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FINANCIAL VARIABLES AND ECONOMIC ACTIVITY: FORECASTING ISSUES

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ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Abstract

The present research investigates the forecasting performance of various monthly indicators for the US industrial production growth rates in long horizon. Our focus in on financial variables that are often associated with future output growth, such as stock prices, interest rates and interest rate spreads. We also include housing and precious metal (gold) prices as well as commodity prices such as oil prices to see whether they produce marginal forecasting information. We use out of sample forecast evaluation and especially the iterated multistep approach, implementing forecast combination across observation windows of different lengths. For each observation window we use the sequential procedure of Bai and Perron (1998, 2003) to take into consideration the multiple structural breaks. The empirical results indicate that estimations without structural breaks lose in forecasting stability. Therefore we re-estimate taking into consideration five break points for each observation window. We also confirm the significant role of monetary policy in taking economic decisions.

Keywords: forecasting accuracy; h step-ahead forecast; estimation window; Theil coefficient; output growth; monetary policy; causality chain

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Περίληψη

Σκοπός της παρούσας διατριβής είναι η διερεύνηση της προβλεπτικής ικανότητας διαφόρων μηνιαίων μεταβλητών στον ρυθμό ανάπτυξης της βιομηχανικής παραγωγής των ΗΠΑ σε μεγάλους ορίζοντες. Συγκεκριμένα, θα εστιάσουμε στις χρηματοοικονομικές μεταβλητές που συχνά συνδέονται με τον ρυθμό αύξησης της παραγωγής, όπως είναι οι τιμές των μετοχών, τα επιτόκια και τα spreads. Επίσης, θα συμπεριλάβουμε στις εκτιμήσεις μας μεταβλητές όπως τιμές ακινήτων, πολύτιμων μετάλλων (χρυσός) καθώς και τις τιμές των βασικών εμπορευμάτων, όπως οι τιμές του πετρελαίου προκειμένου να διαπιστώσουμε την ύπαρξη οριακής προβλεπτικής ικανότητας (marginal forecasting information). Χρησιμοποιούμε την εκτός δείγματος προβλεπτική μέθοδο (out of sample forecast method) και συγκεκριμένα με την επαναλαμβανόμενη προσέγγιση πολλαπλών βημάτων (iterated multistep approach), εφαρμόζοντας συνδυασμούς προβλέψεων (forecast combination) σε διαφορετικά παράθυρα εκτιμήσεων (estimation windows). Για κάθε παράθυρο εκτιμήσεων (estimation window) χρησιμοποιούμε τη διαδικασία Bai και Perron (1998, 2003) για να λάβουμε υπόψη μας τις διαρθρωτικές αλλαγές στις σειρές (structural breaks). Τα εμπειρικά αποτελέσματα έδειξαν ότι οι εκτιμήσεις χωρίς διαρθρωτικές αλλαγές ελαχιστοποιούν τη σταθερότητα των προβλέψεων (forecast stability). Έτσι, επανεκτιμούμαι λαμβάνοντας υπόψη πέντε structural breaks για κάθε παράθυρο εκτιμήσεως (estimation window). Τέλος, επιβεβαιώνεται ο σημαντικός ρόλος της νομισματικής πολιτικής στη λήψη οικονομικών αποφάσεων.

Λέξεις κλειδιά: ακρίβεια προβλέψεων, παράθυρο εκτιμήσεων, εκτιμητής Theil, ρυθμός ανάπτυξης, νομισματική πολιτική, σχέσεις αιτιότητας

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Contents

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

1. Introduction

A critical component of many decisions are forecasts of real economic activity. Both businesses and policymakers rely on such forecasts. The former in making their production plans and the latter when choosing the path of monetary policy or when forming the national budget. Analysts often use financial variables to help predict real activity and inflation. Economists have long understood that financial market variables contain considerable information about the future economy. Forecasts based on financial variables offer readily accessible information and the data are readily available and less prone to measurement error, whereas macroeconomic models are often hindered by the lack of timely and accurate data and the complexity of the forecasting model. In addition, financial variables can add predictive power that maintains its strength even at longer horizons as well as they are less prone to measurement error.

Our purpose in this thesis is to investigate the ability and the degree up to which a number of financial variables can predict the level of future economic activity in long horizon. We will focus our study on US economy. Financial variables examined are those that are often associated with future output growth, such as stock prices, interest rates and interest rates spreads. We will also include housing and precious metal (gold) prices as well as commodity prices such as oil prices. As a measure of economic activity we are going to use industrial production index.

In the following section we will present a review of the literature on financial variables as predictors of economic activity. This review covers a total of 22 journals and working papers. The rest of the thesis is organized as follows:

The second part describes our data and the econometric method. For the conduction of our research we will use out of sample evaluation and especially the standard rolling window approach, implementing forecast combination across observation windows of different lengths[1,2]. In addition, for each observation window we use the sequential procedure of Bai and Perron (1998, 2003) to take into consideration the multiple structural breaks.

[1] Pesaran, M. H., Timmermann, 2007. Selection of estimation window in the presence of breaks.
[2] Pesaran, M. H., Pick, A., 2011. Forecast combination across estimation windows.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

The third section summarizes our main conclusions and provides the statistical tables of our econometric tests.

2. Related Literature Review

In the last two decades there has been a huge increase in literature in the growth theory on the relationship between the financial development and the economic growth. One of the most popular financial market variables is the spread between yields on long-term and short-term government instruments, also known as the yield spread, which predictive power for real activity has been recognized beyond academic research circles. For instance the Conference Board uses the yield spread in constructing its Index of Leading Indicators.

Many studies over the past thirty years have examined the extent to which financial variables, namely, stock prices, interest rates, interest rate spreads and monetary aggregates can be used to forecast future economic activity. Additionally, the last fifteen years have seen considerable research on forecasting economic activity and inflation using asset prices, including interest rates, differences between interest rates (spreads), returns, dividend yields, and exchange rates. The instability in the 1970s and early 1980s of forecasts of output and inflation based on monetary aggregates and of forecasts of inflation based on the (non-expectational) Phillips curve led to, at least in part, a growing interest in the research on asset prices as leading indicators. Asset prices and returns typically are observed in real time with negligible measurement error.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

2.1 Forecasting Economic Growth and Inflation using Asset Prices

J. H. Stock and M. W. Watson (2003)[3] examined the old and new evidence on the predictive performance of asset prices for inflation and real output growth. By the notion asset prices they interpreted interest rates, differences between interest rates (spreads), returns, dividend yields, exchange rates and other measures related to the value of financial or tangible assets (bonds, stocks, housing, gold, etc.). They undertook an empirical analysis using quarterly data on up to 38 candidate indicators (mainly asset prices) for seven OECD countries over 1959-1999. For identifying the variables that can be used as predictors of output and inflation they used an in-sample autoregressive distributed lag (ADL) model and out-of-sample procedure. As far as the out of sample analysis is concerned, they quantified the out of sample forecast performance by computing the mean square forecast error of a candidate forecast relative to a benchmark. As a candidate forecast they used the following univariate regression:

$y_t = a_0 + \sum_{i=1}^{m} a_i Y_{t-i} + e_{1t}$ while as benchmark forecast they used the following bivariate model: $Y_t = b_0 + b_1 \sum_{i=1}^{m} Y_{t-i} + b_2 \sum_{j=1}^{n} C_j Y_{t-j} + e_{2t}$

Then, the h-step ahead mean squared forecast error (MSFE) of forecast i, relative to that of the benchmark forecast, was:

$$\frac{\dfrac{1}{T_2 - T_1 - h + 1} \sum_{t=T_1}^{T_2 - h} (Y_{t+h}^h - \hat{Y}_{i,t+h/t}^h)^2}{\dfrac{1}{T_2 - T_1 - h + 1} \sum_{t=T_1}^{T_2 - h} (Y_{t+h}^h - \hat{Y}_{0,t+h/t}^h)^2}$$

If its relative MSFE is less than one, the candidate forecast is estimated to have performed better than the benchmark.

Through their analysis they were lead to the following four main conclusions.

First, some asset prices have been useful predictors of inflation and/or output growth in some countries in some time periods. The term spread was a useful

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[3] Stock, J.H. and M.W. Watson (2003), “Forecasting output and inflation: the role of asset prices”.

predictor of output growth in the United States and Germany prior to the mid-1980s. Although term spread was a good predictor for those two countries, its good performance in some periods and countries was offset by poor performance in other periods and countries.

Second, forecasts based on individual indicators are unstable. There is considerable instability in bivariate and trivariate predictive relations involving asset prices and other predictors.

Third, although the most common econometric method of identifying a potentially useful predictor is to rely on in-sample significance tests such as Granger causality tests, doing so provides little assurance that the identified predictive relation is stable. Indeed, the empirical results indicate that a significant Granger causality statistic contains little or no information about the predictive content of an indicator.

Finally, simple methods for combining the information in the various predictors, such as computing the median of a panel of forecasts based on individual asset prices, seem to circumvent the worst of these instability problems. Forecasts of output growth constructed as the median or trimmed mean of the forecasts made using individual asset prices regularly exhibit smaller pseudo out-of-sample MSFEs than the autoregressive benchmark and typically perform nearly as well as or better than the combination forecast based on all predictors. In this sense, asset prices, taken together, have predictive content for output growth. Moreover, the combination forecasts are stable in contrast to the individual predictive relations.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

2.1.1 Yield Spreads

The process of financial liberalization and innovations in the 1980s and the perceived breakdown in the link between monetary aggregates and the level of economic activity have brought poor forecasting records. Therefore, the use of alternative indicators of monetary policy, in particular financial spreads, as predictors of aggregate output and prices have gain growing interest among years. The most frequently used financial spread is the yield curve (or term structure), the difference between the long-term interest rate (i.e. the yield on long-term government bonds) and the short-term interest rate. According to the expectations hypothesis of the term structure, the differential between long- and short-term interest rates provides an indication of economic agents' expectations about future inflation (Mishkin, 1989).

Resent research has shown that the yield spread between long-term and short-term bonds helps predict real activity in the US and in some OECD countries. Hence, a positive yield spread (higher long-term than short-term interest rates) is associated with future economic expansion while a negative with future economic contraction. In addition, the larger the spread, the faster the rate of real economic growth in the future. This empirical relationship can be justified by two reasons.

First, the yield spread may reflect the stance of monetary policy. Both short-term and long-term interest rates rise but the latter usually by less, when monetary policy is tightened. As a result, the yield spread narrows or even turns negative.

Another explanation is that, the yield spread reflects market expectations of future economic growth. Whether market participants expect real income to rise in the future, an increase in profitable investment opportunities today may be implied. Businesses increase their borrowing and issue more bonds in order to take advantage of these investment opportunities. The higher supply of longer term bonds reduces their price and increases their yield, therefore long-term rates will rise relative to short-term rates, steepening the yield curve. This steepening of the yield curve will be associated with a future increase in real economic activity as long as these expectations for economic growth are at least partially realized.

