The Role of Financial Variables in Predicting Economic Activity

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Abstract

This paper should not be reported as representing the views of the IMF, the ECB or the Eurosystem.

Previous research has noticed that the US business cycle leads the European cycle by a few quarters, and can therefore a useful conditioning information in predicting euro area GDP. In this paper we investigate whether additional predictive power beyond that provided by lagged GDPs may arise from selected financial variables belonging to either the US or the euro area. We use vector autoregressions (VARs) which include the US 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. In-sample analysis based on impulse response functions shows that shocks to financial variables influence real activity with a peak around 4 to 6 quarters after the shock. Out-of-sample RMFE evidence that adding financial variables produces a smaller error in forecasting US economic activity, especially at a five-quarter horizon, although the magnitude of this gain declines thereafter. This already weak macro-financial linkage is even less prominent in the euro area, where financial indicators do not improve short and medium term GDP forecasts even when their timely availability relative to GDP, is exploited. As the euro area GDP lags behind the US GDP, and the prediction of the US GDP at some horizons can be improved by considering financial variables, then it can be conjectured that neither US nor European financial variables affect euro area GDP as the US GDP has already embodied this information. The same conclusion is reached when one employs quarterly industrial production indices. By contrast, looking at monthly industrial production figures, the predictive ability improves significantly, as almost all models including financial variables fare better than model considering only past economic activity. Overall, however, the gain is rather limited and always lower than 5% of the RMSE made by the autoregressive models. The finding that financial variables have no predictive power for future activity in the euro area also relates to the unconditional nature of the RMFE metric. When forecasting ability is assessed *as if* in real time (i.e. conditionally on the information available at the time when forecasts are made), we find that models using financial variables would have been preferred in several episodes and in particular between 1999 and 2002. Results from the historical decomposition of a VAR model indeed suggest that in that period shocks were predominantly of financial nature.

JEL Classification Numbers: F30, F42, F47

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Non-Technical Summary

Real developments in the US have systematically anticipated those in the euro area, a linkage that has been fruitfully exploited for forecasting purposes. In this paper we investigate whether financial variables have any role in explaining this stylized fact.

There are at least two potential explanations which could account for an active role of financial markets in anticipating business cycles developments. First, tighter financial and credit conditions limit the potential for firms' activity to expand and for households to consume during harsh times. Second, asset prices capture expected firms' profitability, which is linked to the future rate of growth of the economy, an argument associated with the branch of the literature analyzing the usefulness of financial data in forecasting GDP cycles.

To check whether financial variables helps tracking the observed real developments in the US and in the euro area as well as the linkages between these two areas, we consider Vector Autoregressive models and we look at both in-sample and out-of-sample evidence. In the former, we find evidence of a relation between financial variables and real activity both domestically and internationally, a relation that has become stronger after 1985. 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, 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, in real time forecasting, the values of financial variables are known well-ahead of the release of GDP estimates).

When looking at 'unconditional' forecasts, we find that in the United States financial variables provide non-negligible information for future activity. The picture is however different for the euro area, where adding various combinations of the financial variables leads to a worsening in the out-of-sample performance. Conditioning the forecasts on the financial data next 1 or 2 periods does not change this conclusion.

However, this result may conceal periods during which financial variables did play a significant role. We investigate this by means of appropriate econometric tests, designed to identify periods, as opposed to the full sample evidence, in which models that include financial data would be preferred over simpler models. Our results show that the information content provided by financial variables would have improved the forecast for the euro area GDP between 1999 and 2002, although with a rather wide dispersion across models. Indeed, the historical decomposition suggests that in that period financial shocks had a prominent role. In general, one could hypothesize that system-wide financial shocks do not occur very frequently and therefore their predictive power can be rather marginal when evaluated on a large out-of-sample period. Alternatively one could think that financial prices affect real activity in a nonlinear way, a channel of transmission which is blurred within a linear framework.

I. INTRODUCTION[1]

Large bank losses and financial turbulences have been the last consequences of the subprime mortgages crisis that erupted in the United States around July 2007 and which took around two years to show the first signs of cooling off. The financial turmoil, together with the occurrence of a global recession, contributed to revive the debate on the intensity of macro-financial linkages and the associated role of financial factors as amplifiers of the international transmission of real shocks. The traditional analysis of the transmission of shocks views the trade channel as the main source of spillovers: a slowdown in the US 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, US 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 US business cycles by a few quarters could therefore be hardly justified on account of rather limited trade openness.

Several explanations have been put forward to rationalize the importance of the US-euro area common cycle (e.g. Giannone and Reichlin, 2004, Giannone et al., 2008, and Favero and Giavazzi, 2008). First, the bilateral US-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 economically significant. 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] Dees, di Mauro, Smith and Pesaran (2005) show indeed, using a Global VAR model, that a 4% fall in US real equity prices not only reduces US output by -0.4% within a year, but also depresses European financial markets by around 4% and euro area GDP growth by 0.4% 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

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[1] This paper has been presented at the conference "International Linkages" hosted by the Asian Development Bank Institute (Tokyo, October 2008), at the FESAMES meeting of the Econometric Society (Tokyo, August 2009), as well as at seminars at the IMF European Department in December 2008 and at the IMF Strategy Policy Review and Western Hemisphere Department in February 2009. We received very useful input from an anonimous referee, Tamin Bayoumi, Domenico Giannone, Michele Lenza, Bin Li, Filippo di Mauro, Martin Mühleisen, Huw Pill and Lucrezia Reichlin as well as discussants at these seminars. Comments by Song-cho Young are gratefully acknowledged. The views expressed in the paper belong to the authors only and should not be attributed to either the IMF, 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.

typically swamp the impact on growth played by the trade channel or the commodity price channel.

There are at least two potential explanations which could account for an active role of financial markets in anticipating 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, 2008, and 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 difficult task.

A second explanation is somehow less structural and underlies a less active role: 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 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 tool that we will be employing throughout the paper is a VAR including economic activity and combinations of selected financial market indicators; given that we use only very basic identification assumptions, this instrument does not offer the possibility to ascertain if, the predictive power of financial variables, if any, comes from their 'forward-looking role' or instead from a more active role in affecting economic activity, including influence on wealth effects, credit availability, investment decisions, risk aversion.

Overall, the literature evidences a lack of clear-cut results about the role of financial variables in forecasting economic activity. To some extent, this may also relate to the variety of indicators available and hence to an inherent difficulty in picking the most favorable combination. 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, the so-called Fama-French factors – can help predict future US 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 to the aim of predicting real activity. Guichard et al. (2009) look at how the variables included in a financial conditions index for the United States, the euro area, Japan and the United Kingdom are able to affect GDP. These variables, i.e. short and long term real interest rates, bond spreads, stock market capitalization, credit standards and the real effective exchange rate are inserted in a VAR together with GDP, core inflation and the underlying fiscal deficit. They show that some of the variables included in the index do affect GDP over a 4 to 6 quarters horizon, although their results refer to an in-sample analysis and provide therefore no indication about out-of-sample predictability.

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 the channel driven by 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 US 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 in a number of industrial countries took place within 6 quarters after turbulence in the banking sector. These episodes were sharper the more leveraged were households and firms – although results are not supported by a formal out-of-sample assessment. Among the papers listed so far, those with empirical applications tend to focus mainly on the United States and only relatively few studies have concentrated on the euro area; a recent 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.

Taking a different avenue, Junttila (2007) looks at the predictive power of Economic Tracking Portfolios (ETP), a weighted average of asset returns chosen with the aim of maximizing their correlation with economic activity. Using monthly data for industrial production in a number of countries and a rolling estimation based on windows of 60 months, the author shows that the RMSE made in forecasting economic activity through ETP as well as term spreads and dividend yields is much lower than the corresponding figure obtained when a VAR including industrial production, inflation and the short rate is employed. However, as these encouraging results supporting a predictive role of financial indicators for economic activity are referred to the industrial production index sampled at a monthly frequency, it is difficult to single out whether the additional predictability – relative to what can be achieved with GDP – stems from the different measure of economic growth of from the different sample frequency. Also the sample period over which the analysis is conducted (1982-2001 in Junttila against 1970-2007 in our paper) could play a role, as also could the window upon which the out-of-sample results are based (60 months against 48 months in our paper).

Our analysis looks at growth prediction in both the United States and the euro area and the variables we use are mainly price-related, although we also consider some different (quantity-based and risk-based) indicators. Also, we explicitly consider the international environment of the euro area. Specifically, we estimate a number of VAR models, constructed around the GDPs of 2 or 3 economic areas (US, euro area and a seven-country aggregate called Rest of the World) and extended to include selected financial variables and look at their performance in predicting real activity. The main aim is to understand whether considering financial variables helps improving the forecasts of economic activity with respect to forecasts produced by only looking at past activity levels. Among financial variables we give a prominent role to the slope of the yield curve, the short term rate, the stock market return and its time-varying volatility, the dividend yield of the stock market. We focus attention on these indicators as all of them have been already employed to forecast economic activity. It has to be pointed out, however, that their role can be significantly changing through time especially for the presence of risk premiums which can lead asset prices to deviate from fundamentals, weakening their linkages with subsequent changes in such fundamentals. As an example, while rising equity prices should signal economic expansions ahead, they could actually lead to an economic slowdown if the rise in equity – being unrelated to fundamentals – is suddenly reversed and induces significantly negative wealth effects. The IT-bubble between 1995 and 2000 can represent an example of this reasoning. To further control for the robustness of our results we also look at some non-price information (bank claims, financial firms' distance-to-default), indicators of fragility of the banking sector, as measured by the US Ted spread or the commercial paper less the Treasury bill rate spread, indicators of industrial firms' fragility, as proxied by the differential between the yield on 10-year bonds issued by industrial US firms rated Baa and the corresponding 10-year US Government bond yield, 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) or refer only to the stocks of listed banks. Other potentially interesting financial series cannot be included in the analysis due to i) the long sample period over which we focus (1970-2007) and ii) the possibility of recovering the same indicators for our Rest of the World aggregate. In addition, for additional robustness and especially to address the evidence favoring the predictive power of financial indicators documented in Junttila (2007), we repeat the estimation and the out-of-sample predictability analysis for some of the previous models after replacing GDP with industrial production and considering both the quarterly and the monthly frequency.

We look at both in-sample and out-of-sample evidence. In the former, we find that impulse responses support the existence of a relation 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 US shocks as well as by '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 counterfactual GDP values which are much closer to the actual GDP figures relative to the case when no financial variables are considered. 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 estimating the VAR models up to time t as well as several types of 'conditional' forecasts in which 'future' values (next 1 or 2 quarters after time t) of financial variables are assumed to be known, while parameters are still referred to the VAR estimation up to time t or t-1 (and indeed, in real time forecasting, the values of financial variables are known well-ahead of the release of time-t GDP estimates).

When looking at ‘unconditional’ forecasts, we find that in the United States financial variables provide non negligible information for future activity, especially 5 quarters ahead, while their contribution declines thereafter, although it remains a positive one. The picture is however different for the euro area: here a model which includes the GDPs of the two or three economic areas achieves the best performance in terms of forecast Root Mean Square Error (RMSE) across the eight VAR models considered. 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 knowing next period financial data does not change this conclusion. Also considering the quarterly values of the industrial production index instead of the GDP, as in Junttila (2007), does not lead to significant changes in the conclusion that financial variables lack significant predictive power for future economic activity, both for the United States and the euro area. By contrast, financial variables do help forecasting monthly industrial production over a number of horizons, relative to models considering only previous values of the industrial production indices themselves. This gain, however, is overall rather modest, less than 5% of the RMSE recorded by such autoregressive models.

The lack of influence of financial variables for activity found in the euro area is not so neat, however, when one uses 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 preferred over 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. 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 very frequently and therefore their predictive power can be rather marginal when evaluated on a large out-of-sample period. Also, the linear VAR model can be rather unstable therefore failing to detect significant linkages in an out-of-sample exercise. It would be for this reason that the rolling estimation required by the GW test is able to individuate significant relationships between financial conditions and economic activity. 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. All in all, the somewhat conflicting evidence between the RMSE of a linear VAR and the GW tests suggests that the relationships between financial variables and economic activity are rather changing through time. However, this time variation occurs in a rather predictable fashion, an information that while missed within the VAR, can be instead efficiently exploited by ad-hoc tests to find some support for the idea that financial indicators play some effects on real growth.

