e. the number of times that the models listed in the second row of the Table (RW, BiVarC and TriVarC) would have been chosen over the full set of models listed in the first column of the Table, at selected horizons (h = 4, 8 and 12 quarters), according to Giacomini and White's (2006) methodology. The total number of comparisons per model is reported in the last row of the Table. Low values, below half the value in the corresponding cell in the last row of the same column, indicate that the models with financial variables are preferred to the random walk or to the VARs with 2 or 3 GDPs only. 'MDS' and 'MDIS' are the models including the slope as well as, respectively, the median and the interquartile range of the distance to default for a set of financial firms (see Carlson et al., 2008), 'C&I' are the U.S. Commercial and Industrial Loans, 'BL' include Commercial and Industrial Loans, Real Estate Loans and Consumer Credit Loans.