While researchers have shown that the spread is a good predictor of real activity and its predictive power for the United States also has been recognized beyond academic research circles, evidence outside the United States is limited.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Therefore, **C. Bonser-Neal C. and Morley T. R. (1997)**[4] evaluated the ability of the yield spread to forecast real economic activity in 11 industrial countries. They included in their analysis only industrial countries with well-developed financial markets, namely Australia, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, the United Kingdom, and the United States. The fact that they have been included only well-developed countries is in order to ensure that interest rates reflect market expectations rather than government controls. In addition, they used data on interest rates and real economic activity for at least the last 20 years in order to have a sample size large enough for reliably assessed forecast power of the yield curve. In choosing the yield spread, they compared with previous studies along with data availability. As far as the primary measure of real economic activity they use real GDP growth which is available on a quarterly basis. Whether they wanted to estimate on a monthly basis they took the index of industrial production or the unemployment rate. For example, previous studies in US have focused on the spread between 10-year T-bill and the 3-month T-bill rate. Moreover, the forecast power of the yield spread could be employed using in-sample and out-of- sample forecasting techniques.

The results indicated the yield spread was a statistically and economically significant predictor of economic activity in several countries besides the United States. In addition, out-of-sample forecasts of real GDP growth based on the yield spread generally beat forecasts based on past real GDP growth. Moreover, their study showed that the strength of the relationship between the yield spread and future real economic growth varies across the 11 countries. The strongest predictive power of the spread found in Canada, Germany, and the United States. On the other hand, the ability of the yield spread to forecast real economic activity is weakest in Japan and Switzerland. However, in the remaining countries the results are mixed since they found that the yield spread in France explains roughly 30 percent of the following year's real GDP growth but only 10 percent of the change in the unemployment rate. Hence, they concluded that in these countries the measure of real economic activity and the forecast horizon improve the existing model forecasts based on the yield

[4] Bonser-Neal, C., and Morley T. R. 1997. "Does the Yield Spread Predict Real Economic Activity? A Multicountry Analysis,".

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

spread. Finally, they found that the spread helps predict real activity over the one to three next years.

The same year **S. Kozicki**[5] extended the analysis of Bonser-Neal and Morley, examining a wider array of forecast horizons at which the yield spread helps predict real growth. In addition, they investigated whether additional predictive power beyond that summarized by the spread can be found on the level of yields in a broader collection of countries than has previously been analyzed.

The results of his article can be summarized as follows.

First, he found that the spread matters most for predicting real growth whereas the level of short rates matters most for inflation. As for the maximum predictive power of spread, for real growth it is over the next year or so, whereas for inflation is at a much longer horizon of about three years. This can be explained by the fact that the short rate provides a cleaner measure of the stance of monetary policy than spread since the latter also contains information on credit market conditions. Therefore, although both the stance of monetary policy and credit market conditions are important for near term growth, the short rate is a better predictor of inflation over moderate horizons since inflation is primarily a monetary phenomenon in the long run.

Nevertheless, initial studies see Estrella and Hardouvelis (1989), Laurent (1989), Mishkin (1989), Bernanke (1990) employed a single-equation framework, but this approach ignored the influence of other variables upon macroeconomic activity and it treated all variables (except output/inflation) as exogenous variables. To overcome these problems, more recent studies, such as Davis et al. (1994), Davis and Fagan (1995), Bernanke and Blinder (1992) and Friedman and Kuttner (1992), have employed a multi-equation vector autoregression (VAR) framework. However, all existing studies for various countries draw their conclusions entirely on the basis of in-sample performance which does not necessarily imply good out-of-sample performance that is of interest to macroeconomic forecasters and policy analysts.

[5] Kozicki Sharon. (1997),“Predicting Real Growth and Inflation With the Yield Spread”.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Thus, **Sarantis N. and Lin S. X. (1999)**[6] evaluated the potential usefulness of financial spreads in macroeconomic forecasting focusing on out-of-sample forecasts. They use the Bayesian vector autoregressive (BVAR) methodology to develop a quarterly model for the UK economy which is then used in their forecasting analysis. This way they can not only investigate the marginal forecasting information contained in financial spreads over and above the information contained in other variables influencing macroeconomic activity, but also overcome the restrictions of VAR models that mentioned above.

Two models are specified.

The first is a base model consists of the following variables such as real GDP, the price level (measured by the GDP deflator), the public sector borrowing requirement (PSBR) normalized on nominal GDP, the current account balance normalized on nominal GDP, the real sterling effective exchange rate (which measures the degree of international competitiveness), a monetary policy instrument, oil price, and the house price. Three measures are used for monetary policy: the three-month interbank interest rate, broad money (M4) and narrow money (M0).

The second model includes the above variables plus four financial spreads: the yield curve (YC), the reverse yield gap (RYGD), the foreign interest rate differential (FID) and the long-term credit quality spread (CQS).

The BVAR models are initially estimated using data from 1971Q1 to 1988Q4, with the period 1989Q1-1995Q2 utilized for examining the accuracy of out-of-sample forecasts. The choice as to where to begin forecasting is based on the desire to produce forecasts for longer horizons and have a sufficient number of observations for each forecast step. The accuracy of each k-step-ahead forecast is measured by the widely used root mean square error (RMSE) and Theil U statistics, which are defined as

$$RMSE = \left[\sum_{j=1}^{T} \frac{(A_{t+k,j} - {}_tF_{t+k,j})^2}{T} \right]^{0.5}$$

U = RMSE(model)/RMSE(random walk)

where k = 1, 2, . . . ,12 denotes the forecast step, T is the number of observations for each forecast step, and $A_{t+.k,\, j}$ and ${}_tF_{t.+k,\, j}$ are actual and forecast values respectively.

[6] Sarantis N., Lin S. X. (1999), “The role of financial spreads in macroeconomic forecasting: Evidence for the UK”.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

The U statistic is the ratio of the RMSE for the estimated model to the RMSE of the simple random walk model which predicts that the forecast simply equals the most recent information.

Hence,

- ✓ if U < 1, the model performs better than the random walk
- ✓ if U > 1, the random walk outperforms the estimated model.

To evaluate the predictive information of financial spreads they examined not only the magnitude of the RMSE and U statistics, but also whether the forecasts produced with and without financial spreads are statistically different.

In addition, so as to carry out this statistical comparison of forecast accuracy, they employ the Wilcoxon signed-rank test Z_k which is formulated as

$$Z_k = \frac{W_t - [T(2T+1)]/2}{\sqrt{\{[T^2(2T+1)]/12\}}} \qquad k = 1,2,\ldots.12$$

where W_k is the sum of the ranks of the forecast errors produced by the base model $(e^b_{t+k,j})$ and with financial spreads $(e^f_{t+k,j})$ for step k, T is the number of observations, and Z_k is normally distributed for large samples. The null hypothesis is that the forecast errors from the two models are the same, or alternatively that the loss differential $h = L(e^b_{t+k,j}) - L(e^f_{t+k,j})$ is zero. This corresponds to the null of the asymptotic Diebold Mariano test (see Diebold and Lopez, 1996).

It is shown that financial spreads do not appear to contain any predictive information, over and above that contained in other macroeconomic variables, on future GDP, the current account and the real effective exchange rate. In fact, they tend to worsen the out-of-sample forecast accuracy of GDP when adequate attention is paid to the selection of Bayesian priors and to the inclusion of economic variables. On the other hand, financial spreads contain significant predictive information on prices for up to six quarters ahead. Nevertheless, these results remain robust for different combinations of variables, specification of priors, and forecast horizons. For instance, when they examined the predictive information contained in individual financial spreads for future GDP, they found that none of the spreads produces any improvement in forecast accuracy. However, a significant forecast accuracy at all horizons produced with the reverse yield gap and the foreign interest rate differential. They also indicated that among the alternative monetary policy instruments, the short-

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

term interest rate is the best forecaster. Additionally, if there is some additional information for improving forecasts of future real macroeconomic activity, it does not seem to be in financial spreads. Another remarkable contribution of their study is the ability of their estimated base model to capture the direction of change in GDP growth over the 1987-95 period. The timing and scale of the 1988 boom and the 1991 recession can be well predicted by this model; but when financial spreads are included, it worsens to capture the turning points of GDP growth.

Moreover, **I. A. Venetis, I. Paya, D. A. Peel (2003)**[7] examined the strength of the link between yield spread and real GDP and the stability of this link for three countries: United States, Canada and UK for at least the last 40 years. As far as the first matter is concerned they choosed smooth transition nonlinear models that allowed regime-switching nonlinearity, which uncovered by Galbraith and Tkacz (2000), in conjunction with parameter time variation. Smooth transition models (STR) have been found to be useful in univariate modelling of many economic time series. They confirmed that threshold effects exist for a number of forecasting horizons affecting the power of the spread as a leading indicator while linear or nonlinear specifications are not free of parameter time-variation. The data that are used are available on a quarterly basis concerning the real GDP, the 10-year government bond and the 3-month T-bill. They confirmed in their analysis the break in the link between the spreads and future real economic activity. Finally, their results suggested that applied analysts should be careful with the implementation of linear leading indicator models and their research could be readily extended to other leading indicators as well as to multivariate models. The possibility of false alarms (positive or negative) due to the inadequacy of linear models could not be ruled out and researchers should always be cautious on the stability of relations across time.

It is worth mentioned that the yield curve also provides signals about future output growth, since tight monetary policy and high interest rates are associated with a downward-sloping yield curve and vice versa. Hence, a declining yield curve indicates a slowdown in future output growth. Many business economists and

[7] Venetis I. A., Paya I., Peel D. A. (2003), “Re-examination of the predictability of economic activity using the yield spread: a nonlinear approach”.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

financial analysts have been mentioned that a recession is imminent because of the flattening of the yield curve in 1988 and its inversion in early 1989. A flattening of the yield curve predicts a drop in future spot interest rates as well as the lower rates are associated with a lower level of real GNP. Recent empirical work on the term structure of interest rates confirms that changes in the slope of the yield curve predict the correct direction of future changes in spot rates, although there is little empirical work on yield curve predictability in real economic activity.

A. Estrella and G. A. Hardouvelis (1991)[8] examined the predictability of the structure of interest rates in real economic activity. They began their study by examining the empirical relation between future rates of growth in real GNP and its components with the current slope of the yield curve.

Real GNP is observed quarterly, and the sample period is quarterly from 1955 until the end of 1988. The dependent variable in their basic regression is the annualized cumulative percentage change in the seasonally adjusted finally revised real GNP number based on 1982 dollars: $Y_t = (400/k)[\log(y_{t+k} / y_t)]$ (1)

where k denotes the forecasting horizon in quarters, and y_{t+k} denotes the level of real GNP during quarter t + k, and Y_{t+k} denotes the percentage change from current quarter t to future quarter t + k.