II. THE VAR MODELS

A. Data

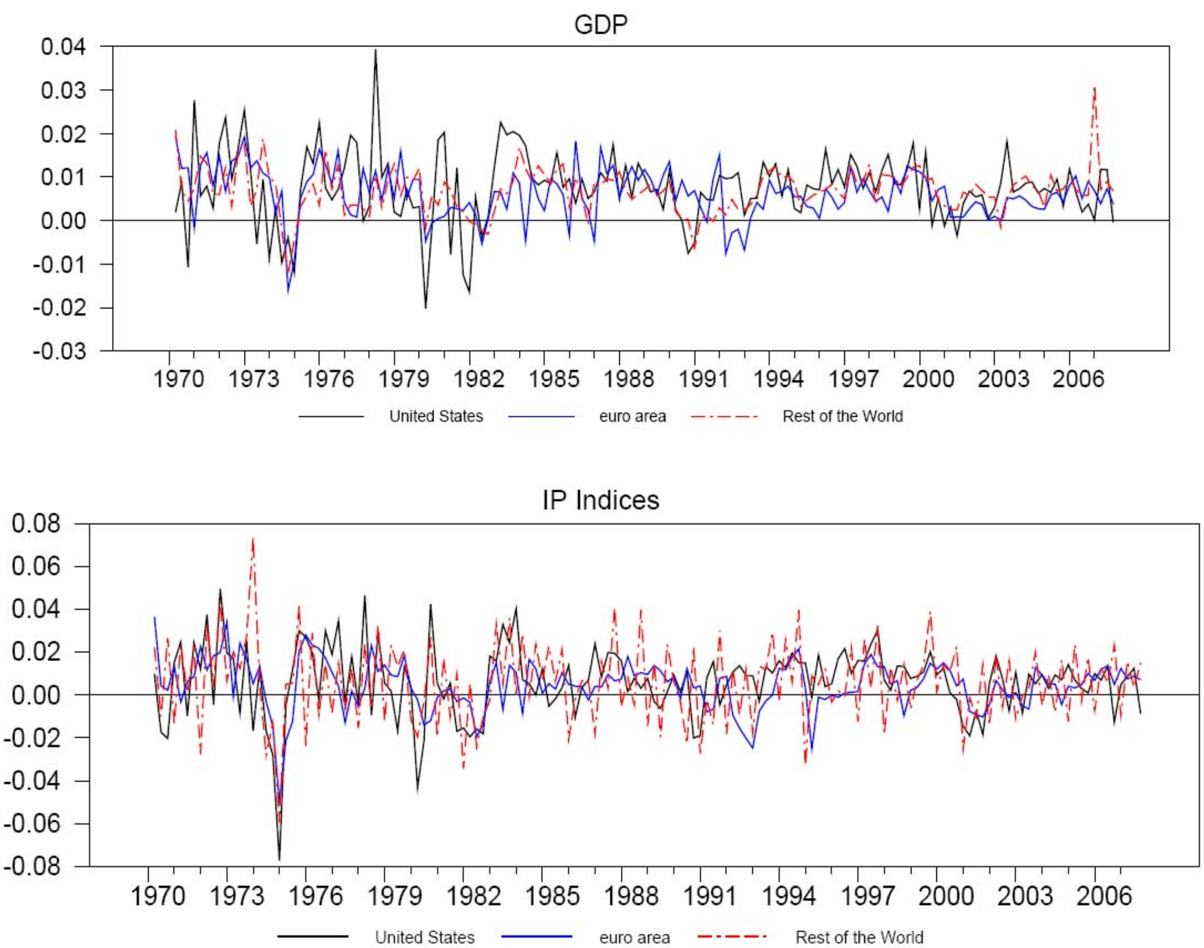
Our measure of real activity in the three economic areas (US, euro area, and Rest of the World) is the seasonally adjusted quarterly real GDP observed between the first quarter of 1970 (1970q1) and the last quarter of 2007 (2007q4). The Rest of the World is an aggregation of seven countries (Australia, Canada, Denmark, Norway, New Zealand, Sweden and Switzerland) that were chosen to represent economies different enough that a shock affecting all of them can indeed 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 US dollars – the results were similar with un-weighted averages). For robustness, we also consider the measures of economic activity provided by the industrial production (IP) index. In this case, we use both the German IP index, when dealing with monthly data, as well as a synthetic euro area index built at a quarterly frequency as a weighted average of the industrial production indices in Germany, France, Italy, Spain, Belgium and the Netherlands. The three GDPs are reported in the top panel of Figure 1 below and, notwithstanding the higher noise of quarterly GDP growth rate relative to annual growth rates, evidence both the commonality in regional business cycles and episodes of clear anticipation of the United States (e.g. the US leads the euro area after its 1990 recession episode). The industrial production indices are in the lower panel of the Figure and despite still higher volatility relative to GDPs overall evidence similar relative developments over time across the three areas.

The cross-correlogram between the rates of change in the United States and the euro area GDP provides a first hint of the amount of linkages across economic areas. Panel I in Figure 2 shows the cross-correlogram across two sub-samples as well as across the full sample. The chart for the 1970-2008 period evidences a strong and prolonged positive spillover of the US GDP on the euro area GDP from quarter t-4 to quarter t-1, in addition to the presence of well-expected synchronous movements at lag zero. The pattern is consistent across sub-samples, although the 1980-2008 period evidences some further spillovers with a peak at quarter t-7 and some negative effect of the euro area on the US GDP at quarter t+5. The size of the latter, however, is not such to make it overwhelmingly significant. The cross-correlogram based on the IP indices provides overall the same message. Some spikes in the IP-based cross-correlogram take place at different leads or lags relative to evidence based on GDPs, also possibly as IP indices refer to the last month of the quarter and have therefore a slightly different information content than quarterly GDP. Panel II reports instead the same cross-correlations calculated on the residuals of a regression of the US and the euro area GDP growth rates on the first four lags of the Rest of the World GDP growth rates. This regression is intended to provide, for illustrative purposes, a measure of the amount of spillovers which is

[3] The euro area GDP series is obtained from the Euro Area Wide Model (see Fagan et al., 2001), the US GDP from the BEA national accounts while the GDP 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 US dollars. All financial data come from the Global Financial Indicators database.

driven by common shocks. Overall, the presence of the rest of the world does not remove the linkage between the US and the euro area GDP in the 1985-2008 period, although it pushed it somewhat more backwards in time than 3 quarters. Also, some stronger spillover between the two areas at the 1-quarter period seems to emerge. Looking at the IP-based cross-correlograms, some different features relative to what suggested by GDPs seem to emerge when the US and the euro area IP indices are first regressed on the Rest of the World IP. This possibly suggests that the estimation of a monthly model could be provide different results relative to a quarterly one.

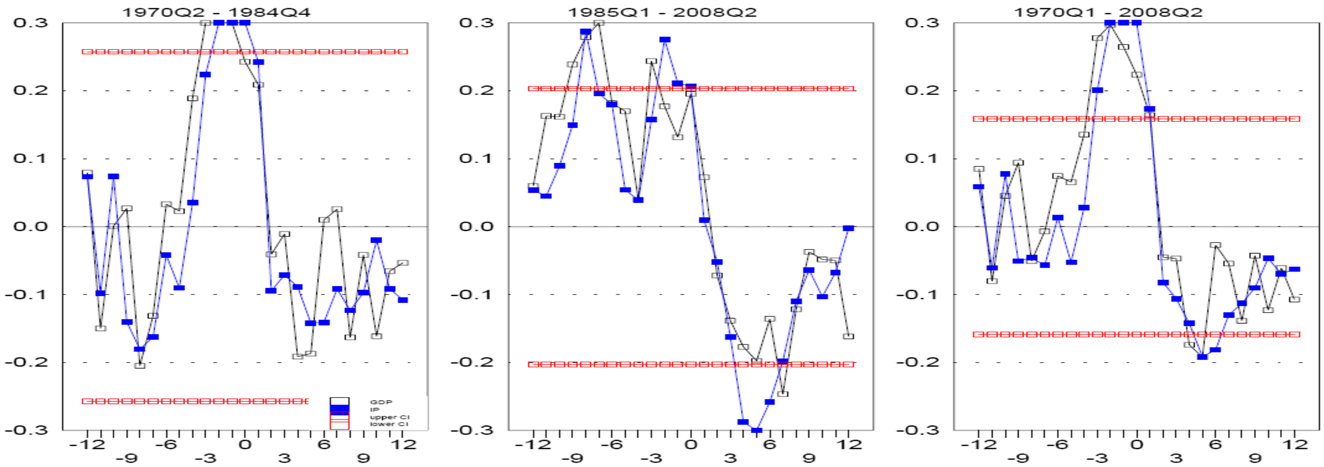
Figure 1. Growth in the three economic areas (q/o/q figures)



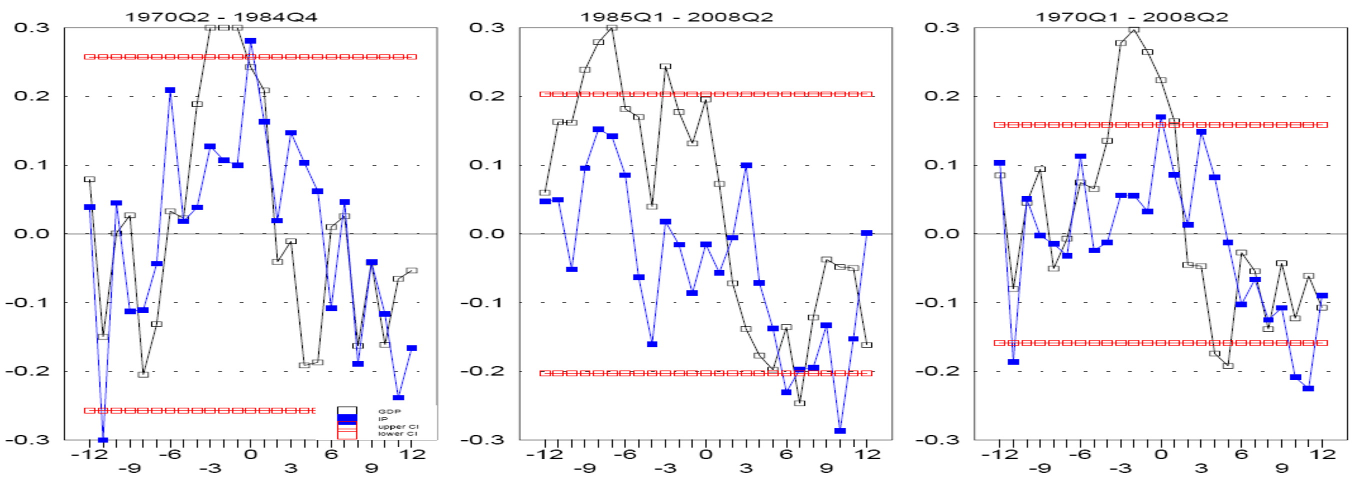
Note: The rest of the world GDP and Industrial production are aggregates based on seven small open economies, see Section II. A for details..

Figure 2. Cross-correlogram of US and euro area GDP and IP indices, across sub-samples

Panel I



Panel II



Note: The Chart shows cross-correlograms between the rates of growth of the US and the euro area GDP across two sub-samples, 1970-1984 and 1985-2008, and the full period 1970Q2-2008Q2. Panel I shows the cross correlogram between the raw rates of change of the two GDPs. Panel II shows instead the cross correlogram of the residuals of a regression of each GDP growth rates on a constant and the first four lags of the growth rates in the Rest of the World GDP. Negative numbers on the x-axis identify cross correlations between lagged US GDP and current euro area GDP. The horizontal lines are standard errors computed via Bartlett approximation, assuming no time series dependency in the data, as $1/T^{0.5}$, where T are the observations employed in the calculation of the cross correlogram, and represent therefore an approximation to the true standard error.

Coming to financial variables, 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] With reference for the US only we also collect the 3-month commercial paper yield as well as the 3-month Eurodollar rate, which we use to create indicators of tensions in the banking sector, by considering their difference relative to the 3-month T-bill rate. 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.[5] For each country, all the financial variables have also been collected at a monthly frequency, between March 1970 and March 2008.[6] These monthly financial variables are used primarily to assess the information content of financial data at an intra-quarter level. To check for the robustness of our results we also collect additional variables which are described in Section IV.C. Last, 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.[7] 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.[8] Based on the trace statistic (Johansen, 1988) we find evidence of at most one cointegrating vector among

[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] For a robustness check we also used a euro area slope obtained as a difference between a 'synthetic euro' 10-year and 2-year government bond yield, calculated from Global Financial Data (Moneta 2005). Results, available upon request, did not change substantially.

[6] 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.

[7] 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 ofthe 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 12-24 months so that the choice of a short lag would automatically limit the measured predictability.

[8] 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.

the three economic areas. The specifications in level are mainly aimed at checking whether imposing cointegrating restrictions actually improves or worsens forecasting ability. 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:

$$Y_t = A_0 + A_1 * Y_{t-1} + A_1 * Y_{t-2} + A_3 * Y_{t-3} + A_4 * Y_{t-4} + C * [\lambda * y_{t-1}] + \varepsilon_t$$

where the vector of endogenous variables Y is partitioned into two subsets as $Y = \left[y \quad fin\right]'$ where *y* is a vector that includes the logarithm of the GDPs and *fin* is a vector that collects two financial variables 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 a minimum of 2×1 to a maximum of 10×1) normally distributed with covariance matrix Σ.[9] The models estimated can be classified as follows:

1. A 2-country model of the US 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 US, 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 ($FiVAR_{3D}$).

In addition to these 6 classes of models and mainly to the aims of robustness, we also consider:

- Two quarterly models including the GDP as before but considering i) the more direct banking crisis indicator represented by the commercial paper – Treasury bill rate differential (the eurodeposit rate – Treasury bill rate differential was not employed for its high correlation with the commercial paper based spread), indicator or fragility of industrial US firms, as measured by the Baa-rated – Treasury bond yield differential, and the yield curve slope; ii) developments in the banks' equity index relative to the broad stock market index in both the United States and the euro area as well as the

[9] The matrices A_0, …, A_4,, 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. The VAR with 4 lags in levels can be always re-written as a VAR with 3 lags in first differences.

yield curve slope.

- Two quarterly models including the IP indices as well as i) the stock market volatility and the slope for the three areas and ii) the stock market index and the slope for the three areas;
- Two monthly models including the US and German IP indices, the latter as a proxy for the euro area, as well as i) the stock market volatility and the slope for the two areas and ii) the stock market index and the slope for the two areas.

III. Characterizing the Models

We assess in this section whether the dynamic relationships among the variables are in accordance with 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 already accounted for by the real variables. This type of identification, which remains a Choleski-type identification 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 US 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 3 and 4 show the orthogonalized Impulse Response Functions (IRFs) coming from the model which includes the three GDP (model 2, with the following causal ordering: euro area, ROW, US) 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.

In addition, the impulse responses confirm the findings of the literature that the US GDP adjusts faster to shocks, and thereby leads other economic areas (see Giannone et al., 2008). We find some spillovers between the US and the rest of the world whereas US - euro area

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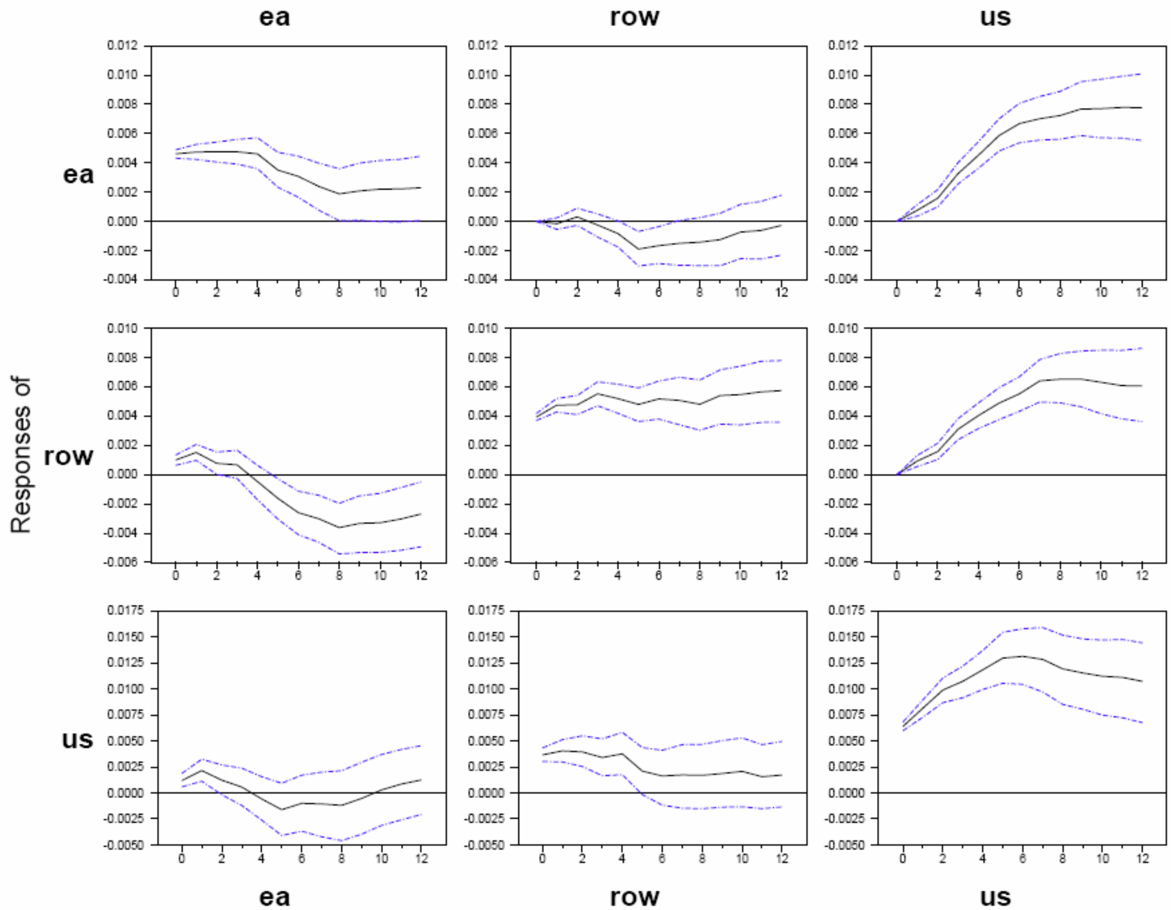
[10] As we estimate reduced form VARs, we need to place restrictions on the A matrix and on the polynomial matrix $B(L)$ in the 'corresponding' structural VAR $y_t = A^{-1}B(L)y_{t-1} + A^{-1}u_t = A^{-1}B(L)y_{t-1} + v_t$, where $v_t = A^{-1}u_t$ are uncorrelated and orthogonal structural shocks with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

spillovers are one-way only – coming from the US.[11] The orthogonalized IRFs from model 3 (Figure 4) 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 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 functions from a trivariate VAR



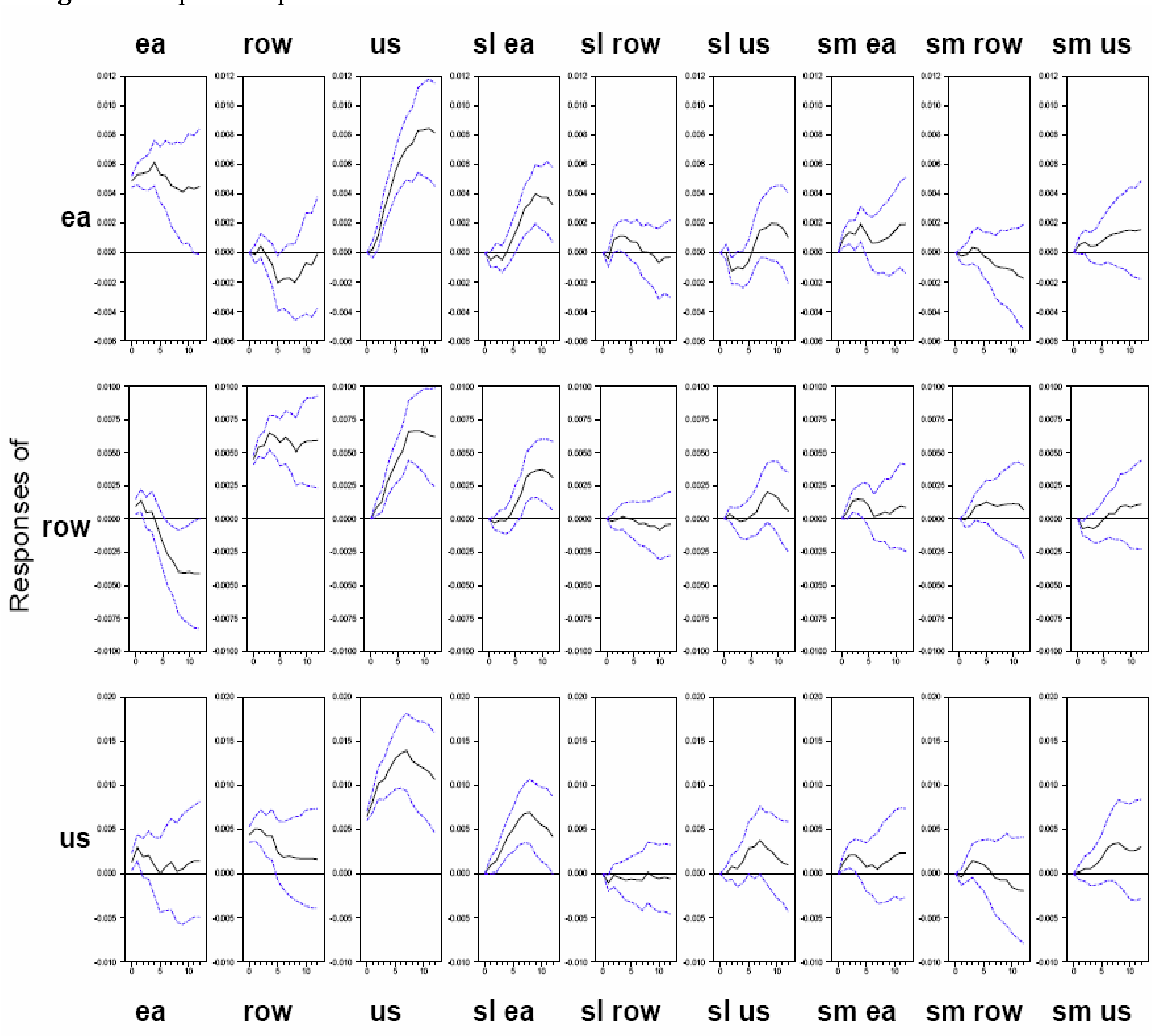
Note: The Chart reports the impulse response functions (solid black lines) and the associated 68% confidence bands (dotted blue lines) from a VAR including the GDP of the United States, the euro area and the rest of the world. The lines indicate the responses of the variables listed in the rows to a 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 with four lags and all the variables are expressed in log-levels.

Hence, the IRFs point at the presence of some influence of financial variables in affecting real cycles, a result previously reported in the literature, e.g. in Bayoumi and Swiston (2007) and

[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.

Dees et al. (2007). The latter authors, in particular, find that a 8% increase in the US 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 US 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.

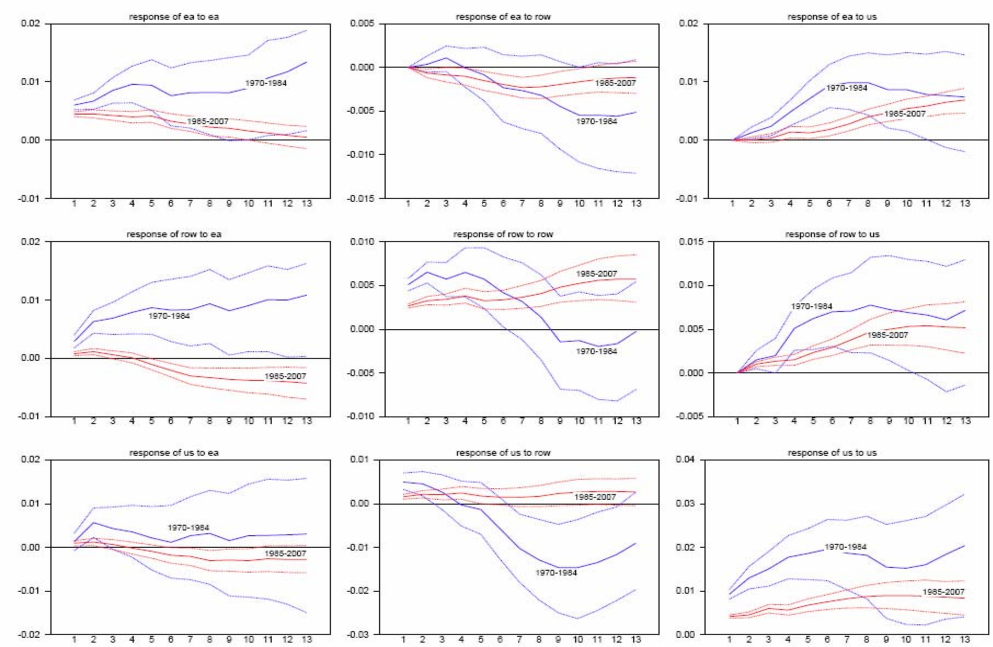
Figure 4. Impulse response function from a 9-variable VAR



Note: The Chart reports the impulse response functions (black lines) and the associated 68% confidence bands (dotted blue lines) from a VAR including the GDP of the United States (us), euro area (ea) and rest of the world (row), 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 with four lags and all the variables are expressed in levels (in log-levels as concerns GDPs).

The Great Moderation period has witnessed a significant drop in US 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. Our VAR models allow us to investigate whether international spillovers have changed before and after the breakpoint that the literature has tended to identify wih 1985 (Dees and Saint-Guilhem, 2008, look at the issue in the context of a Global VAR). To this aim. We re-estimate model 2 (3 GDPs) and model 3 (3 GDPs with slope of the yield curve and stock market volatility) on the sub-samples 1970-1984 and 1985-2007 – see Figure 5.[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 US 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 US 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.

Figure 5. Impulse response function to GDP shocks across sub-samples



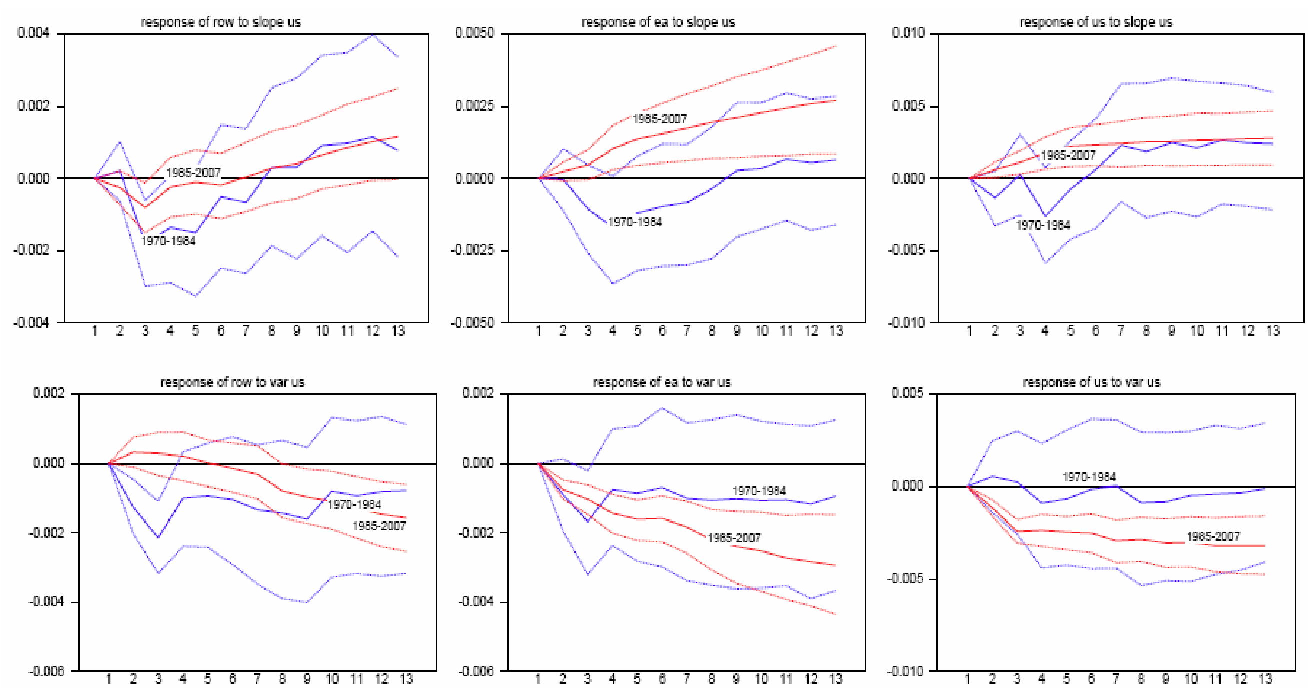
Note: The Chart reports the impulse response functions and the associated 68% confidence bands from a VAR including the GDP of the United States, euro area and rest of the world. The lines indicate the responses of the variables listed in the rows to a shock in the variables listed in the columns. The x-axis records the quarters elapsed after the shock. The blue lines identify the period 1970-1984, the red lines the period 1985-2007. The VAR is estimated between 1970Q1 and 2007Q4 with four lags and all the variables are expressed in log-levels

[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.