They also examined the predictability of the annualized marginal percentage change in real GNP from future quarter t + k - j to future quarter t + k, defined as:

$Y_{t+k-j,t+k} = (400/j)[\log(y_{t+k} / y_{t+k-j})]$ (2)

The cumulative percentage change $Y_{t,t+k}$ is the average of consecutive marginal percentage changes $Y_{t+k-j,t+k}$ for i = 1,2,3,….., k. Hence, each $Y_{t+i-1,t+1}$ provides information on how far into the future the term structure can predict.

They interest rates that they used to construct the slope of the yield curve are the 10-year government bond rate R^L, and the 3-month T-bill rate R^S. Both R^L and R^S are annualized bond equivalent yields. Their measure of the slope of the yield curve is the difference between the two rates $SPREAD_t = R^L - R^S$. (3)

In computing the two rates, they used average quarterly data as opposed to point-in-time data, since their concern in their study is to predict real GNP and point-in-time

[8] Estrella, A. and Hardouvelis G. A. (1991). "The Term Structure as a Predictor of Real Economic Activity".

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

data are not essential. On the contrary, it seems that GNP would be more closely associated with average interest rates over the quarter. Furthermore, averaged data provide an opportunity to check the robustness of previous results on the predictive power of the term structure that used only point-in-time data.

Their basic regression equations have the following general form:

$$Y_{t,t+k} = a_0 + a_1 SPREAD_t + \sum_{i=1}^{N} \beta_i X_{it} + \varepsilon_t \qquad (4)$$

where $Y_{t,t+k}$ and $SPREAD_t$, are defined by equations (1) and (3) above, and X_i, represents other information variables available during quarter t. Their sampling period was quarterly, but the forecasting horizon k varied from one to 20 quarters ahead. The data overlapping generates a moving average error term of order k - 1, where k is the forecasting horizon. The moving average does not affect the consistency of the OLS regression coefficients but does affect the consistency of the OLS standard errors. For correct inferences, the OLS standard errors have to be adjusted. They used the Newey and West (1987) method of adjustment. Given that the non-overlapping data may have autocorrelated errors, they allowed for a moving average of order length longer than k - 1. They choosed the lag length of each Newey and West correction after observing the estimated autocorrelation function of the OLS residuals, but the corrected standard errors are not very sensitive to the choice of the lag length.

The evidence showed that a steeper (flatter) slope implies faster (slower) future growth in real output, which is consistent with current thinking. All constant terms are positive which implies that a negative slope does not necessarily predict negative future real GNP growth.

As far as the cumulative changes in real output, they are more predictable than marginal changes. The predictive power for cumulative changes lasts for about 4 years, while the predictive power of consecutive marginal changes in real output lasts for about 6 to 7 quarters. The marginal predictive power results indicate that financial market participants are able to predict events that will occur 6 to 7 quarters ahead. These changes can be helped to calculate how low would have to be the yield curve in order to predict a future recession. Moreover, the forecasting accuracy in predicting cumulative changes is highest 5 to 7 quarters ahead and thereore SPREAD explains more than one-third of the variation in future output changes.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Next Estrella and G. A. Hardouvelis tried to answer the question of whether the yield curve may be a better predictor of a binary variable X_t that simply indicates the presence ($X_t = 1$) or absence ($X_t = 0$) of a recession. For this purpose they estimated a nonlinear model that relates the probability of a recession as dated by the National Bureau of Economic Research (NBER) (the indicator variable X_t) during current quarter t to the slope of the yield curve of quarter t-4:

$\Pr[X_t = 1 \setminus SPREAD_{t-4}] = F(\alpha + \beta SPREAD_{t-4})$, where Pr denotes probability, F is the cumulative normal distribution, and X_t equals unity during those quarters considered as official recessions by NBER. The NBER definition of a recession corresponds essentially to two consecutive quarters of negative real GNP growth. The model above is the usual probit model, and its log-likelihood function is as follows:

$$\log L = \sum_{X_t = 1} \log F(a + \beta SPREAD_{t-4}) + \sum_{X_t = 0} \log F(1 - \alpha - \beta SPREAD_{t-4}) \quad (5)$$

Maximizing the log-likelihood function (5) with respect to the unknown parameters a and β over the quarterly sample period from 1956:l through 1988:4 they showed that an increase in the spread between the long and short term interest rates implies a decrease in the probability of a recession 4 quarters later. In addition, the relation between the probability of a recession and the spread is statistically significant, but because the relation is nonlinear it is difficult to assess the quantitative significance of the association.

In the final step of their study they examined more closely the comparative value of the information in the yield curve. They added to the basic regression equation a number of information variables that are widely thought to predict future real economic activity and examined whether or not the slope of the yield curve continues to have extra predictive power. They chose the recent growth in the index of leading indicators, the lagged growth in real output, and the lagged rate of inflation as the information variables. The index of leading indicators is the first obvious choice and consists of twelve macroeconomic variables.

Hence, the evidence showed that:

1. $SPREAD_t$ continues to have explanatory power over the entire forecasting horizon. Its regression coefficients are statistically significant up to 3 years into the future.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

2. An increase in the real federal funds rate predicts a drop in real GNP for about 6 quarters into the future.
3. An increase in the index of leading indicators predicts a future increase in real GNP. However, the predictive power lasts for only up to 3 quarters ahead. This is very weak predictive power when compared to the predictive power of the slope of the yield curve.
4. The lagged growth in output has a negative coefficient showing a slight mean reversion.
5. The lagged rate of inflation also shows a negative coefficient, which is statistically significant at all horizons beyond two quarters.

The quality of the information in the slope of the yield curve can be assessed by comparing its forecasting performance with the forecasting performance of survey evidence. They used data from mid-quarter surveys conducted by the American Statistical Association and the NBER since the beginning of 1970. The data were median forecasts of current real GNP and the real GNP of the next 2 quarters. They also had data for the median forecast of 3 quarters ahead since 1981. Therefore, they concluded that SPREAD is a better predictor of future output growth than the median survey forecast. They regressed the realized percentage change in real GNP on the predicted change by the survey and on the slope of the yield curve. The survey forecasts have predictive power for one and 2 quarters ahead but not for 3 quarters ahead. Furthermore, adding the survey forecast as an additional regressor in the SPREAD, regressions does not increase the R^2.

Finally, considering the out-of-sample forecasting results they showed that for all three forecasting horizons, the root mean squared error (RMSE) of the forecast based on all the information variables is the smallest, followed by the RMSE of the forecasts based on the slope of the yield curve alone. Thus, simple econometric models that included SPREAD alone as a forecasting tool seemed to underperform those models that included more variables in addition to SPREAD. Both predictors perform better than the median forecast of the survey. For the forecasting horizon of 3 quarters, the econometric model that included only the slope of the yield curve produces a higher correlation (r^2) with the actual values than the econometric model that includes additional information variables. However, the higher correlation of the former model was offset by a larger bias over the sample period 1982-1988. Although

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

the slope of the yield curve outperformed all the other predictors they examined, the absolute size of the out-of sample root mean squared errors of its forecasts was fairly large compared with the standard deviation of the real GNP growth rate.

Hamilton D. J. and Kim D. Heon (2002)[9] in their study revisited the usefulness of the yield spread for predicting future real GDP growth. They used the 10-year T-bond rate, 3-month T-bill rate, and real GDP from 1953:Q2 to 1998:Q2. From their historical data they observed that the yield curve has flattened or become inverted prior to all seven recessions and episodes illustrated when the gap between two interest rates became negative. Needless to say that the yield curve does not have to become inverted to signal an imminent recession, it may simply flatten relative to normal.

Many previous studies, already previously referred such as Estrella and Hardouvelis (1991), Estrella and Mishkin (1997), Bonser-Neal and Morley (1997), Kozicki (1997) used the following regression to examine the predictability of the yield spread for real activity:

$$y_t^k = a_0 + a_1 SPREAD_t + \varepsilon_t \text{ (6)}$$

$$y_t^k = (400/k)(\ln(Y_{t+k} - Y_t) \text{ (7)}$$

$$SPREAD_t = i_t^n - i_t^1 \text{ (3)}$$

i_t^n, i_t^1 are the n-period interest rate (long-term rate) and one-period interest rate (short-term rate) respectively.

Consider the following definition of the time-varying term premium TP_t:

$$i_t^n = \frac{1}{n}\sum_{j=0}^{n-1} E_t i_{t+j}^1 + TP_t \text{ (8)}$$

where $E_t(i_{t+j}^1)$ denotes the market's expectation at time t of the value of i_{t+j}^1. The term premium TP_t could be viewed, for example, as the sum of a liquidity premium (η_t) and risk premium (θ_t) : $TP_t = \eta_t + \theta_t$.

Equation (8) can alternatively be written $i_t^n - i_t^1 = (\frac{1}{n}\sum_{j=0}^{n-1} E_t i_{t+j}^1 - i_t^1) + TP_t$ (9).

[9] Hamilton, J. D. and. Kim D. H 2002. "A Re-Examination of the Predictability of Economic Activity using the Yield Spread".

The above equation implied that the spread can be decomposed into two terms.
The first term on the right-hand side is the difference between short-term interest rates expected over the next n periods and the current rate.
The second term is the time-varying term premium.
Thus, if a fall in the spread predicts U.S. recessions, it could either be because a temporarily high short-term rate suggests a coming recession or a fall in the premium on long-term bonds relative to short-term bonds suggests an economic recession.
Hamilton and Kim showed that both the expected change of the short-term rate over n periods (the simple expectations hypothesis) and the time-varying term premium help predict real GDP growth up to 8 quarters ahead. They also suggested that the contribution of the future expected change of short-term rates to prediction of real GDP growth is statistically significantly bigger than that of the term premium. Hence, the most important reason for predicting slower real GDP growth, when using a negative yield spread, is that a low spread implies falling future short-term interest rates. One factor that should matter for the term premium is the volatility of interest rates, but higher interest rate volatility is associated with a decrease in the spread and an expected drop in interest rates.