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 6). 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 US slope). The IRF of the Rest of the world GDP to a shock in the US 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 6 highlights that the US stock market volatility - perhaps providing a good proxy for business or consumer confidence (see the arguments in 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 US 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.

Figure 6. 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 US slope of the yield curve (slope us) and the volatility of the US stock market index (var us). The x-axis records the quarters elapsed after the shock. The VAR is estimated across two sub-samples, from 1970Q1 to 1984Q4 (blue lines) and from 1985Q1 to 2007Q4 (red lines), has four lags in both periods and the variables are included in levels (in log-levels as GDP are concerned).

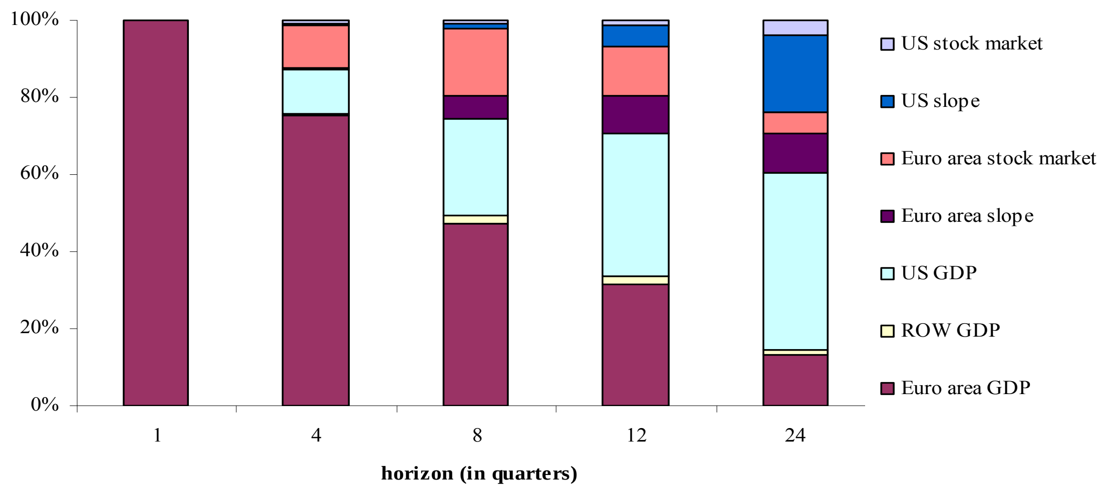
B. Linkages and the role of financial shocks

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 US and euro area slope and stock market index, and is computed at the 1-, 4-, 8-, 12- and 24-quarter horizons. The US GDP and slope (Figure 7) 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 US 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 GDPs, we fix to zero the coefficients of the euro area and the rest of the world lags in the US 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 placing 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 US 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 US 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.

[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 $\Sigma_{s=0}^{K-1} \Sigma_{i=1}^{N} \Phi_s G e(i) e(i) G \Phi_s' = \Sigma_{i=1}^{N} \Sigma_{s=0}^{K-1} \Phi_s G e(i) e(i) G \Phi_s'$ 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.

Figure 7. Forecast error variance decomposition for the euro area GDP



Note: The VAR includes the 3 GDPs as well as the US and the euro area slope and stock market. All variables are inserted in the VAR in levels (in log-levels as GDP are concerned).

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 seem to have also some influence. The historical decomposition (see figure 8 below)[14] confirms that the role of euro area financial shocks is limited, either because these shocks do not occur frequently enough or because they have a small impact on activity.

More specifically, the historical decomposition is consistent with a simple picture of the euro area history: the 1974 recession was worsened by negative US and Rest of the World cycles. Growth was hurt in the early 80s by restrictive monetary policy, especially in the US. 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.

Figure 8 shows the log-differences of the euro area GDP together with the revisions, with respect to the baseline forecast (not reported) coming from each of the other five variables included in the VAR. Shocks attributed to the US stock market did not play a major role throughout the US 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

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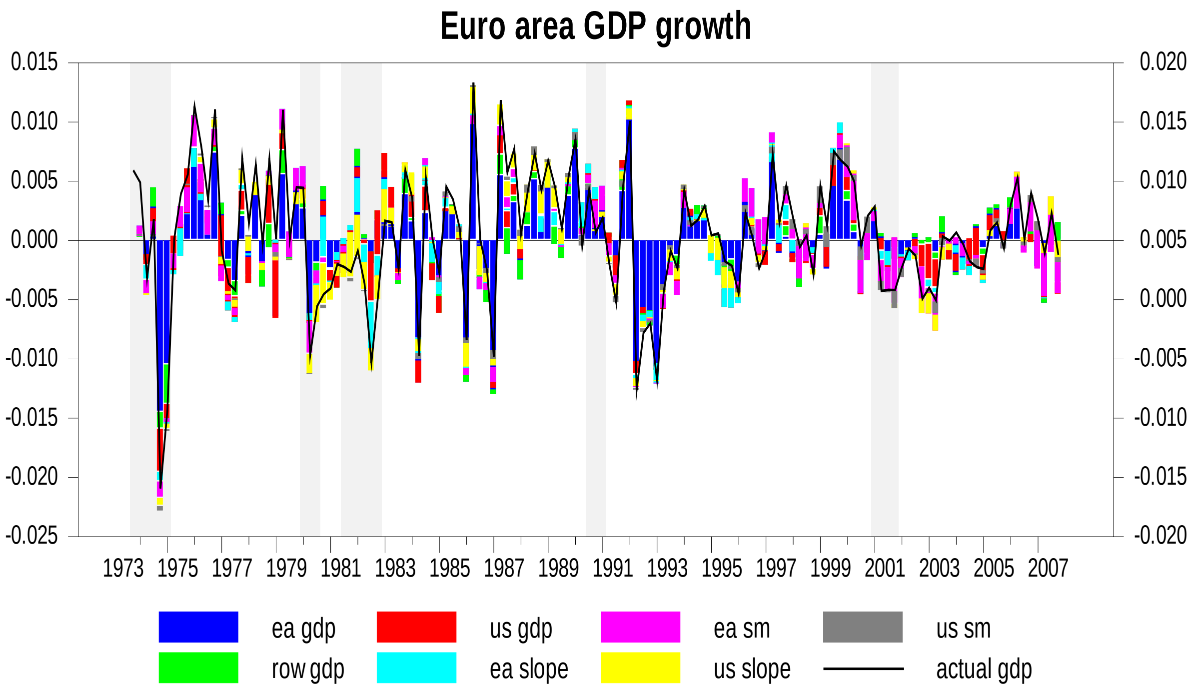
[14] The historical decomposition of the variance decompose a time series in a projection and the accumulated effects of current and past innovations, basically $y_{T+j} = \Sigma_{s=0}^{j-1} \Phi_s u_{T+j-s} + X_{T+j} \cdot \beta + \Sigma_{s=j}^{\infty} \Phi_s u_{T+j-s}$ with the first sum being the part due to innovations from T+1 to T+j and the second being the forecast of y_{T+j} based on information available as of time T. The decomposition does not depend on any Choleski orthogonalization. We base the historical decomposition on a VAR where the 3 GDPs are complemented by the US and euro area stock market indexes and slopes.

particularly sizeable between 1979 and 1983, but has since then played a rather marginal role. The same story holds for the US 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 incompatible with each other.

Figure 8. Historical decomposition



Note: Shaded areas correspond to US recessions identified by the NBER. The decomposition comes from a VAR including the US, euro area and rest of the world GDP and the US and euro area slopes of the yield curve (ea slope, us slope) as well as the euro area and the US stock markets (ea sm and us sm), The model is estimated between 1970Q1 and 2007Q4 with four lags and all the variables are considered in levels (in log-levels as the GDP are concerned). The actual GDP (black solid line) is reported on the right hand side scale. All remaining histograms refer to the left hand side scale.

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 an 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 3a and 3b shows the 'unconditional predictive ability' RMSE (i.e. the RMSE for euro area 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.

Starting from the euro area (Table 3a) highlights that, with the exception of the 1-step-ahead forecast, over 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 co-movements 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.

Beyond the RMSE, also the Diebold and Mariano (1995) tests suggests that financial variables provide no help in forecasting real activity. The Diebold – Mariano tests are reported in Table 6 for both the US and the euro area GDP and are obtained as the t-ratio on the coefficient of a regression of the difference between the absolute values of the forecast errors (for euro area GDP) from competing models on the constant itself. Entries in the Table larger than 1.64 indicate that the model in the second row of the Table is not overperformed by the model in the first column. All of the GDP forecasts upon which the tests are based rest on the parameters estimated on the full-sample and are therefore unconditional in a broader sense than implied by the RMSE, which was based on expanding window estimates. By using parameters based on a full-sample estimation in the construction of the Diebold – Mariano test

[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.

we wish to control for parameter uncertainty, which should be mitigated in the larger 1970-2007 period. The random walk model has been eliminated from these comparisons as, unconditionally, we would have had the same GDP forecast for all the sample period (the average GDP growth rate) and we checked only the performance of the BiVarC and the TriVarC models relative to all of the remaining models at three horizons, 4, 8 and 12 quarters. In no comparisons the VAR which include financial variables would have been preferred to the BiVarC and the TriVarC at forecast horizons of 4 and 8 quarters, while in most cases at the 12-quarter ahead horizon the test would be indifferent between models with and without financial variables. For the US GDP there is a much higher proportion of comparisons between pairs of models for which the test finds no major differences in predictive ability.

When one looks at RMSE for the US GDP (cf. Table 3b), the picture is slightly different from the euro area in two main respects. On the first hand, the RMSE is higher for the US GDP than for the euro area GDP, by around 20% on average (from around 4 to around 5). This of course reflects the fact that US GDP is first in the causal link, as evidenced by the counterfactual calculations in Table 2, and is as a consequence more difficult to predict than the other variables. By contrast, once US GDP is known, the euro area GDP is easier to predict. On the other hand, the difference in RMSE between models that only look at past GDP and models that look at past GDP as well as financial variables is basically nil after the 4-quarter horizon, unlike what seen for the euro area, where at horizons below 8 the RMSE coming from this second class of models remained as high as 15-20% with respect to the RMSE attained by the first class of models.

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 surveys 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 et al. (2005) analyze the information content of around 200 macroeconomic releases for the US 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+1and GDP as of time t.[17]

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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.

The results are presented in Table 4a and 4b, panels I and II. 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 the RMSE that they produce is lower than the RMSE coming from unconditional forecasts, i.e. if information dated *t* and *t*+1 is richer than information dated *t* only.

In the case of United States (Table 4b), even more strikingly than for the 'unconditional' out-of-sample RMSE, financial variables produce a sizeable gain in predicting GDP, relative to a model that only looks at past GDP values. The gain peaks at the 5-quarter horizon and thereafter remains broadly positive but overall not so large. Another less sizeable gain is reached at the 11th step ahead. This predictability pattern is typical to all types of models with financial variables. The predictability pattern in terms of gain/loss in RMSE has been reported also in Figure 9, in addition to Tables 3 to 5.

Coming to the euro area (Table 4a) and looking at panel I, 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 II 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 I. Hence, it seems 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 three GDP 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).

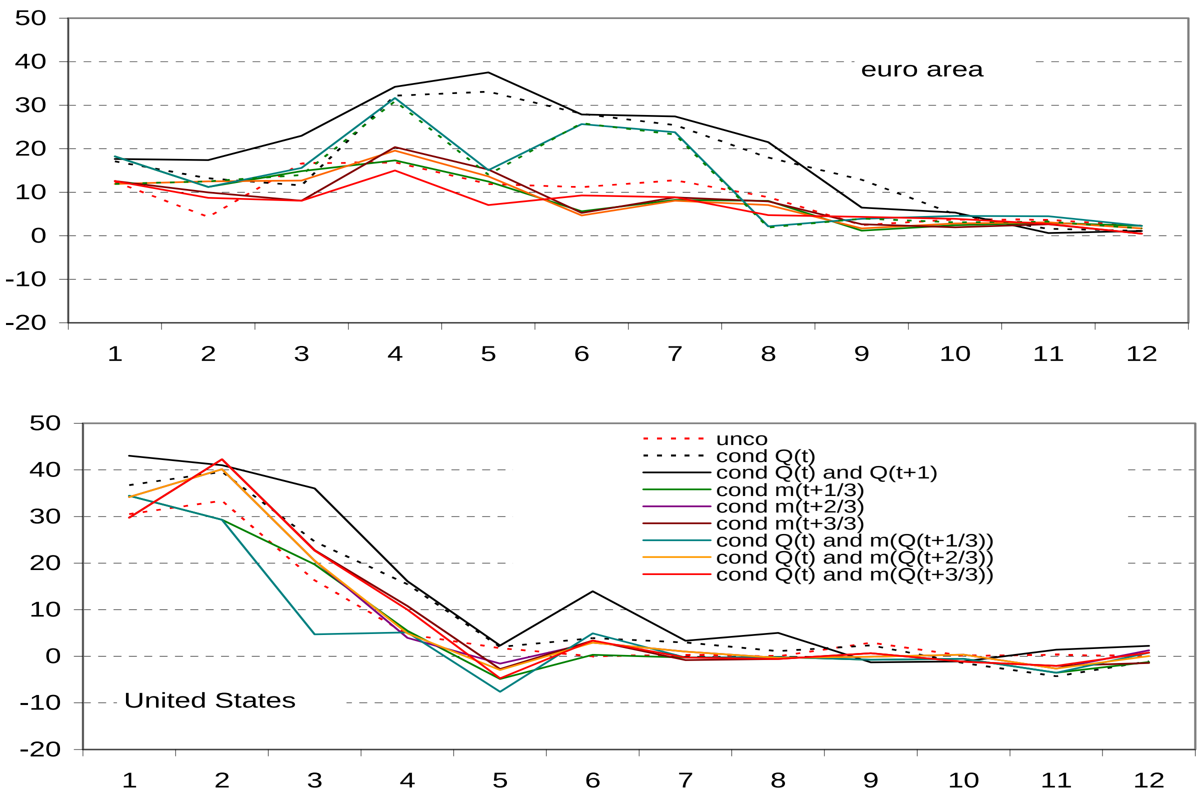
Overall, our forecasting exercise shows that the more general 'GDP models' consistently beat the random walk over all the considered horizons for the euro area. In particular, models with 2 or 3 GDPs, also including stock market volatility and the slope of the yield curve, consistently improve the forecasts. Adding other combinations of financial variables tends to worsen predictions (a result in line with the US 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

[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.