In sum, they examined the usefulness of long-term and short-term rates for predicting GDP growth. They have shown how to decompose this effect into an expectations effect and a term premium effect. Both effects are statistically significant although the first effect (the expectations effect) is slightly more important quantitatively and statistically. A forecast of falling short-term interest rates is associated with a forecast of slower GDP growth, and an increase in the expected return from rolling over 1-period bonds relative to an n-period bond is also associated with a forecast of slower GDP growth.
Additionally, they proposed a simple model for interpreting the second effect (the term premium effect) based on time-variation in the variance of short-term interest rates. According to this model, the spread and term premium fall at the end of the expansion could be explained by an increase in interest rate volatility at the end of an expansion. They found that volatility is an empirically important determinant of the spread and the term premium and a useful predictor of future interest rates. However, cyclical movements in volatility appear to be unable to account for the usefulness of the spread and term premium for forecasting GDP.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Many years later, **A. Ang et al. (2006)**[10] motivated from the absence of arbitrage in bond markets, they presented a model of yields and GDP growth for forecasting GDP in an attempt to model the dynamics of yields jointly with GDP growth. Therefore based on the assumption of no-arbitrage, they built a model of the yield curve in which a few yields and GDP growth are observable state variables. This helps them to reduce the dimensionality of a large set of yields down to a few state variables. The dynamics of these state variables are estimated in a vector autoregression (VAR). Bond premia are linear in these variables and are thus cyclical.

Regarding the predictability of GDP in the non-arbitrage framework, they tried to address two issues. They first demonstrated that the yield-curve model can capture the same amount of conditional predictability that is picked up by simple OLS regressions. However, OLS approaches and the forecasts implied by their model yield different predictions. Using the term structure model, they attributed the predictive power of the yield curve to risk premium and expectations hypothesis components and showed how the model could generate the OLS coefficient patterns observed in data in small samples.

The second question we investigated is how well GDP growth could be predicted out-of-sample using term structure information, where the coefficients in the prediction function were either estimated directly by OLS, or indirectly, by transforming the parameter estimates of our yield-curve model.

They found that their yield-curve model had several main advantages over unrestricted OLS specifications.

1. The model advocated using a select number of factors to summarize the information in the whole yield curve. These factors followed a VAR, and long-term forecasts for these factors and GDP are simply long-horizon forecasts implied by the VAR.
2. The yield-curve model guided them in choosing the right spread maturity in forecasting GDP growth. They found that the maximal maturity difference is the best measure of slope in this context.

[10] Ang, A., Piazzesi M., and Wei M. (2006): “What does the yield curve tell us about GDP growth?”.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

3. The nominal short rate dominated the slope of the yield curve in forecasting GDP growth both in- and out-of-sample. They found that the factor structure was largely responsible for most of the efficiency gains resulting in better out-of-sample forecasts.
4. Their model is a better out-of-sample predictor of GDP than unrestricted OLS. This finding was independent of the forecasting horizon and of the choice of term structure regressor variables. The better out-of-sample performance from our yield-curve model is driven by the gain in estimation efficiency due to the reduction in dimensionality and imposing the cross-equation restrictions from the term structure model.

Nevertheless, some studies consider the predictive content of the term spread for inflation. According to the expectations hypothesis of the term structure of interest rates, the forward rate (and the term spread) should embody market expectations of future inflation and the future real rate. With some notable exceptions, the papers in this literature generally find that there is little or no marginal information content in the nominal interest rate term structure for future inflation. Much of the early work, which typically claims to find predictive content, did not control for lagged inflation. In U.S. data, Mishkin (1990a) found no predictive content of term spreads for inflation at the short end of the yield curve, although Mishkin (1990b) found predictive content using spreads that involve long bond rates. Philippe Jorion and Mishkin (1991) and Mishkin (1991) reached similar conclusions using data on ten OECD countries, results confirmed by Gerlach (1997) for Germany using Mishkin's methodology. Estrella and Mishkin (1997), and Kozicki (1997) examined the in-sample marginal predictive content of the term spread, given lagged inflation. Kozicki (1997) and Estrella and Mishkin (1997) included only a single lag of inflation, but doing so the marginal predictive content of the term spread for future inflation over one to two years substantially reduced. For instance, in lagged inflation, Kozicki (1997)[11] found that the spread remained significant for one-year inflation in only two out of the ten OECD countries she studied.

[11] Kozicki Sharon. (1997),"Predicting Real Growth and Inflation With the Yield Spread".

In this framework, the recent financial crisis has brought new interest into the literature on bond spreads and economic activity. Economic activity has declined during a Great Recession and bond spreads have become more volatile after the collapse of Lehman Brothers in September 2008. Therefore, Gilchrist, Yankov and Zakrajšek (2009), Gilchrist and Zakrajšek (2012) and Faust et al. (2012) have conducted the most recent research in US bond markets using US bond market data. Their study employs a bottom up approach to the construction of spreads in order to remove the prepayment and liquidity risks. Gilchrist, Yankov and Zakrajsek (2009) constructed a bond spread index from monthly data on prices of senior unsecured corporate debt traded in the secondary market over the 1990-2008 period, issued by about 900 U.S. nonfinancial corporations. They concluded that most of the predictive power of spreads comes from the middle of the bond-quality spectrum. They used a structural VAR framework to further assess the impact on the macroeconomy of movements in the bond spread and they found that unexpected increases in the bond spreads cause large and persistent contractions in economic activity. For example, bond market shocks explain 30% of the variance in economic activity at two- to four-year horizons.

Therefore, **M. Bleaney, P. Mizen and V. Velean (2012)[12]** examined the relationship between real activity and financial market tightness in Europe. They evaluated the importance of bond spreads, and excess bond premiums extracted by removing the predictable part of the spread, in predicting real activity at the individual country level. They found that the bond spreads and excess bond premiums consistently predict changes in real activity, in contrast with other measures of monetary policy tightness and signals from leading indicators of economic performance. However the results are robust to different measures of the bond spreads and are consistent at different forecast horizons. They also found that only the core European countries have similar magnitudes for coefficients on the bond spreads, when comparing the predictive ability of the bond spread and the excess bond premium in individual countries within the euro area and outside the euro area.

[12] Bleaney, M., Mizen P. and Veleanu V. (2012), “Bond Spreads as Predictors of Economic Activity in Eight European Economies”.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Finally, another indicator that has predictive content primarily for real economic activity is default spreads. It is the difference between the interest rates on matched maturity private debt with different degrees of default risk. Bernanke (1983) when studied the credit channel during the Great Depression showed that during the interwar period the Baa-Treasury bond spread was a useful predictor of industrial production growth. Stock and Watson (1989) and Friedman and Kuttner (1992) studied the default spread as a predictor of real growth in the postwar period.

Moreover, Stock and Watson (1989) and Friedman and Kuttner (1992) found that the spread between commercial paper and U.S. Treasury bills of the same maturity (three or six months; the “paper-bill” spread) was a potent predictor of output growth using monthly data from 1959–88 and quarterly data from 1960-90 respectively). Subsequent literature focused on whether this predictive relationship is stable over time. Bernanke (1990) confirm the strong performance of paper-bill spread as predictor of output using in-sample statistics, but when the sample is splitted up this relation weakened during the 1980s.

However, there are four nonexclusive arguments have been put forth on why the paper–bill spread had predictive content for output growth during the 1960s and 1970s. First, Stock and Watson (1989) suggested the predictive content arises from expectations of default risk, which are in turn based on private expectations of sales and profits. On the other hand, Bernanke (1990) and Bernanke and Blinder (1992) suggested that the paper-bill spread is a sensitive measure of monetary policy, and this is the main source of its predictive content. Then, Friedman and Kuttner (1993a,b) suggested that the spread is detecting influences of supply and demand (i.e. liquidity) in the market for private debt. As for inflation, Feldstein and Stock (1994) found that although the paper-bill spread was a significant in-sample predictor of real GDP, it did not significantly enter equations predicting nominal GDP.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

2.1.2 Stock Returns

Previous empirical studies have tried to identify the most appropriate financial variables, such as stock market returns, short-term interest rates, interest rate spreads, and exchange rates. Fama (1981) examined the sources of variations in stock returns, including shocks to expected cash flows, predictable stock return variation caused by changes in the discount rate over time, and shocks to discount rate in the valuation models of stock prices. He concluded that large fractions of annual stock variances can be traced to forecasts of crucial variables, such as real GNP, industrial production and investment. These variables are determinants of firms' cash flows.

Lee (1992) employed a multivariate vector-autoregressive model to investigate causal relations and dynamic interactions among asset returns, real activity, and inflation in the United States during the postwar period. Hence, he proved that stock returns appear to Granger cause real activity and also explains its variation. **Estrella and Mishkin (1998)**[13] focused on out-of-sample performance from one to eight quarters ahead in order to examine the performance of financial variables as predictors of U. S. recession, resulting that stock prices can predict real output from one to three quarter horizons. Choi *et al*. (1999) investigated the relationship between industrial production growth rates and lagged real stock returns in the G-7 countries, concluding that, except Italy, correlation between the two variables is significant in all countries. Stock and Watson (2003) indicated the importance of other variables, such as money supply, exchange rates, and oil prices in predicting output growth in the case of the United States. Kuosmanen and Vataja (2011) also investigated the forecasting content of stock returns and volatility, and the term spread for GDP, private consumption, industrial production and the inflation rate in Finland. They suggested that the term spread compared to stock market variables have more predictive power for real activity, during normal times, but during the financial crisis, the combination of the term spread and the stock market information improve the forecast.

[13] Estrella, A. and Frederic S. Mishkin (1998). "Predicting U.S. Recessions: Financial Variables as Leading Indicators".

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Thailand's' industrial production has been in a rising trend even though there was a large interruption from the 1997 financial crisis. Generally, movements in real activity can be affected by movements in stock market index. Therefore, **K. Jiranyakul (2012)**[14] attempted to investigate the ability of stock market return to predict industrial production growth or real activity in Thailand. Even though most previous studies focus on mature markets, this study is an example of the predictive power of stock return on real activity in an Asian emerging market. The standard Granger causality test and the estimations of the nested models are used for forecasting the monthly data of stock market return and industrial production growth during the period from January 1993 to December 2011.

Under the assumption that investors and portfolio managers will usually forecast the market index for their investment decision, the author uses the nominal stock return. Hence, the data are divided into two periods: the in-sample period starts from January 1993 to December 2006, and the out-of-sample period starts from January 2007 to December 2011. There are 164 and 60 observations for the in sample and out-of- sample periods, respectively. The test of equal forecasting ability for these two nested models is also used.

Finally, this study concluded that the stock market return has a predictive power in a short horizon of three months or a quarter. In addition, investors, portfolio managers and policymakers gain a useful insight to the role of stock market in forecasting real economic activity since an increase in stock market return is a signal for an increase in real activity in the next three months. On the contrary, a decline in stock market return will signal a fall in real activity or industrial output growth in the same manner.

However, Stock and Watson (1990) showed that the relationship between stock returns and economic growth has not been stable over time, and that the systematic predictive information of stock returns for future activity is also contained in other financial variables, such as yield spreads between 10 year and 3 month government bonds or between T-bills and commercial paper that use Estrella and Hardouvelis (1991). In addition, Binswanger (2000) presented evidence for a

[14] Jiranyakul K. (2012), "The Predictive Role of Stock Market Return for Real Activity in Thailand".

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

breakdown in the relation between stock returns and future real activity in the US economy since the early 1980s.

Thus, **Ó. T. Henry et al. (2004)**[15] revisited the issue of whether stock prices have predictive power for changes in aggregate output. They used a panel of quarterly data for 27 countries comprising both OECD and non-OECD Asian economies in an effort to investigated the link between the stock market and output, not assuming linear dynamic relationship between them. They employed a non-linear model that allows the dynamics underlying the quarterly change in output to be affected by whether or not the economy is in recession.

Given data on the level of GDP, Y_{it} and stock prices, X_{it} at time t for country i, a natural starting point for an analysis of the relation between stock returns and output growth is the linear functional form,

$$y_{i,t} = \alpha + \sum_{j=1}^{p} \beta_j y_{t-j} + \sum_{k=1}^{q} \delta_k x_{i,t-k} + \varepsilon_{i,t} \qquad (1)$$

where $y_{i,t} = \log(Y_{i,t} / Y_{i,t-1})$ represents real GDP growth between quarters t and t-1 for country i, α_i is a fixed effect and $x_{i,t} = \log(X_{i,t} / X_{i,t-1})$ represents stock returns.

While the functional form (1) is intuitively appealing in estimating a causal or predictive relationship between two variables, it nevertheless imposes restrictions upon the empirical relationship. In particular, the linearity of the functional form imposes a symmetric relationship between positive and negative shocks to output. Symmetric response to shocks implies that only the size, and not the sign, of the output innovation is the important consideration in assessing the impact of a shock to growth. Thus positive and negative shocks to growth of equal absolute magnitude would have equal short and long run impacts on output growth.

To relax the symmetry constraint, they employ the idea first found in Beaudry and Koop (1993), that the "current depth of recession" (hereafter CDR) produces an asymmetry in output growth. This asymmetry is reflected in what is sometimes known as a "bounce-back" effect (when output growth recovers strongly following a recent recession). When output falls below its previous peak, the CDR approach treats the historical maximum level of output as an attractor that influences the dynamics of

[15] Henry, Ó. T., Olekalns N., and Thong J. (2004), "Do Stock Market Returns Predict Changes to Output? Evidence from a Nonlinear Panel Data Model".

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

output growth. Therefore, they included a CDR term in the estimated model. The CDR was defined as the gap between the current level of output and the economy's historical maximum level.

It was expressed as: $CDR_{i,t} = \max\{Y_{i,t-s}\}_{s=0}^{t} - Y_{i,t}$ (2)

The CDR term would take non zero values either when output drops below its historical maximum due to a negative shock or in the aftermath of a positive shock as the economy begins to expand.

Their purpose for including the CDR term was to identify a possible asymmetry in quarterly output growth and to correct any possible misspecification that may arise from the estimation of such linear models in the presence of asymmetry. The model they estimated was: $y_{i,t} = \alpha + \sum_{j=1}^{p} \beta_j y_{t-j} + \sum_{k=1}^{q} \delta_k x_{i,t-k} + \sum_{i=11}^{r} \lambda_i CDR_{i,t-i} \varepsilon_{i,t}$ (3)

If the estimates of $\lambda_1,\ldots,\lambda_r$ are significantly different from zero, the symmetry restriction can be rejected.

An important advantage of (3) was that tests of the null hypothesis of linearity could be performed using an F-test of the null hypothesis, in contrast to many other popular non-linear specifications.

Finally, using a witching panel regression there is evidence that stock returns contain information that is useful for predicting growth when the economy is contracting. In non-recession periods there is no evidence that equity returns can be usefully employed to predict growth.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

2.1.3 Other Financial Indicators (i.e. housing prices) and Commodity Prices (i.e oil prices)

Housing gets significant weight in the CPI in many countries as well as constitutes a large component of aggregate wealth. Generally, housing prices suggest a broader channel by which housing prices might forecast real activity, inflation, or both. They are a volatile and cyclically sensitive sector, and measures of real activity in the housing sector are known to be useful leading indicators of economic activity, at least in the United States (Stock and Watson 1989; 1999a). For instance, housing starts (a real quantity measure) have some predictive content for inflation (Stock 1998; Stock and Watson 1999b), in the United States. Higher house prices raise the cost of living for workers, causing them to demand higher wages. These may eventually affect goods and services prices to increase since firms may react to higher wage demands by raising their prices.

Another connection between asset prices and economic activity arises from imperfections in the credit market. Asymmetric information in credit markets constrains firms and households in their borrowing, giving rise to adverse selection and moral hazard problems. As long as the net worth of firms and households remains low, these problems will be more severe and due to the less collateral available to secure loans, borrowing constraints will be arise. An increase in asset prices raises the borrowing capacity of firms and households due to the increased value of collateral. The additionally available credit can be used to purchase goods and services, leading to even higher consumer price inflation. Part of the additionally available credit may also be used to purchase assets, pushing up asset prices even further, so that a self-reinforcing process can evolve.

However, studies of the predictive content of housing prices confront difficult data problems. **Goodhart and Hofmann** (2000a) constructed a housing price data set for twelve OECD countries. They found that residential housing inflation has significant in-sample marginal predictive content for overall inflation in a few of the several countries they study.

In addition, house prices do have a weaker, but just significant, effect outside the USA. Unlike many other countries, cyclical movements of housing prices have been comparatively mild in the USA aggregate, perhaps because the ready availability of

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

land and cheap wooden building has increased the elasticity of supply. Be that as it may, the addition of housing prices does not provide any real help in explaining US inflation, and US experience becomes projected as a universal truth.

More recent empirical research had demonstrated that oil price changes have asymmetric effects on the macroeconomy. For example, some studies had shown that oil price increases have had a significantly negative impact on GNP growth in the U.S. as well as when oil price decreases did not necessarily lead to increased output growth. In addition, this asymmetry has also presented in most other OECD countries. However, others have shown that unexpected oil price growth has a highly significant and asymmetric impact on output growth when the former is deflated by oil price volatility. In fact, they argued that the dramatic rise in oil price volatility since the mid-1980s has led to a breakdown in the empirical relationship between oil prices and economic activity in the U.S. Additionally, Hamilton (1983) observed that all except one of the recessions in the United States between the end of World War II and 1973 were preceded by a sharp rise in the price of oil showing that the price of oil Granger-caused aggregate output and was exogenous with respect to the broader macroeconomy.

The negative correlation between oil prices and economic activity have been explained by several different channels.

First, the real balances channel. According to this, oil price increases leading to inflation which lowers the quantity of real balances in the system. This in turn produce recessions through familiar monetary channels.

Second, others have argued that counter inflationary monetary policy responses to oil price increases are responsible for the real output losses associated with these shocks.

Another channel comes from the demand-side. Oil price increases lead to income transfers from countries that are net importers of oil, such as the U.S., to oil exporting countries, having a depressing effect in the aggregate demand.

A fourth explanation for the oil price-output correlation focuses on the supply-side of the economy and potential output. If oil and capital are complements in the production process and oil price increases this will lead to negative transitional output growth since utilization of both oil and capital will reduce.

Thus, in answering questions, such as whether oil price shocks adversely affect the economy through the sectoral shocks and uncertainty channels, to what extent the real effects of oil price shocks can be explained by the reaction of monetary policy, or to what extent each of these channels can account for the asymmetric relationship between oil price changes and output growth, **Ferderer J.P. (1996)**[16] used daily spot market oil prices from a previously unexploited data source, *Platt's Oil Price Handbook and Oilraanac*, estimating the level (monthly mean) and volatility (monthly standard deviation) of real oil prices. The first and second moments of oil prices are then introduced into unrestricted vector autoregression (VAR) models along with two different measures of monetary policy and aggregate output. This way, they are able to examine the response of economic activity to the other variables in the system as well as they can also investigate how monetary policy and oil price volatility respond to increases and decreases in the level of oil prices.

Their results can be summarized below.

First, there is evidence that oil market disruptions affected the U.S. economy through the sectoral shocks and uncertainty channels over the 1970 to 1990 sample period. In addition, despite the high degree of co-variability between variables that makes it difficult to isolate these two channels, it is indicated that there is important independent information in oil price volatility that helps forecast industrial production growth.

Second, there is evidence that monetary tightening in response to oil price increases can explain part of the output-oil price correlation. In particular, they showed that two measures of monetary policy (non-borrowed reserve growth fell and the Federal funds rate rose due to oil price increases) affected output growth. However, the oil price variables have a stronger and more significant impact than the monetary variables, suggesting that the monetary channel provides, at best, a partial explanation for why oil price increases adversely affect the economy.

Finally, the Federal Reserve raised the Federal funds rate in response to oil price increases by about as much as they lowered it in response to oil price decreases. Moreover, inclusion of monetary variables into output equations does not cause the coefficients on oil price increases and decreases to converge in value. In contrast, oil

[16] Ferderer J. P. (1996), "Oil price volatility and the Macroeconomy".

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

price volatility rises during both positive and negative oil price shocks and the coefficients on oil price increases and decreases become much closer in value when oil price volatility is introduced into the output equations. Hence, the sectoral shocks and uncertainty channels offer a partial solution to the asymmetry puzzle.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

2.1.4 A group of Financial Variables

It has been proved in both empirical and theoretical literature that financial variables contain useful leading information toward economic activity and therefore it can be used in forecasting GDP growth. However, the relationship between the financial development and the economic growth as well those of forecasting economic growth using financial variables, are mainly based on linear econometric models. Hence, when nonlinearities could exist in the relationship between the variables, the linear models could be less powerful in forecasting GDP growth rates.

M. Forni et al. (2003)[17] tried to evaluate good predictions for the Euro-area industrial production and consumer price indexes by pooling information from a broad group of financial variables. In fact, they evaluated the predictive contents of suitably selected averages of many variables, instead of evaluating the predictive contents of single financial variables. They extracted data from a large panel of monthly time series for the six main economies of the Euro area which contains industrial production (by sectors and nations), prices (by sectors and nations), money aggregates (by nations), a variety of potentially leading variables (survey data and others), and financial variables such as interest rates (nominal and real, for different countries and maturities), spreads, and exchange rates.

For evaluating forecasting performances at different time horizons they used out of sample simulation exercise. In addition, for evaluating the role of financial variables, they use both FHLR's[18] and SW's[19] methods on a data set which contained different blocks of variables. In addition, they evaluated changes in forecasting performance when financial variables are excluded.

In this model, each time series in the panel was represented as the sum of two components: the common[20] and the idiosyncratic[21] components.

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[17] Forni, M., M. Lippi, M. Hallin and L. Reichlin (2003), "Do financial variables help forecasting inflation and real activity in the euro area?".

[18] FHLR is the acronym for the generalized dynamic factor model proposed and discussed in Forni et al (2001b) and is specifically designed for large panels of dynamically related time series.

[19] SW is the acronym for the foreacasting strategy suggested by Stock and Watson (1999).