[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.

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 US shocks.[20]

Figure 9. Gain/losses (in %) in terms of RMSE achieved by models with financial variables with respect to bivariate or trivariate models of the GDPs only, at various horizons.



Note: The two panels in the Chart report the gain or the loss in terms of RMSE of models with financial variables relative to the minimum RMSE achieved by a bivariate or a trivariate VAR model including GDPs only, at various horizons, expressed in quarters. The gain and the losses are expressed in percentages. "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. "m_1", "m_2" and "m_3" refer to the model forecast when conditioning on current GDP and 1.2 and 3 months ahead financial data. "$m_{1,t-1}$", "$m_{2,t-1}$" and "$m_{3,t-1}$" refer to the model forecast when conditioning on last quarter GDP and 1, 2 and 3 months ahead financial data.

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

[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).

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?

To anticipate, the answer is rather favourable to models which include the financial variables in the case of the United States GDP and less favourable in the case of the euro area GDP, mainly because the lagged dependency between the US and the euro area GDP and the lagged dependency between the US GDP and the US financial variables is such that the influence of financial variables on the euro area GDP is conveyed indirectly by the US GDP rather than directly. This finding is discussed at length in Section V below.

C. Additional explanatory factors and prediction of industrial production indices

Before moving to test the conditional predictive ability of the models, 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. Also we look at the existence of differences in the behavior of the models in forecasting industrial production indices sampled at different frequencies instead than GDP.

As described in more detail in the Introduction, according to recent research (see Liew and Vassalou, 2000, Gilchrist et al., 2008, and Carlson et al., 2008) some narrower equity price information than the one employed so far in this paper (the broad market index) or non-price financial information seem to improve predictions of real activity. We repeated the same forecasting exercise envisaged in previous sub-sections using, along with the three GDPs and the three yield curve slopes, also i) the Fama and French (1993) factors (high-minus-low, hml, and small-minus-big, smb), ii) the distance-to-default measure employed in Carlson et al. (2008) for a set of US financial firms alone and iii) together with its cross-sectional dispersion, measured by the interquartile range, iv) the Consumer and Industrial bank loans alone and v) together with consumer credit loans and real estate loans, vi) the 3-month US commercial paper spread, the difference between the US Baa industrial yield and the 10-year US Government bond yield, viii) the difference between the US and euro area banking sector stock market indices and the corresponding broad equity market indices.[21]

[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 - 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 being 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. The Fama and French factors are computed as zero investment portfolios which are long – short positions in firms with specific characteristics (size and value).

The out-of-sample RMSE from some of these additional models (from i) to v)) are also reported in Tables 3 to 5, Panels II, (those for specifications vi) and vii) are also reported for the 'unconditional forecasts' in Table 3 – lines identified by 'TB' and 'banks') and overall show that while some of such financial variables lead to some improvement in out-of-sample forecasting ability relative to the benchmark models with fianancial indicators described in Panels I of the same Tables, they lead nonetheless to a worsening of predictions relative to VAR models which consider only the 2 or the 3 GDPs as endogenous variables.

Motivated by the analysis of Junttila (2007), who showed that specific portfolios of financial variables can indeed beat, when evaluated out-of-sample, models that only look at past industrial production to the aim of forecasting industrial production indices in a number of countries, we repeat the same forecasting exercise as before, for a more limited number of models, using quarterly and monthly industrial production indices. We do not use the portfolios identified by Junttila, but two of the combinations of financial variables employed so far. The outcome of such estimation is reported in Table 7 for the euro area and the United States. As for quarterly IP data, the models that we estimated are the combinations that include: i) the US and euro area IP indices, ii) the three IP indices, iii) the three IP indices, the three slopes and the three stock market volatilities, iv) the three IP indices, the three slopes and the three stock market indices. The models with financial variables are again evaluated in two ways (lines with the superscripts 'a' and 'b' in the Table): i) estimating the models up to time t and predicting the IP indices also on the ground of the values of the financial variables at t+1, ii) estimating the models up to time t-1 and predicting the IP indices also on the ground of the values of the financial variables at t and t+1. As for monthly IP data, euro area data would have been incomplete and therefore we chose to work only with US and Germany data spanning the full period 1970-2007. The estimated models in this case are: i) the US and euro area IP indices, ii) the two IP indices, the two slopes and the two stock market volatilities, iv) the two IP indices, the two slopes and the two stock market indices. The lines identified by 'a' and 'b' have the same meaning as before.

All in all the quarterly IP figures confirm the results based on GDP figures, i.e. the results based on the bivariate or the trivariate models that only include past GDPs cannot be improved when one considers financial variables (Table 7, panel I). However, the findings of Junttila (2007) are basically confirmed when one aims at predicting the monthly activity: in this case, in fact, nearly all of the models including financial variables, conditional on information dated t or t-1, fare better than the VAR for the two GDPs or than the random walk. The decrease in the RMFE, however, does not look as particularly sizeable, ranging at most between 2% and 4%, relative to either the bivariate VAR or the random walk. Overall, therefore, although some predictability exists, it does not appear to be as dramatic as to change previous findings based on GDP.

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 RMSE calculated over 12-quarter windows are reported for classes of models, at 4- and 8-quarters-ahead horizons 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. Looking at classes of models, Figure 10 suggests 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 (first two panels of Figure 10).

Looking instead at the specific models that produce the gain in predictive ability (last two panels of Figure 10) 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 more successful.

B. Conditional Predictive Ability Test

The rolling RMSE is not a formal test of model performance but has the advantage to be applicable to very short estimation windows and as such provides a hint about the 'instantaneous' predictive ability of a model. For a formal assessment of the predictive ability, the GW test allows 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, among other things, the question "which forecasts will be better at a given point in time?" or "which model among a set of competing models should one choose at a given point in time?"[22]

The conditional predictive ability evaluation is particularly suitable to fine-tune the forecast evaluation to the underlying economic conditions. The test consists of regressions of the difference in the absolute forecast error from competing models over its lag and a constant.

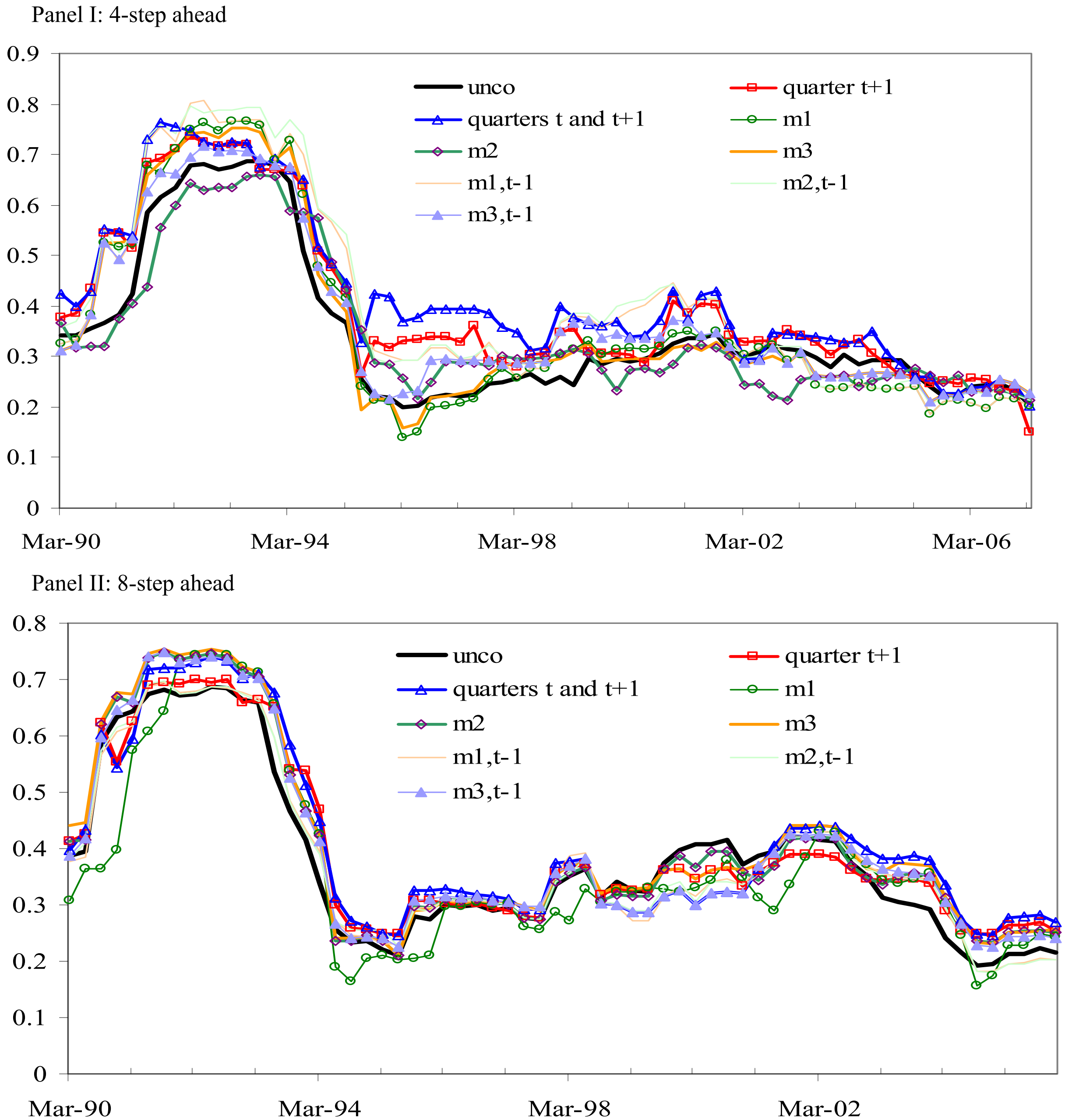
For each forecast series of the GDP in the euro area coming from a different model and for selected horizons (1, 4 and 8) we compute pairwise tests of equal conditional predictive ability of model 'a' against model 'b' through an absolute value loss function. Specifically, for lags τ = 1, 4 and 8 quarters we test

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

where L is the loss function, 'ma' stands for model 'a' and 'mb' for model 'b'.

[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

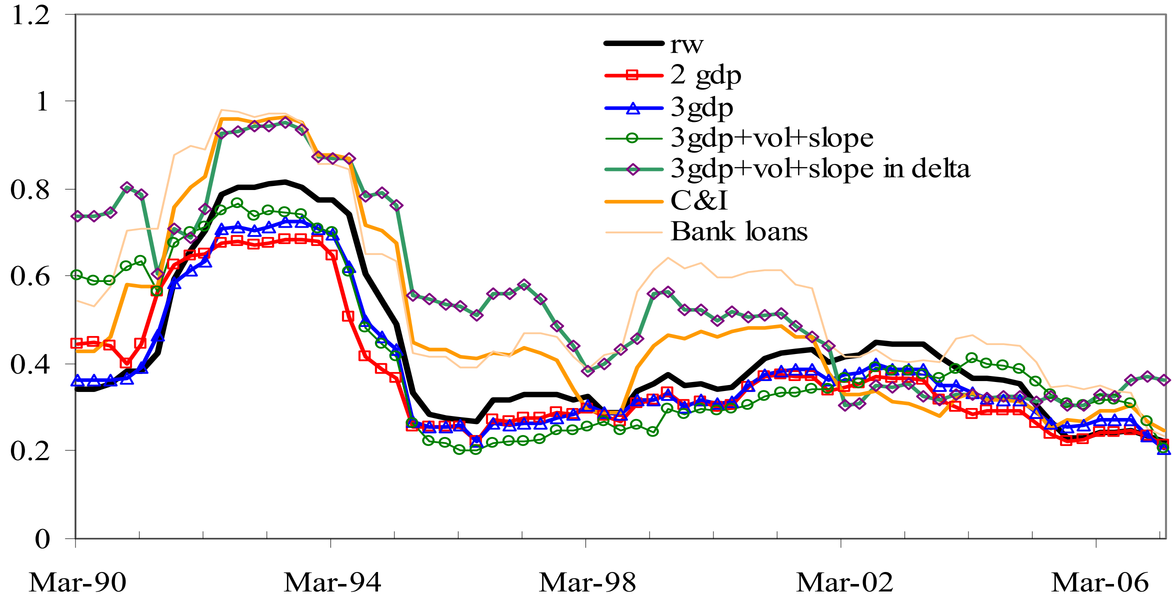
Figure 10. RMSE from competing classes of models and from individual models