[20] This is a component which captured most of the multivariate correlation.

[21] This is a component which is poorly cross-sectionally correlated.

The common components in the cross section have, so to speak, 'reduced rank', meaning they are all driven by a few common shocks. Such low dimensionality implies that common components can be consistently estimated and forecasted on the basis of few regressors, i.e. the present and the past of the common shocks, or linear combinations of them.

On the other hand, in SW model, the averages used in prediction are simply the static principal components of the variables in the panel.

Finally, compared the performances of the two multivariate methods (FHLR and SW) with those of simple univariate autoregressive models they reached the following results.

They showed that the multivariate methods outperform the univariate ones in forecasting inflation at all horizons, and industrial production at 1 and 3 months, as well as that financial variables do help forecasting inflation, at all horizons, but not industrial production.

However, one faces numerous decisions and challenges in forecasting macroeconomic and financial variables, especially when they consider a large, complex, dynamic system such as the world economy. For example, except the target variable what variables to model, what type of economic theory to utilize (short-run and/or long-run), how to select functional forms, estimation windows and lag lengths, and so on.

M. H. Pesaran et al. (2009)[22] employed the Global Vector Autoregressive (GVAR) model covering 33 countries, grouped into 26 countries/regions to examine and evaluate some of these choices. They generated out-of-sample one- and four-quarter-ahead forecasts of real output, inflation, real equity prices, exchange rates over the period 2004Q1–2005Q4. The forecasts are compared with univariate autoregressive and random walk models. They found that when GVAR forecasts are averaged over different model specifications and estimation windows (the "AveAve" forecasts), the results tend to outperform forecasts based on individual models, especially for output and inflation. The above helped to deal with model and observation window uncertainties. They also examined the potential use of financial

[22] Pesaran M. H., T. Schuermannd, L. V. Smith (2009), "Forecasting economic and financial variables with global VARs".

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

variables such as long-term interest rates and real equity prices for forecasting macroeconomic variables, particularly real output and inflation. According to macro-finance literature, they would expect financial variables to be important for forecasting the real economy. Finally, they found that the inclusion of long-term interest rates and real equity prices does indeed improve forecasts of real output and inflation in the case of some advanced economies, whereas in particularly the US and Canada, this did not happen generally.

Another empirical study that tried to investigate whether financial variables provide additional predictive power is the working paper of **R. Espinoza, F. Fornari and Marco J. Lombardi (2009)**[23]. The main purpose was to understand whether considering financial variables helps improving the forecasts of economic activity with respect to forecasts produced looking at past activity levels only. Their analysis is foced on the US and the Euro area, using mainly financial variables although they also consider some different indicators (quantity-based and risk-based). As financial variables they focused attention on indicators have been already employed to forecast economic activity, such as the slope of the yield curve, the short term rate, the stock market return and its time-varying volatility, and the dividend yield of the stock market. However, it has been indicated that a significant change in their role through time. In particular, the presence of risk premiums, lead asset prices to deviate from fundamentals, weakening the relationships between asset prices and the change in funadamentals. For example, although economic expansions ahead can be signaled through equity prices rise, an economic slowdown could also provoke the rise in equity – being unrelated to fundamentals –which is suddenly reversed with adverse effects on balance sheets and wealth. The IT-bubble between 1995 and 2000 was an example of such a possibility. Moreover, they look at both in sample and out-of-sample evidence so as to investigate the linkage between financial conditions and real activity. They used a VAR model of the US and the euro area GDPs and extended it to take into account common global shocks and information provided by selected combinations of financial variables.

Hence, their results can be summarized above.

[23] Espinoza, R., F. Fornari and M. J. Lombardi (2009), "The role of financial variables in predicting economic activity".

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

In-sample evidence suggested that 'financial shocks' do matter for euro area and US real activity. However, a RMFE metric in out-of-sample forecasts showed[24] that financial variables do not help forecasting real activity in the euro area, even when taking into account their timeliness. Evidence was more favorable to a role of the financial variables in predicting real activity in the United States but the gain is concentrated at a few forecast horizons (5 and 11 quarters) and the loss in predictive power at the shortest horizons was remarkable.

In addition, conclusions do not change when employing industrial production indices, either at a quarterly and a monthly frequency. Nevertheless, when conditional predictive ability tests are considered, the previous results changes. In fact, financial variables played a role in the prediction of the euro area GDP especially in 1999 and between 2001 and 2003, showing that financial shocks were indeed prominent in these periods.

Finally, caveat which also entails some directions for future research relates to the linear framework employed throughout the paper. Therefore, their findings and statements about the forecasting power of financial variables should be interpreted within the setting of linear models. As a consequence, it could indeed be the case that financial variables have a nonlinear impact on macroeconomic variables.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

[24] Espinoza R., F. Fornari and Marco J. Lombardi (2009) shared the same conclusion with Stock and Watson (2003).

2.2 Do macro variables, asset markets, or surveys forecast inflation better?

As we mentioned above, accurate forecasts of future inflation is crucial for policymakers conducting monetary and fiscal policy, for investors hedging the risk of nominal assets, for firms making investment decisions and setting prices and for labor and management negotiating wage contracts.

Economists use four main methods to forecast inflation.

- ✓ The first using time series models of the ARIMA variety.
- ✓ The second builds on the economic model of the Phillips curve, leading to forecasting regressions that use real activity measures.
- ✓ The third uses information embedded in asset prices, in particular the term structure of interest rates so as to forecast inflation.
- ✓ Finally, survey-based measures use information from agents (consumers or professionals) directly to forecast inflation.

A. Ang et al. (2007)[25] in their article tried to comprehensively compare and contrast the ability of these four methods for forecasting inflation out of sample in contrast to the previous literature concentrated on only one or two of these methodologies. Thus, their contribution in the literature was the fact that they are the first that comprehensively compare the four methods: time-series forecasts, forecasts based on the Phillips curve, forecasts from the yield curve, and surveys (the Livingston, Michigan, and SPF surveys[26]). The superiority of a particular forecasting method cannot be justified due to the lack of a study comparing these four methods of inflation forecasting.

In their study, they developed forecasting models that used all available data and impose no-arbitrage restrictions. The no-arbitrage framework allowed them to extract forecasts of inflation from data on inflation and asset prices taking into account potential time-varying risk premia. No-arbitrage constraints were reasonable in a world where hedge funds and investment banks routinely eliminated arbitrage

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[25] Ang A., Bekaertb G., Weic M. (2007) "Do macro variables, asset markets, or surveys forecast inflation better?".

[26] The SPF is the acronym for Survey of Professional Forecasters which is the oldest quarterly survey of macroeconomic forecasts in the United States. The survey began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

opportunities in fixed income securities. Imposing theoretical no-arbitrage restrictions may also lead to more efficient estimation and accurate forecasts of inflation.

Moreover, they thoroughly investigate combined forecasts. They investigated five different methods of combining forecasts which are simple means or medians, OLS based combinations, and Bayesian estimators with equal or unit weight priors.

Additionally, their main focus was forecasting inflation rates. Due to the long-standing debate in macroeconomics on the stationarity of inflation rates, they also explicitly contrasted the predictive power of some non-stationary models to stationary models. Therefore, they considered whether forecasting inflation changes alters the relative forecasting ability of different models.

Their major empirical results can be summarized as follows.

First, survey forecasts (the median Livingston and SPF survey forecasts) outperformed the other three methods in forecasting inflation. Presumably many of the best analysts use time-series and Phillips curve models which makes this result reasonable. However, even participants in the Michigan survey who are consumers, not professionals, produce accurate out-of-sample forecasts, only slightly worse than those of the professionals in the Livingston and SPF surveys. They also find that the best survey forecasts are the survey median forecasts themselves, whereas adjustments to take into account both linear and non-linear bias yield worse out-of-sample forecasting performance.

Second, term structure information did not generally lead to better forecasts and often leaded to inferior forecasts than models using only aggregate activity measures. The relatively poor forecasting performance of term structure models extends to simple regression specifications, iterated long-horizon VAR forecasts, no-arbitrage affine models, and non-linear no-arbitrage models. These results suggest that while inflation is very important for explaining the dynamics of the term structure (see, e.g., Ang et al., 2006b), yield curve information is less important for forecasting future inflation.

Finally, combining forecasts did not generally lead to better out of sample forecasting performance than single forecasting models. In particular, simple averaging, like using the mean or median of a number of forecasts, does not necessarily improve the forecast performance, whereas linear combinations of forecasts with weights computed based on past performance and prior information generate the biggest gains. Even the Phillips curve models using the Bernanke et al. (2005) forward-looking aggregate measure of real activity mostly do not perform well relative to simpler Phillips curve models and never outperform the survey forecasts. The strong success of the surveys in forecasting inflation out-of-sample extends to surveys dominating other models in forecast combination methods. The data consistently place the highest weights on the survey forecasts and little weight on other forecasting methods.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

3. Data and definitions

All series are retrieved mainly from Datastream and our investigation focus is on United States. We should note that some data are made available from Federal Reserve Bank of St. Louis. The data are monthly seasonally adjusted observations of the aggregate stock price index, nominal short term interest rates, the consumer price index (CPI), the industrial production index, the housing prices, the oil prices, the precious metal prices: gold and the money supply (M2). The sample period spans from January 1968 to September 2013 since during this time US economy experienced different financial crises. All the time series, including short-term interest rates, were transformed to logarithmic first differences.

As a measure of the economic activity we use the industrial production index. The Federal Reserves monthly index of industrial production and the related capacity indexes and capacity utilization rates cover manufacturing, mining, and electric and gas utilities. The industrial sector, together with construction, accounts for the bulk of the variation in national output over the course of the business cycle. The industrial detail provided by these measures helps illuminate structural developments in the economy. The industrial production index measures real output and is expressed as a percentage of real output in a base year. In addition, it is computed as Fisher indexes since 1972 the weights are based on annual estimates of value added.

For stock return index we use the S&P composite stock index (dividends are included).

In the previous chapter we present a set of recent studies[27], which conclude that asset prices help forecast both inflation and output. Therefore, we also include in our analysis asset prices such as nominal short-term interest rates, housing prices, gold, term spreads as well as commodity prices such as oil prices.

As short-term interest rate we take the 3-Month Treasury Bill Secondary Market Rate on a Discount Basis and as the term structure of interest rate we define the difference between 10 year government bond rate and 3-month Treasury Bill.

[27] Such as Forni *et al.* (2003) and Stock and Watson (2003).

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

It is evidenced that housing is a volatile and cyclically sensitive sector. At least in the United States, measures of real activity in the housing sector are known to be useful leading indicators of economic activity, (Stock and Watson 1989; 1999a), suggesting a broader channel by which housing prices might forecast real activity, inflation, or both. In the United States, housing starts (a real quantity measure) have some predictive content for inflation (Stock 1998; Stock and Watson 1999b).