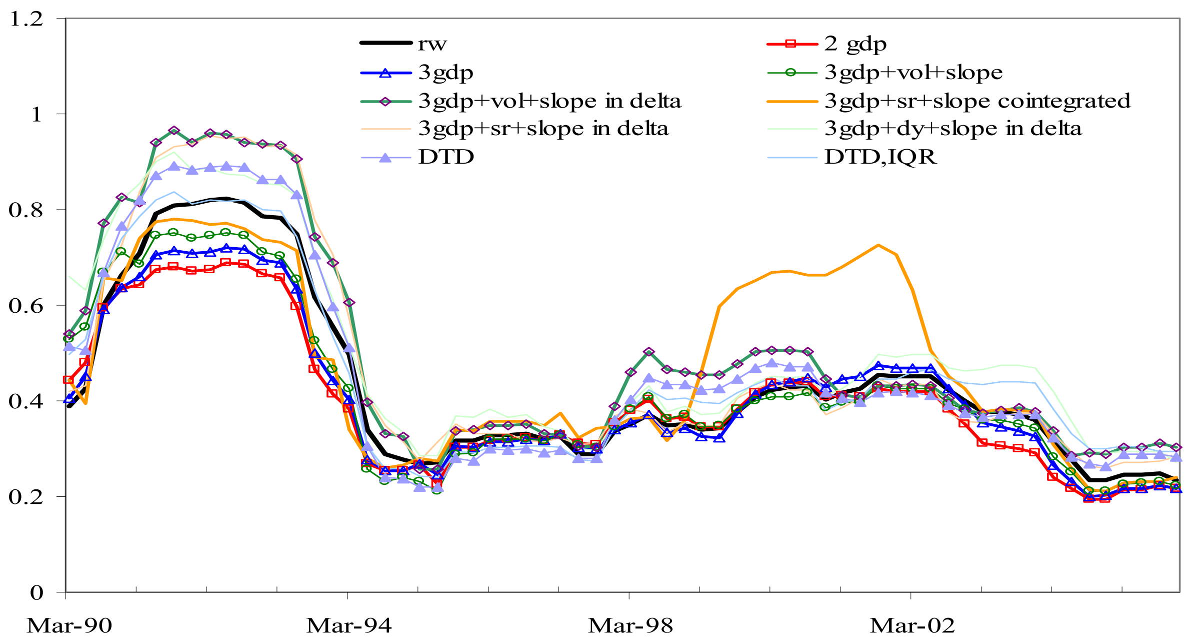
Note: In these first two panels of the Figure, "unco" refers to the model with financial variables, with forecast estimated without any conditioning. "quarters *t* and *t*+1" refers to the model estimated up to *t*-1, and the forecast is conditional on financial data at time *t* and *t*+1. "quarter *t*+1" refers to a model estimated up to *t*, with the forecast conditional on financial variables at time *t*+1. "m_1", "m_2" and "m_3" refer to the model forecast when conditioning on current GDP and 1.2 and 3 months ahead financial data. "$m_{1,\, t\text{-}1}$", "$m_{2,\, t\text{-}1}$" and "$m_{3,\, t\text{-}1}$" refer to the model forecast when conditioning on last quarter GDP and 1, 2 and 3 months ahead financial data.

Figure 10. RMSE from competing classes of models (ctd.)

Panel A: 4-step ahead



Panel B: 8-step ahead



Note: In these last two panels of the Figure, rw is the random walk model (model 0), 2gdp and 3gdp are the bivariate and trivariate models including GDPs only (model 1 and model 2), 3gdp+vol+slope is model 3l while 3gdp+svar+slope in delta is model 4, 3gdp+sr+slope cointegrated is model 5, 3gdp+sr+slope in delta is model 6 and 3gdp+dy+slope in delta is model 7. Finally DTD (distance to default) is model 8 and DTD, IQR (the distance to default together with its interquartile range) is model 9.

When the information set upon which the test is built is such that G_t=F_t then the test is a conditional test, whereas when G_t includes the full sample ([0,∞[) it is an unconditional test (the equivalent of the Diebold-Mariano test).[23] The conditional test is a powerful tool in fine-tuning the choice of a predictive model depending on the underlying environment. In simple terms, the choice of model '*a*' over model '*b*' is based on regressing $\Delta L_{t+\tau}$ defined above on a constant and its first lag ($\Delta L_{t+\tau} = \alpha + \beta \cdot \Delta L_{t-1+\tau} + \eta_{t+\tau}$) and then preferring model '*a*' to model '*b*' if the predicted value of the error gap between the two models, i.e. $\alpha + \beta \cdot \Delta L_{t-1+\tau}$ exceeds a given threshold. Of course, the above regression can be extended to include additional lags of the error gap as well as predetermined variables which one may think of as relevant in the determination of the performance of a given class of models (recession/expansion dummies, industrial production or GDP growth rates and so on).

Figures 11 to 13 report 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*.

The three figures report the choice function, which equals one when the second model in the pairwise comparison would have been preferred over the first model at each quarter *t*.[24] 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.

Beyond the conditional choice test between pairs of models, Giacomini and White also provide the conditional counterpart of the Diebold – Mariano test. This is obtained by regressing the difference between the absolute values of the forecast errors from competing models, all based on rolling estimation referred to moving windows of the same length on a

[23] Giacomini and White (2006) show that the test statistics can be computed as $n{\cdot}R^2m$ where R^2 is the uncentered squared multiple correlation coefficient for the artificial regression of the constant unity on $(h_t.\Delta L_{m,t+1})$ where $h_t = (1, \Delta L_{m,t})$. In addition, if $\Delta L_{m,t}$ is assumed to be homoskedastic the test can be based on the $n{\cdot}R^2$ of the regression of $\Delta L_{m,t+1}$ on h_t.

[24] 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 Figures 11-13).

constant and some time t-1 and possibly older information, with the typical choice being a constant and first lag of the differential itself. Table 8 shows these conditional tests based on regressions with one lag of the differential, the test being obtained as the T^*R^2 of the regression, which is found to be distributed as a chi-square with two degrees of freedom. Overall, the pattern is fairly consistent with the average of 'ones' reported in Figures 11-13.

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. The evidence is however more favorable in terms of predictability of the United States GDP.

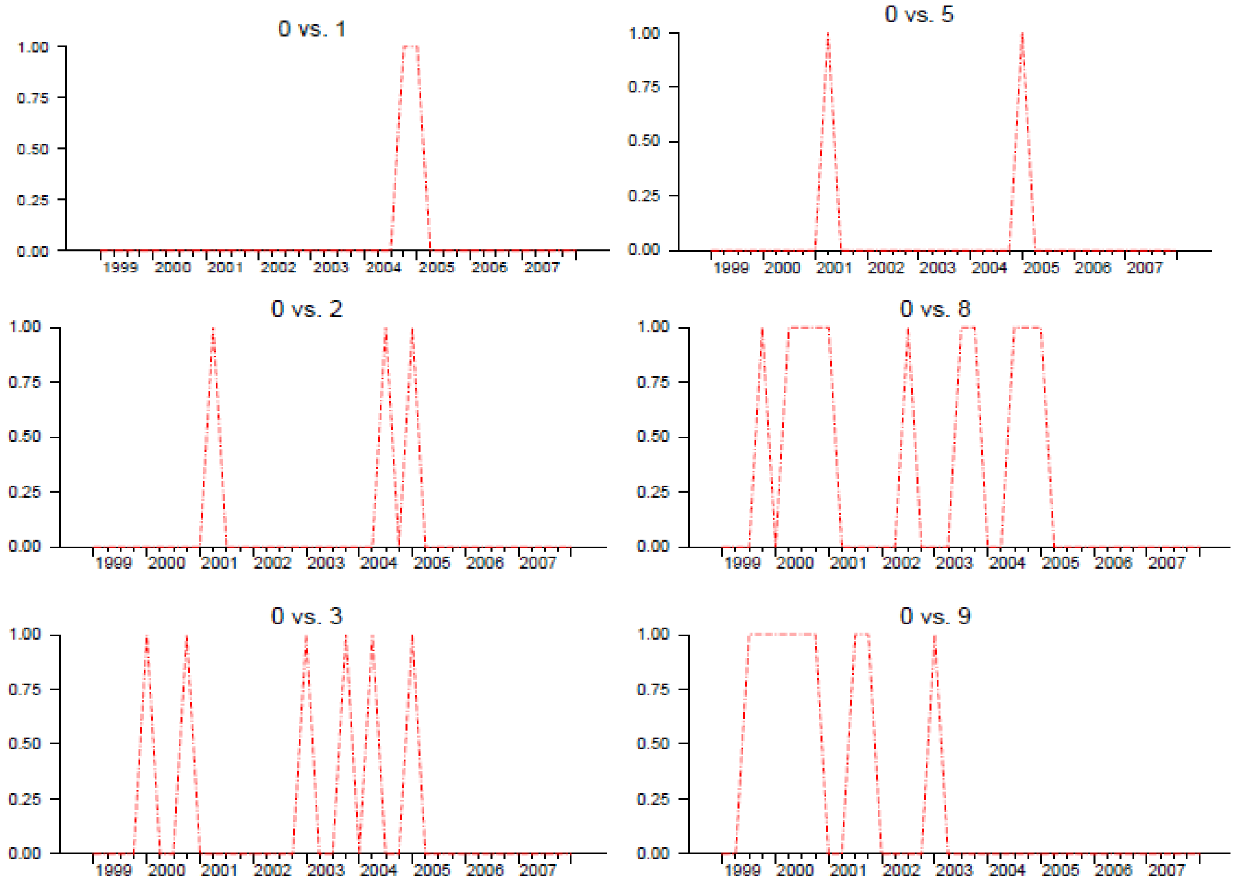
VI. CONCLUSIONS

Against the background of the ongoing financial turmoil originated by a declining US housing market which culminated in a synchronized recession in the United States and in the main economic areas, 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 and US 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 in the euro area, even when taking into account their timeliness. In the United States the evidence is more favourable to a role of the financial variables in predicting real activity but the gain is concentrated at a few forecast horizons (5 and 11 quarters) and the loss at the shortest horizons is remarkable. 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 derived 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) show that financial variables, domestic and global, do help forecast business cycle phases in the United States, the euro area and in Japan. There are many other ways in which financial developments can affect nonlinearly the predictability of GDP. For example, one can suppose that the forecasting power of the financial variables may be larger when their movements are more synchronised both across countries and type of indicators, as things may be more surely negative when all the financial variables are providing a similar signal. This is certainly an interesting avenue for future research.

Figure 11. GW test for conditional predictive ability vis-à-vis the random walk model

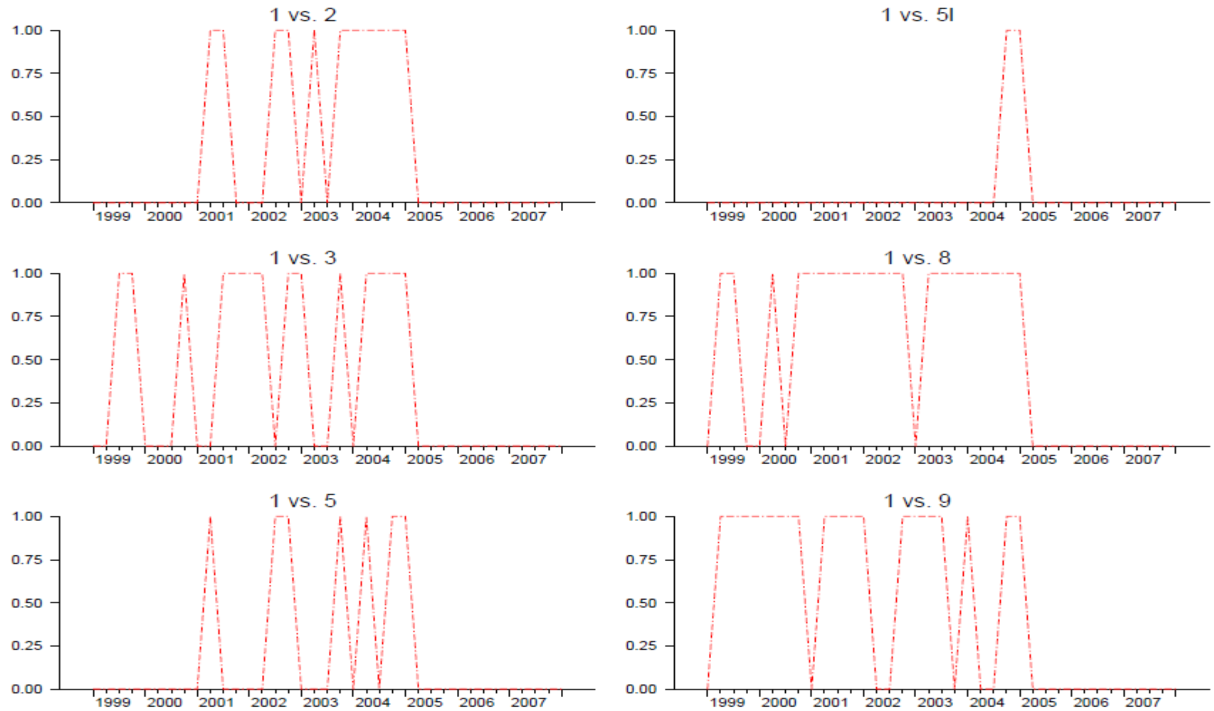
Conditional choice: model 0 (random walk) vs. selected competing models (4-step ahead)



Note: The panels in the Figure show the results of the conditional model choice test 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 differences between absolute out-of-sample forecast errors (4 quarters ahead) on their first four lags. The mean of the forecast errors is used a threshold for model's choice. The out-of-sample estimation is based on a moving window of 48 quarters. Model 1 is a bivariate VAR for US 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, the C&I, real estate and consumer credit bank loans.

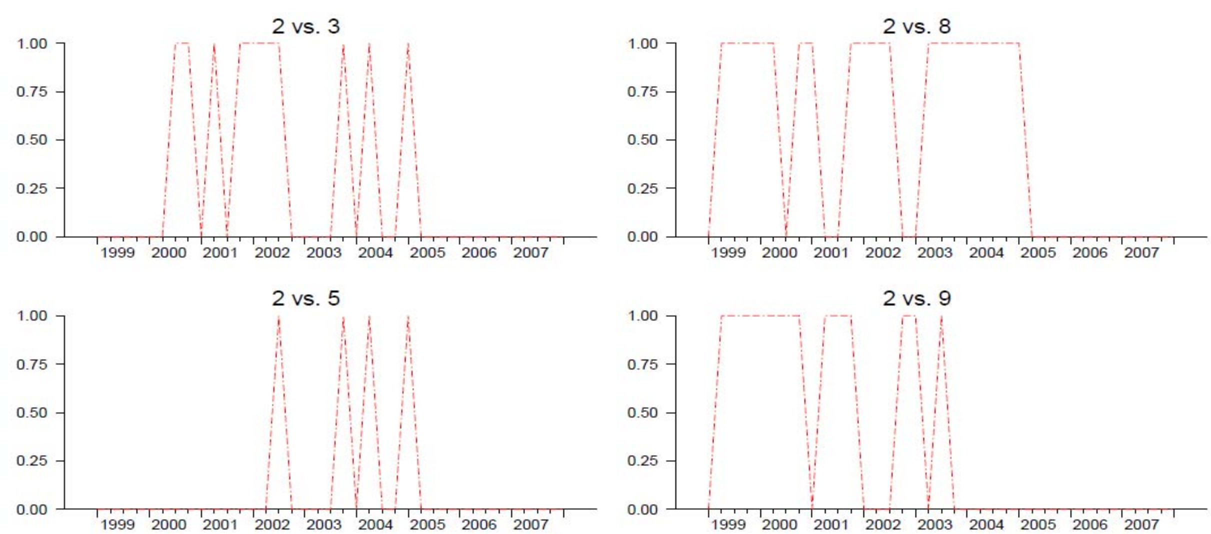
Figure 12. GW test for conditional predictive ability - 2 GDP VAR

Conditional choice: model 1 vs. selected competing models (4-step ahead)



Note: see Figure 11.