As housing prices we take the housing starts. They are an economic indicator that reflects the number of privately owned new houses (technically housing units) on which construction has been started in a given period.

For robustness we use Consumer Price Index for All Urban Consumers: Housing.

There is widespread agreement that unexpected large and persistent fluctuations in the real price of oil are detrimental to the welfare of both oil-importing and oil-producing economies. Central banks and private sector forecasters view the price of oil as one of the key variables in generating macroeconomic projections and in assessing macroeconomic risks. Oil prices have an impact in the U.S. economy. Higher oil prices directly affect gasoline, home heating oil, manufacturing and electric power generation. According to the EIS (Energy Information Administration)[28], 96% of the transportation relies on oil, 43% of industrial product, 21% of residential and commercial, and (only) 3% of electric power. However, if oil prices rise, then so does the price of natural gas, which is used to fuel 14% of electric power generation, 73% of residential and commercial, and 39% of industrial production.

We use spot oil prices WTI[29] as a measure of oil prices. For robustness we include crude oil prices WTI in our estimations. Crude oil prices measure the spot price of various barrels of oil, most commonly either the WTI or the Brent Blend.

Then, gold prices are a good indicator of how healthy the U.S. economy is. In fact, investors tend to gold when they are protecting their investments from either a crisis or inflation. The economy is healthy usually when gold prices drop because investors have left gold for other, more lucrative, investments like stocks, bonds or real estate.

[28] An independent statistical agency of the U.S. Department of Energy-DOE.

[29] WTI is the acronym for West Texas Intermediate. WTI crude oil is of very high quality, because it is light-weight.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

In addition, the U.S. dollar is known for having an inverse relationship with the price of gold, which is traded on international markets. Import and Export function theory says that the appreciation of the domestic currency will make gold imports cheaper and therefore the price of gold falls. In addition, US gold production greatly increased during the 1980s, due to high gold prices and the use of heap leaching (an industrial mining process to extract precious metals, copper, uranium, and other compounds via a series of chemical reactions) to recover gold from disseminated low-grade deposits in Nevada and other states. Therefore, we decide to include in our model this precious metal. Especially, we use the Gold Bullion measured in U$/Troy Ounce.

We also include the Consumer Price Index for All Urban Consumers: All Items (CPI), a measure of the average monthly change in the price for goods and services paid by urban consumers between any two time periods. It can also represent the buying habits of urban consumers. This particular index includes roughly 88 percent of the total population, accounting for wage earners, clerical workers, technical workers, self-employed, short-term workers, unemployed, retirees, and those not in the labor force. We should note that the U.S. Bureau of Labor Statistics measures two kinds of CPI statistics: CPI for urban wage earners and clerical workers (CPI-W), and the chained CPI for all urban consumers (C-CPI-U). However, from the two types of CPI, the C-CPI-U is a better representation of the general public, because it accounts for about 87% of the population.

Finally, it is accepted that money has a powerful effect on economic activity since it is used in virtually all economic transactions. An increase in the supply of money works both through lowering interest rates, which spurs investment, and through putting more money in the hands of consumers, making them feel wealthier, and thus stimulating spending. Business firms, however, increase their sales by ordering more raw materials and increasing production. Therefore, the increased business activity raises not only the demand for labor but also the demand for capital goods. In a buoyant economy, stock market prices rise and firms issue equity and debt. If the money supply continues to expand, prices begin to rise, especially if output growth reaches capacity limits. As the public begins to expect inflation, lenders insist on higher interest rates to offset an expected decline in purchasing power over the life of their loans.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Then, we choose to include on our estimations M2 which includes a broader set of financial assets held principally by households and consists of M1 plus:

(1) savings deposits (which include MMDAs[30]),

(2) small-denomination time deposits (time deposits in amounts of less than \$100,000),

(3) balances in retail MMMFs[31].

Seasonally adjusted M2 is computed by summing savings deposits, small-denomination time deposits, and retail MMMFs, each seasonally adjusted separately, and adding this result to seasonally adjusted M1.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

[30] MMDAs is the acronym for money market deposit accounts.
[31] MMMFs is the acronym for money market mutual funds.

4. Transmission Mechanism of Monetary Policy

In this section we will try to establish the channels that affect the economic activity and therefore we can justify why we select the above variables as indicators in our estimations. Monetary policy is now at the center stage in discussions about how to promote sustainable growth and low inflation in the economy. Both economists and politicians in recent years advocate that the stabilization of output and inflation be left to monetary policy. Indeed, in recent years we have seen central banks in many countries pursuing a strategy of raising interest rates proactively in order to prevent an increase in inflation arising from an overheated economy.

4.1 Traditional Interest Rate Channels

Interest rates channels are a standard feature for over fifty years and a key monetary transmission mechanism in the basic Keynesian IS-LM.

According to the traditional Keynesian IS-LM view of the monetary transmission mechanism we know the following.

An expansionary monetary policy leads to a fall in real interest rates, which in turn lowers the cost of capital, casing a rise in investment spending and so leading to an increase in aggregate demand and output growth.

In addition, the interest rate channel of monetary transmission mentioned above applies to consumer spending (residential housing and consumer durable expenditure). It is often the real long-term interest rate and not the short-term interest rate that is viewed as having the major impact on spending. In a world with rational expectations, when expansionary monetary policy lowers the short-term nominal interest rate it also lowers the short-term real interest rate. The expectations hypothesis of the term structure (long interest rate is an average of expected future short term interest rates) suggests that the lower real short-term interest rate leads to a fall in the real long-term interest rate, rising business fixed investment, residential housing, consumer durable expenditure and inventory investment, all of which produce the rise in aggregate output.

Finally, with nominal interest rates at a floor of zero, an expansion in the money supply can raise the expected price level and hence expected inflation,

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

lowering the real interest rate and stimulating spending through the interest rate channel.

Thus, this mechanism indicates that monetary policy can still be effective even when nominal interest rates have been driven by the monetary authorities.
This is a key element in monetarist discussions of why the U.S economy during Great Depression was not stuck in a liquidity trap and why expansionary monetary policy could have prevented the sharp decline in output.

4.2. Equity Price Channels

There are two channels involving equity prices that are important to the monetary transmission mechanism: Tobin's q theory of investment and the wealth effects on consumption.

Tobin's q theory. According to this theory, monetary policy affects the economy through its effects on the valuation of equities. Tobin defines q as the market value of firms divided by the replacement cost of capital. If q is high the market price of firms is high relative to the replacement cost of capital, and new plant and equipment capital is cheap relative to the market value of business firms. Companies can then issue equity and get a high price for it relative to the cost of the plant and equipment they are buying. Thus, investment spending will rise because with only a small issue of equity firms can buy a lot of new investment goods.

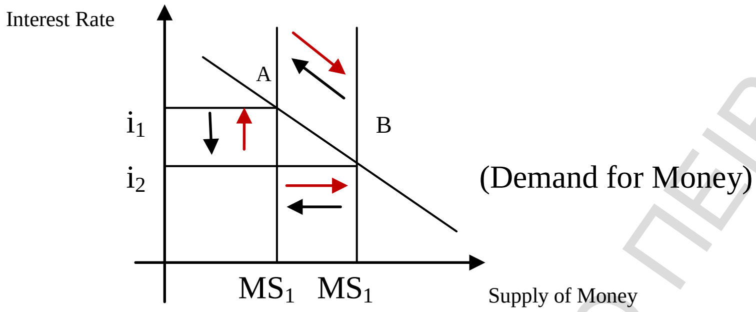
When money supply rise, public tries to reduce the holdings of money by increasing their spending. In the stock market one can spend more, increasing the demand for equities and consequently raising their prices. Keynesian reached the same conclusion observing the fall in interest rates that have a negative impact on the demand for bonds, causing the prices of equities to rise. Hence, higher equity prices will lead to higher q and so higher investment spending leads to an increase in output.

Wealth effects. A major component of financial wealth is common stocks. When stock prices raise the value of financial wealth increases, thus increasing resources of consumers, consumption should rise. Therefore, an expansionary monetary policy can lead to a rise in stock prices which in turn increases the wealth of consumer and so consumption concluded in an increase in the output.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

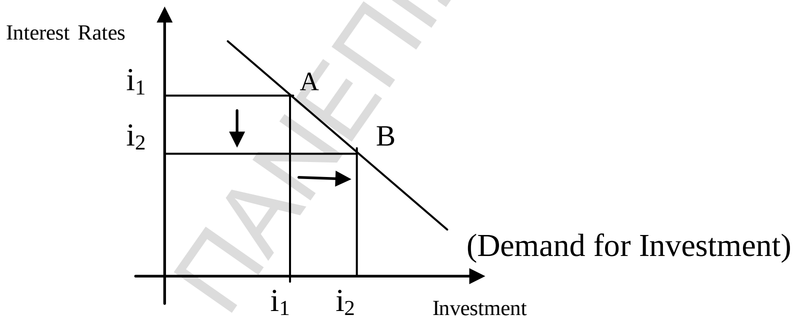
Housing and Land Price Channels. The monetary transmission mechanism also operates through the land and housing prices channels. An increase in housing prices, which raises their prices relative to replacement cost, lead to a rise in Tobin's q for housing, stimulating its production. Similarly, housing and land prices are an extremely important component of wealth. Therefore, rises in these prices increase consumption and so aggregate demand.

Finally, we will try to show the above mechanism using diagrams.
If money supply increases, the interest rate drops.



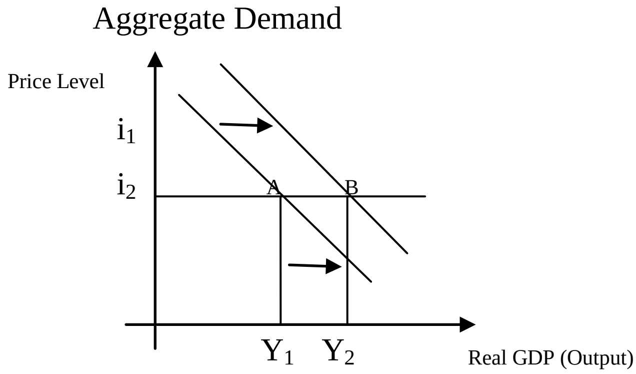
This drop in interest rates motivates investment by both households and businesses. This happens because businesses may want to take advantage of the reduction in opportunity costs by investing in new machines and plants. Households may decide to invest in real estate.