Figure 13. GW test for conditional predictive ability - 3 GDP VAR
Conditional choice: model 2 (3GDPs) vs. selected competing models (4-step ahead)



Note: see Figure 11.

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Table 1. Variance decomposition of the GDP in the three areas

Euro area GDP	Euro area GDP	ROW GDP	US GDP	Euro area slope	Euro area stock market	US slope	US 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
US 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, US GDP, euro area slope and stock market, US slope and stock market.

Table 2. R^2 of a regression of the first differences in log GDP on its counterfactual values

PANEL I: (full sample)			
common factor	US	euro area	row
US	0.90	0.14	0.21
euro area	0.04	0.80	0.14
row	0.01	0.10	0.61
PANEL II: (across decades)			
	US	euro area	row
US 1970s	0.70	0.23	0.27
US 1980s	0.81	0.21	0.42
US 1990s	0.87	0.25	0.46
US 2000s	0.89	0.36	0.29
	US	euro area	row
euro area 1970s	0.03	0.45	0.01
euro area 1980s	0.00	0.86	0.00
euro area 1990s	0.23	0.89	0.60
euro area 2000s	0.18	0.95	0.31
	US	euro area	row
row 1970s	0.00	0.10	0.55
row 1980s	0.00	0.21	0.22
row 1990s	0.23	0.12	0.51
row 2000s	0.08	0.25	0.80

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 $\Delta\log \text{GDP} = \alpha+\beta \Delta\log G\hat{D}P + \varepsilon_t$, 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 US shocks are restricted to zero and the US is therefore the common factor for the other two countries.

Table 3a. Unconditional out-of-sample RMSE for the euro area GDP

	Forecast horizon	1	2	3	4	5	6	7	8	9	10	11	12
	Panel I												
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 cointegrated	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 cointegrated	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 cointegrated	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 II												
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	FF factors, slope	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, slope	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, slope	0.54	0.48	0.52	0.59	0.58	0.61	0.61	0.64	0.60	0.57	0.53	0.49
TB	Cp spread, baa, slope	0.49	0.48	0.52	0.55	0.52	0.54	0.53	0.52	0.51	0.51	0.53	0.54
Banks	Banks us+ea, slope	0.55	0.50	0.52	0.53	0.52	0.53	0.51	0.48	0.47	0.46	0.50	0.48
	Panel III												
	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 added 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. 'var' is the stock market volatility, 'slope' is the slope of the yield curve, 'dy' is the dividend yield of the aggregate stock market index, 'median dist' and 'iqr' are the median and the interquartile range of the distance to default for a set of financial firms (see Carlson et al., 2008), 'C&I Loans' are the US Commercial and Industrial Loans, 'Bank Loans' include Commercial and Industrial Loans, Real Estate Loans and Consumer Credit Loans. 'Cp spread' is the spread between the 3-month US commercial paper yield and the 3-month US T-bill rate, 'baa' is the yield differential between 10-year baa-rate US industrial bonds and the US Treasury bond., Banks'us+ea' is the one-quarter yield differential between the US banking equity index and the US broad stock market index as well as the corresponding series for the euro area.

Table 3b. Unconditional out-of-sample RMSE for the United States GDP

	Forecast horizon	1	2	3	4	5	6	7	8	9	10	11	12
	Panel I												
RW	RANDOM WALK	0.51	0.52	0.53	0.53	0.53	0.53	0.54	0.54	0.54	0.54	0.55	0.55
BiVARC	2 gdp cointegrated	0.51	0.49	0.52	0.51	0.52	0.52	0.53	0.53	0.53	0.53	0.54	0.54
BiVARL	2 gdp level	0.52	0.51	0.53	0.52	0.54	0.55	0.56	0.56	0.56	0.57	0.57	0.57
TriVARC	3 gdp cointegrated	0.56	0.53	0.52	0.52	0.53	0.53	0.53	0.54	0.54	0.55	0.55	0.55
TriVARL	3 gdp level	0.57	0.55	0.57	0.59	0.61	0.62	0.63	0.64	0.64	0.66	0.66	0.66
FIVAR1C	var slope cointegrated	0.72	0.68	0.66	0.56	0.54	0.55	0.54	0.52	0.55	0.55	0.56	0.54
FIVAR1L	var slope level	0.94	0.95	0.96	0.83	0.77	0.78	0.73	0.77	0.77	0.82	0.83	0.86
FIVARD	var slope in delta	1.11	0.75	0.74	0.67	0.58	0.64	0.64	0.65	0.67	0.55	0.54	0.52
FIVAR2C	sm slope cointegrated	0.90	0.84	0.76	0.71	0.68	0.70	0.63	0.65	0.76	0.59	0.63	0.77
FIVAR2L	sm slope level	1.39	1.15	1.19	1.10	1.12	1.15	1.13	1.23	1.41	1.16	1.36	1.41
FIVAR2D	sm slope in delta	0.69	0.72	0.62	0.54	0.53	0.53	0.55	0.56	0.59	0.59	0.57	0.54
FIVAR3D	dy slope in level	0.88	0.89	0.97	0.99	0.93	1.01	1.01	0.93	1.02	1.01	0.98	1.00
FIVAR3L	dy slope in delta	0.74	0.75	0.68	0.64	0.65	0.58	0.58	0.57	0.61	0.63	0.64	0.65
	Panel II												
MDS	median dist, slope	0.69	0.66	0.60	0.54	0.59	0.53	0.53	0.53	0.56	0.55	0.54	0.53
MDIS	median dist, iqr, slope	0.77	0.70	0.63	0.54	0.61	0.51	0.54	0.55	0.55	0.55	0.55	0.54
FF	FF factors, slope	0.77	0.67	0.65	0.58	0.60	0.59	0.57	0.55	0.55	0.53	0.55	0.54
C&I	C&I Loans, slope	0.67	0.68	0.65	0.63	0.59	0.55	0.54	0.53	0.55	0.55	0.55	0.54
BL	Bank loans, slope	0.84	0.86	0.76	0.77	0.77	0.68	0.69	0.63	0.59	0.56	0.56	0.55
TB	Ted spread, baa, slope	0.67	0.69	0.69	0.69	0.70	0.68	0.68	0.68	0.74	0.78	0.78	0.76
Banks	Banks us+ea, slope	0.83	0.80	0.75	0.78	0.70	0.76	0.79	0.76	0.76	0.74	0.74	0.77
	Panel III												
	minimum all	0.51	0.49	0.52	0.51	0.52	0.51	0.53	0.52	0.53	0.53	0.54	0.52
	minimum fin	0.67	0.66	0.60	0.54	0.53	0.51	0.53	0.52	0.55	0.53	0.54	0.52
	relative gap	0.16	0.16	0.08	0.02	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.00
	% gap	30.54	33.37	16.30	4.73	1.74	0.00	0.27	0.00	2.92	0.09	0.33	0.00

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 added at each step of 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. 'var' is the stock market volatility, 'slope' is the slope of the yield curve, 'dy' is the dividend yield of the aggregate stock market index, 'median dist' and 'iqr' are the median and the interquartile range of the distance to default for a set of financial firms (see Carlson et al., 2008), 'C&I Loans' are the US Commercial and Industrial Loans, 'Bank Loans' include Commercial and Industrial Loans, Real Estate Loans and Consumer Credit Loans. 'Cp spread' is the spread between the 3-month US commercial paper yield and the 3-month US T-bill rate, 'baa' is the yield differential between 10-year baa-rate US industrial bonds and the US Treasury bond., Banks'us+ea' is the one-quarter yield differential between the US banking equity index and the US broad stock market index as well as the corresponding series for the euro area.

Table 4a. Out-of-sample RMSE for the euro area, conditional on quarterly inforrmation.

	Forecast horizon	1	2	3	4	5	6	7	8	9	10	11	12
Panel I: estimation up to t, forecasts conditional on time t+1 information													
FIVAR1C	var slope cointegrated	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 cointegrated	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	FF factors, slope	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, slope	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, slope	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

	Forecast horizon	1	2	3	4	5	6	7	8	9	10	11	12
Panel II: estimation up to t-1, forecasts conditional on time t and t+1 information													
FIVAR1C	var slope cointegarted	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 cointegrated	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	FF factors, slope	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, slope	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, slope	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 I, 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 II, 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 added to the previous sample 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. 'var' is the stock market volatility, 'slope' is the slope of the yield curve, 'dy' is the dividend yield of the aggregate stock market index, 'median dist' and 'iqr' are the median and the interquartile range of the distance to default for a set of financial firms (see Carlson et al., 2008), 'C&I Loans' are the US Commercial and Industrial Loans, 'Bank Loans' include Commercial and Industrial Loans, Real Estate Loans and Consumer Credit Loans.

Table 4b. Out-of-sample RMSE for the United States, conditional on quarterly information.

	Forecast horizon	1	2	3	4	5	6	7	8	9	10	11	12
	Panel I: estimation up to t, forecasts conditional on time t+1 information												
FIVAR1C	var slope cointegrated	0,92	0,89	0,91	0,99	0,92	0,89	0,81	0,74	0,66	0,66	0,65	0,59
FIVAR1L	var slope in level	1,19	0,98	0,98	0,93	0,77	0,77	0,70	0,72	0,84	0,90	0,89	0,91
FIVARD	var slope in delta	0,81	0,77	0,64	0,59	0,59	0,63	0,62	0,63	0,61	0,54	0,51	0,51
FIVAR2C	sm slope cointegrated	1,08	0,88	0,82	0,81	0,76	0,70	0,68	0,61	0,76	0,65	0,57	0,79
FIVAR2L	sm slope in level	1,63	1,26	1,22	1,17	1,19	1,13	1,10	1,16	1,33	1,18	1,23	1,39
FIVAR2D	sm slope in delta	0,78	0,72	0,73	0,59	0,53	0,53	0,55	0,55	0,59	0,60	0,59	0,56
FIVAR3D	dy slope in level	1,06	0,87	0,96	1,18	1,09	0,94	1,22	1,01	1,06	1,12	1,06	1,06
FIVAR3L	dy slope in delta	0,77	0,73	0,74	0,67	0,67	0,64	0,59	0,57	0,59	0,64	0,66	0,64
MDS	median dist, slope	0,70	0,71	0,71	0,61	0,57	0,57	0,55	0,53	0,56	0,55	0,55	0,54
MDIS	median dist, iqr, slope	0,85	0,77	0,73	0,65	0,60	0,57	0,54	0,54	0,55	0,53	0,56	0,54
FF	Fama French factors	0,76	0,79	0,68	0,62	0,56	0,58	0,59	0,57	0,56	0,54	0,56	0,55
C&I	C&I Loans	0,71	0,69	0,70	0,66	0,62	0,58	0,57	0,54	0,54	0,55	0,56	0,55
BL	Bank loans	0,85	0,86	0,93	0,77	0,77	0,73	0,69	0,64	0,62	0,58	0,57	0,58
	minimum	0,70	0,69	0,64	0,59	0,53	0,53	0,54	0,53	0,54	0,53	0,51	0,51
	gain/loss over unco	0,19	0,20	0,13	0,08	0,01	0,02	0,02	0,01	0,01	-0,01	-0,02	-0,01
	% gap	36,74	39,60	24,62	15,47	2,00	3,89	2,96	1,09	2,34	-1,45	-4,30	-1,09

	Forecast horizon	1	2	3	4	5	6	7	8	9	10	11	12
	Panel II: estimation up to t-1, forecasts conditional on time t and t+1 information												
FIVAR1C	var slope cointegrated	1,50	1,60	1,66	1,70	1,66	1,75	1,54	1,40	1,30	1,28	1,23	1,18
FIVAR1L	var slope in level	2,03	0,99	1,02	0,99	0,86	0,72	0,72	0,93	1,03	1,00	1,00	0,99
FIVARD	var slope in delta	1,01	0,71	0,76	0,70	0,62	0,65	0,65	0,68	0,62	0,54	0,55	0,53
FIVAR2C	sm slope cointegrated	1,67	0,91	0,90	0,88	0,71	0,70	0,68	0,61	0,67	0,64	0,62	0,63
FIVAR2L	sm slope in level	2,68	1,44	1,23	1,22	1,16	1,09	1,18	1,16	1,27	1,23	1,32	1,44
FIVAR2D	sm slope in delta	0,80	0,71	0,74	0,59	0,53	0,58	0,56	0,59	0,60	0,60	0,58	0,55
FIVAR3D	dy slope in level	1,49	0,87	1,11	1,38	1,21	1,18	1,30	1,22	1,22	1,12	1,17	1,13
FIVAR3L	dy slope in delta	0,75	0,73	0,75	0,72	0,66	0,66	0,59	0,57	0,60	0,67	0,68	0,62
MDS	median dist, slope	0,73	0,76	0,72	0,62	0,56	0,60	0,55	0,56	0,53	0,54	0,55	0,55
MDIS	median dist, iqr, slope	0,89	0,81	0,75	0,68	0,58	0,61	0,55	0,55	0,52	0,53	0,56	0,55
FF	Fama French factors	0,89	0,81	0,75	0,68	0,58	0,61	0,55	0,55	0,52	0,53	0,56	0,55
C&I	C&I Loans	0,73	0,70	0,70	0,67	0,62	0,60	0,57	0,57	0,55	0,55	0,56	0,57
BL	Bank loans	0,85	0,92	0,93	0,78	0,77	0,72	0,75	0,78	0,60	0,58	0,57	0,56
	minimum	0,73	0,70	0,70	0,59	0,53	0,58	0,55	0,55	0,52	0,53	0,55	0,53
	gain/loss over unco	0,22	0,20	0,19	0,08	0,01	0,07	0,02	0,03	-0,01	-0,01	0,01	0,01
	% gap	43,05	41,01	36,04	16,10	2,31	13,96	3,35	5,01	-1,28	-1,08	1,40	2,23

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 I, 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 II, 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 added to the previous sample 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. 'var' is the stock market volatility, 'slope' is the slope of the yield curve, 'dy' is the dividend yield of the aggregate stock market index, 'median dist' and 'iqr' are the median and the interquartile range of the distance to default for a set of financial firms (see Carlson et al., 2008), 'C&I Loans' are the US Commercial and Industrial Loans, 'Bank Loans' include Commercial and Industrial Loans, Real Estate Loans and Consumer Credit Loans.

Table 5. Out of sample RMSE for the euro area, conditional on monthly information.

Panel I: estimation up to t, forecasts conditional on month t+1/3 information

	Forecast horizon	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
FIVAR1C	var slope cointegrated	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 cointegrated	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 II: estimation up to t, forecasts conditional on month t+2/3 information

	Forecast horizon	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
FIVAR1C	var slope cointegrated	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 cointegrated	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 III: estimation up to t, forecasts conditional on month t+3/3 information

	Forecast horizon	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
FIVAR1C	var slope cointegrated	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 cointegrated	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 three panels of the Table show the out-of-sample RMSE for a number of models between 1 and 12 quarters ahead. In the three panels 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, respectively, quarter $t + 1$ month, 2 months and 3 months. 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 added to the previous sample 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. For the definition of some variables see note to Table 3 and 4.

Table 6. Diebold – Mariano tests for unconditional predictive ability at selected horizons

	h=4		h=8		h=12	
	BiVarC vs.	TriVarC vs.	BiVarC vs.	TriVarC vs.	BiVarC vs.	TriVarC vs.
euro area						
BiVarC						
BiVarL	-0.57	-1.69	0.05	-0.72	0.27	-0.21
TriVarC	1.52		0.94		0.59	
TriVarL	1.43	-0.62	1.45	0.16	0.88	0.18
FiVar1C	0.81	-0.20	0.81	0.12	-0.44	-1.12
FiVar1L	0.73	-0.17	0.67	0.19	0.05	-0.17
FiVar1D	2.10	1.62	2.77	2.39	-0.38	-0.69
FiVar2C	0.94	-0.02	1.69	1.38	0.45	-0.15
FiVar2L	0.59	0.22	0.16	0.00	-0.36	-0.43
FiVar2D	2.15	1.79	0.24	0.07	0.12	0.04
FiVar3D	3.47	2.78	3.14	2.90	1.30	1.18
MDS	3.66	3.09	2.31	1.84	0.04	-0.32
MDIS	3.31	2.71	2.46	2.03	0.69	0.36
FF	2.48	1.99	2.64	2.39	-0.27	-0.72
C&I	2.53	1.94	2.31	2.11	0.40	0.16
BL	1.94	1.40	3.13	2.94	0.47	0.27
United States						
BiVarC						
BiVarL	-0.57	-0.25	-0.02	0.10	-0.08	-0.03
TriVarC	-0.33		-0.93		-1.03	
TriVarL	-0.48	-0.27	0.22	0.33	0.59	0.64
FiVar1C	-0.46	'0.36	-0.34	-0.25	-0.89	-0.85
FiVar1L	-0.34	-0.27	-0.70	-0.65	-0.34	-0.31
FiVar1D	0.51	0.57	1.43	1.50	0.00	0.05
FiVar2C	-0.93	-0.85	0.92	1.11	0.36	0.47
FiVar2L	0.48	0.53	0.32	0.34	0.02	0.03
FiVar2D	-0.25	-0.21	0.78	0.81	0.10	0.11
FiVar3D	0.60	0.67	1.52	1.59	2.82	2.85
MDS	-0.58	-0.50	0.47	0.58	1.53	1.62
MDIS	-0.80	-0.74	0.67	0.77	1.48	1.53
FF	0.37	0.46	1.20	1.38	0.27	0.35
C&I	-1.50	1.60	2.19	2.32	0.69	0.77
BL	1.59	1.68	1.66	1.78	0.50	0.58

Note: The Table reports the Diebold-Mariano tests for unconditional predictive ability between pairs of models. The test is the t-ratio on the constant in a regression of the differential between the absolute values of the forecast errors produced by competing models on the constant. The headings h = 4, h = 8 and h = 12 denote the forecast horizons. Entries larger than 1.96 indicate that the models reported in the second row of the Table (BiVarC and TriVarC) are not overperformed by the corresponding competing model in the first column. For a brief description of the models see, for example, Tables 3a or 3b. 'var' is the stock market volatility, 'slope' is the slope of the yield curve, 'dy' is the dividend yield of the aggregate stock market index, 'median dist' and 'iqr' are the median and the interquartile range of the distance to default for a set of financial firms (see Carlson et al., 2008), 'C&I Loans' are the US Commercial and Industrial Loans, 'Bank Loans' include Commercial and Industrial Loans, Real Estate Loans and Consumer Credit Loans.

Table 7: Out of sample RMSE for the IP indices

	Forecast horizon	1	2	3	4	5	6	7	8	9	10	11
Panel I: euro area: QUARTERLY FREQUENCY												
RW	RANDOM WALK	0.709	0.939	0.952	0.991	0.999	0.994	0.999	1.003	1.008	1.009	1.014
BiVARC	2 gdp cointegrated	0.970	1.112	1.167	1.118	1.017	0.983	1.010	1.006	1.007	1.001	1.017
TriVARC	3 gdp cointegrated	0.970	1.112	1.167	1.137	1.039	1.004	1.035	1.030	1.035	1.031	1.048
FIVAR1C	var slope cointegrated	0.970	1.112	1.160	1.123	1.026	0.991	1.022	1.017	1.022	1.018	1.034
FIVAR2C	sm slope cointegrated	1.074	1.165	1.266	1.226	1.224	1.227	1.197	1.107	1.123	1.111	1.085
FIVAR1C[a]	var slope cointegrated	1.102	1.018	1.120	1.192	1.188	1.076	1.003	1.021	1.029	1.022	1.014
FIVAR1C[b]	var slope cointegrated	1.975	1.246	1.260	1.175	1.063	1.011	1.013	1.023	1.015	1.021	1.018
FIVAR2C[a]	sm slope cointegrated	2.122	1.199	1.292	1.340	1.335	1.287	1.274	1.230	1.155	1.118	1.118
FIVAR2C[b]	sm slope cointegrated	2.271	1.394	1.331	1.391	1.337	1.260	1.169	1.129	1.097	1.103	1.035
Panel II: United States												
RW	RANDOM WALK	1.014	1.025	1.034	1.062	1.064	1.072	1.080	1.088	1.095	1.098	1.098
BiVARC	2 gdp cointegrated	1.481	1.355	1.227	1.085	1.174	1.244	1.242	1.230	1.155	1.151	1.082
TriVARC	3 gdp cointegrated	1.481	1.355	1.232	1.120	1.208	1.282	1.284	1.267	1.195	1.193	1.128
FIVAR1C	var slope cointegrated	1.481	1.355	1.225	1.107	1.193	1.266	1.268	1.251	1.179	1.178	1.113
FIVAR2C	sm slope cointegrated	2.039	1.829	1.678	1.723	1.557	1.700	1.845	1.559	1.796	1.649	1.482
FIVAR1C[a]	var slope cointegrated	1.535	1.414	1.276	1.221	1.204	1.266	1.266	1.294	1.224	1.164	1.140
FIVAR1C[b]	var slope cointegrated	2.496	1.496	1.271	1.322	1.288	1.242	1.300	1.268	1.244	1.121	1.107
FIVAR2C[a]	sm slope cointegrated	2.086	1.924	1.844	1.844	1.701	1.683	1.765	1.677	1.835	1.599	1.416
FIVAR2C[b]	sm slope cointegrated	3.067	2.007	2.072	1.813	1.659	1.630	1.727	1.508	1.510	1.451	1.320
Panel I: Germany, MONTHLY FREQUENCY												
RW	RANDOM WALK	1.321	1.328	1.329	1.331	1.333	1.335	1.335	1.333	1.335	1.338	1.339
BiVARC	2 gdp cointegrated	1.272	1.326	1.333	1.344	1.337	1.341	1.336	1.333	1.334	1.336	1.335
FIVAR1C	var slope cointegrated	1.265	1.290	1.291	1.298	1.293	1.293	1.290	1.291	1.292	1.296	1.292
FIVAR2C	sm slope cointegrated	1.292	1.323	1.303	1.295	1.295	1.297	1.291	1.292	1.293	1.294	1.291
FIVAR1C[a]	var slope cointegrated	1.971	1.276	1.299	1.292	1.308	1.295	1.294	1.290	1.290	1.292	1.297
FIVAR1C[b]	var slope cointegrated	1.542	1.302	1.306	1.303	1.294	1.289	1.288	1.289	1.294	1.294	1.291
FIVAR2C[a]	sm slope cointegrated	1.974	1.313	1.345	1.327	1.318	1.285	1.297	1.294	1.290	1.294	1.295
FIVAR2C[b]	sm slope cointegrated	1.593	1.346	1.334	1.308	1.280	1.292	1.293	1.289	1.294	1.293	1.290
Panel II: United States												
RW	RANDOM WALK	2.022	2.032	2.029	2.033	2.037	2.036	2.029	2.027	2.030	2.033	2.037
BiVARC	2 gdp cointegrated	1.808	2.079	2.044	2.059	2.044	2.042	2.032	2.028	2.027	2.033	2.036
FIVAR1C	var slope cointegrated	1.773	2.042	1.999	2.011	1.986	1.991	1.983	1.986	1.980	1.985	1.982
FIVAR2C	sm slope cointegrated	1.809	2.092	2.029	2.026	1.986	1.987	1.981	1.986	1.982	1.987	1.985
FIVAR1C[a]	var slope cointegrated	1.764	2.061	2.009	2.017	1.987	1.987	1.983	1.985	1.980	1.986	1.983
FIVAR1C[b]	var slope cointegrated	1.830	2.018	2.023	1.990	1.985	1.976	1.981	1.977	1.983	1.985	1.980
FIVAR2C[a]	sm slope cointegrated	1.816	2.128	2.071	2.051	2.011	1.986	1.979	1.984	1.982	1.987	1.985
FIVAR2C[b]	sm slope cointegrated	1.795	2.106	2.093	2.039	2.010	1.975	1.979	1.979	1.983	1.986	1.982

Note: Panel I of the Table shows the out-of-sample RMSE made in forecasting the euro area and the US quarterly IP index, via a number of models, between 1 and 12 quarters ahead. All models except BiVARC include three economic areas. Panel II shows the same results as Panel I but all models include two economic areas only, Germany and the United States, and are based on monthly data. In the rows labeled with a superscript 'a', forecasts are made as of time *t* conditional on the values of the IP Indices as of time *t* and on the financial variables as of *t*+1. In the lines characterized by the superscript 'b', the forecast are made as of time *t*-1 conditional on the values of the IP Indices 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 or in 1970M1 and ends in 1986Q4 or in 1986M12. One observation at the time is added to the previous sample in the rolling procedure. 'var' is the stock market volatility, 'slope' is the slope of the yield curve.

Table 8. Conditional Giacomini - White tests for predictive ability: choice between models (Panel I) at selected horizons (4, 8 and 12 quarters) and all-sample conditional test (panel II).

	Panel I: conditional model choice									**Panel II: conditional GW test**		
	h=4			h=8			h=12			h=∞		
	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	20			9			1			0.34		
BiVarL	20	4		10	24		16	15		0.11	0.53	
TriVarC	7	6		11	14		3	9		0.05	0.06	
TriVarL	11	6	31	13	22	26	17	18	19	0.14	0.23	0.18
FiVar1C	6	10	9	13	16	22	6	12	10	0.05	0.07	0.07
FiVar1L	4	12	14	26	26	25	17	18	18	0.12	0.06	0.11
FiVar1D	2	21	21	10	17	15	5	8	6	0.00	0.00	0.00
FiVar2C	3	14	10	2	5	5	2	5	4	0.53	0.16	0.07
FiVar2L	2	4	2	0	2	0	0	0	0	0.36	0.48	1.05
FiVar2D	3	25	29	4	6	3	15	17	18	0.00	0.00	0.00
FiVar3D	3	27	29	22	23	22	20	22	19	0.17	0.48	0.24
MDS	2	28	23	13	21	21	11	19	19	0.11	0.07	0.10
MDIS	2	26	26	17	22	26	9	16	20	0.03	0.09	0.16
FF	2	15	21	12	17	18	20	19	13	0.00	0.00	0.01
C&I	2	13	17	6	11	8	14	21	17	0.01	0.01	0.02
BL	2	10	10	12	16	14	14	16	15	0.46	0.45	0.46
Total # of cases	**38**	**38**	**36**	**30**	**30**	**28**	**24**	**24**	**24**			

Note: In the columns reported in Panel I, under the headings *h* = 4, *h* = 8 and *h* = 12, the Table shows 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. The last three columns of the Table, Panel II, report instead the all-sample conditional predictive ability test, always 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 overperformed by the model in the first column. For a brief description of the models see for example Tables 3a and 3b. '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 US Commercial and Industrial Loans, 'BL' include Commercial and Industrial Loans, Real Estate Loans and Consumer Credit Loans.