Demand for Investment (Household)

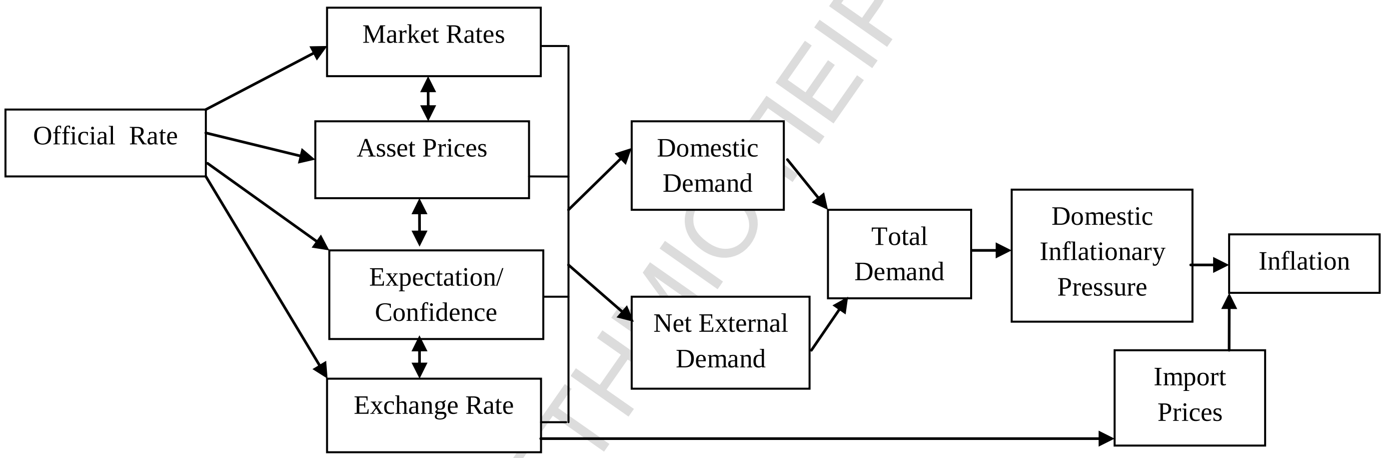


As investment increases, aggregate demand also increases at a given level and therefore output increases.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ



The transmission mechanism of monetary policy: Linked in the chain



ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

5. Description of econometric procedures

What we want to test empirically, using the data that were presenting in the previous chapter, is the ability of a number of financial variables (stock prices, term structure of interest rates, short term interest rates) to predict the level of future economic activity. Our main purpose is to give a clear answer concerning to the following questions: Is it Finance that can be used by analysts to forecast the level of economic activity in long horizon? Although there is in-sample granger causality, there is also out- of sample forecast ability? In order to give answer to these questions, first, we will make a Granger Causality Test to prove the cause relationship of same of the variables mentioned in previous section. Additionally, we will construct iterated multistep model studying their predictive ability on a long horizon. In this framework we will try to investigate the marginal forecasting information of other financial variables such as asset, commodity prices or monetary instruments.

Before proceeding to the presentation of our model we are going to use, we will show some reasons for preferring and implementing this method instead of the direct forecast when we wish to make a long horizon time series forecast.

In the case of univariate linear models and quadratic loss, the “iterated” forecast (sometimes called a “plug-in” forecast) entails first estimating an autoregression, then iterating upon that autoregression to obtain the multiperiod forecast. On the other hand, the forecast based on the multiperiod model (defined by the literature “direct” forecast) entails regressing a multiperiod ahead value of the dependent variable on current and past values of the variable. The choice between these two types of forecasts entails a tradeoff between bias and estimation variance: the iterated method produces more efficient parameter estimates than the direct method, but it is prone to bias if the one-step ahead model is misspecified.

Marcellino M., Stock J.H., Watson M. W. (2006), in their paper, undertakes an empirical comparison of iterated vs. direct forecasts using data on 170 U.S. macroeconomic time series variables, available monthly from 1959 to 2002. Their study tries to answer questions of whether the iterated or direct forecasts are more accurate on average for the population of U.S. macroeconomic time series, and whether the distribution of MSFEs for direct forecasts is statistically and substantively below the distribution of MSFEs for iterated forecasts. In addition, in both cases, they

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

consider models with fixed lag order and models with data-dependent lag order choices, using the Akaike Information Criterion (AIC) or, alternatively, the Bayes Information Criterion (BIC).

They reach the following conclusions.

First, when the lag length in the one-period ahead model is selected particularly by AIC, iterated forecasts tend to have lower sample MSFEs than direct forecasts. Second, direct forecasts become increasingly less desirable as the forecast horizon lengthens, a finding that is consistent with the efficiency of the iterated forecasts outweighing the robustness of the direct forecasts.

Finally, for series measuring wages, prices, and money, direct forecasts improve upon iterated forecasts based on low order autoregressions, but not upon iterated forecasts from high-order autoregressions. In contrast, iterated forecasts from low-order autoregressive models outperform direct forecasts for real activity measures and the other macroeconomic variables in their data set.

5.1 Univariate Models

Let X_t denote the level or logarithm of the series of interest. The objective is to compute forecasts of X_{t+h}, using information at time t. Let y_t denote the stationary transformation of the series after taking first or second differences. Specifically, suppose that X_t is integrated of order d (is I(d)), then $y_t = \Delta^d X_t$, where d = 0, 1, or 2 as appropriate.

Iterated AR forecasts. The one-step ahead AR model for y_t is

$$y_{t+1} = \alpha + \sum_{i=1}^{p} \phi_i y_{t+1-i} + \varepsilon_t \qquad (1)$$

For the iterated AR forecasts, the parameters α, $\varphi_1, \ldots, \varphi_p$ in (1) are estimated recursively by OLS, and the forecasts of y_{t+h} are constructed recursively as,

$$\hat{y}^{I}_{t+h/t} = \hat{a} + \sum_{i=1}^{p} \phi_i y^{I}_{t+h-i/t} \qquad (2)$$

where $\hat{y}_{j/t} = y_j$ for j ≤ t. Forecasts of X_{t+h} are then computed by accumulating the values of $\hat{y}^{I}_{t+k/t}$ as appropriate in the I(0), I(1) and I(2) cases:

$$\hat{X}^{I}_{t+h/t} = \begin{cases} \hat{y}^{I}_{t+h/t} & \text{if } X_t \text{ is I(0)} \\ X_t + \sum_{i=1}^{h} y^{h\,I}_{t+i/t} & \text{if } X_t \text{ is I(1)} \\ X_t + \sum_{i=1}^{h} \sum_{j=1}^{i} \hat{y}^{I}_{t+j/t} & \text{if } X_t \text{ is I(2)} \end{cases} \qquad (3)$$

Lag length determination. There are four different methods for determined the lag order p: (1) p = 4 (fixed),

(2) p = 12 (fixed),

(3) p chosen by the Akaike Information Criterion (AIC), with $0 \leq p \leq 12$ and

(4) p chosen by the Bayes Information Criterion (BIC), with $0 \leq p \leq 12$.

For the iterated forecasts, the AIC and BIC computed using the standard formulas based on the sum of squared residuals (SSR) from the one-step ahead regression. The AIC and BIC were recomputed at each date, so the order of the selected forecasting model can change from one period to the next, where the model selection and parameter estimates are based only on data through the date of the forecast (period t).

5.2 Multivariate Models

We also present iterated forecasts computed using bivariate vector autoregressions (VARs). For two series i and j, the iterated VARs are specified in terms of the stationary transforms y_{it} and y_{jt}. The iterated forecast is then obtained by iterating forward the VAR and then applying the transformation (3). The h-step direct forecast for series i is obtained from the OLS regression of $y^{h}_{i,t+h}$ against a constant and p lags each of y_{it} and y_{jt}. In both the iterated and direct models, the same number of lags p is used for both regressors as well as the lag length determination done using the four methods mentioned above.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

5.3 Evaluation Forecast

5.3.1 Root Mean Squared Error

The crucial object in measuring forecast accuracy is the loss function:

$L(Y_{t+h}, Y_{t+h,t})$ h=1,2,3,…

Sometimes in the literature it is written as $L(e_{t+h,t})$, which is called h-step-ahead forecasting errors. In addition to the shape of the loss function, the forecasting horizon *h* is of crucial importance. Rankings of forecast accuracy may be very different across different loss functions and different horizons. There are a few important and popular measures of accuracy.

First we should define

Forecast errors: $e_{t+h,t} = Y_{t+h} - Y_{t+h,t}$ and Percent errors: $p_{t+h,t} = \dfrac{Y_{t+h} - Y_{t+h,t}}{Y_{t+h}}$.

Then we have **Mean Error**: $\mathrm{ME} = \dfrac{1}{\mathrm{T}}\sum_{t=1}^{T} e_{t+h,t}$ which measures bias.

The smaller the *ME*, the better is the model.

Mean Squared Error: $\mathrm{ME} = \dfrac{1}{\mathrm{T}}\sum_{t=1}^{T} e^2{}_{t+h,t}$

The squared roots of these measures are often used to preserve units, yielding

Root Mean Squared Error: $\mathrm{ME} = \sqrt{\dfrac{1}{T}\sum_{t=1}^{T} e_{t+h,t}^2}$

Somewhat less popular but nevertheless common accuracy measures are:

Mean Absolute Error: $MAE = \dfrac{1}{T}\left|e_{t+h,t}\right|$

5.3.2 Theil's inequality coefficient U

Thiel's inequality coefficient, also known as Thiel's U, provides a measure of how well a time series of estimated values compares to a corresponding time series of observed values. The statistic measures the degree to which one time series ({Xi}, i = 1,2,3, ...n) differs from another ({Yi}, i = 1, 2, 3, ...n). Thiel's inequality coefficient is useful for comparing different forecast methods. The closer the value of U is to zero,

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

the better the forecast method. A value of 1 means the forecast is no better than a naïve guess.

Thiel's U is calculated as:

$$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t^f - y_t^\alpha)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}y_t^f} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t^\alpha)^2}}$$

where y_t^f is forecast value of y_t , y_t^α is actual value of y_t .

Note that the numerator of *U* is just the root mean squared forecasting error, but the scaling of the denominator is such that *U* will always fall between 0 and 1.

If U=0, then we have $y_t^f = y_t^\alpha$ for all *t* and there is a perfect fit.

If U=1, the predictive performance of the model is as bad as it could possibly be. Hence, the Theil inequality coefficient measures the root mean squared errors in relative terms.

Then, we should define the proportions of inequality

$$U^m = \frac{(\overline{Y^f} - \overline{Y^\alpha})^2}{\frac{1}{T}\sum_{t=1}^{T}(y_t^f - y_t^\alpha)^2} \quad , \quad U^s = \frac{(\sigma_f - \sigma_\alpha)^2}{\frac{1}{T}\sum_{t=1}^{T}(y_t^f - y_t^\alpha)^2} \text{ and}$$

$$U^c = \frac{2(1-\rho)\sigma_f\sigma_\alpha}{\frac{1}{T}\sum_{t=1}^{T}(y_t^f - y_t^\alpha)^2}$$

The proportions U^m , U^s and U^c are called the bias, the variance, and the covariance proportion of U, respectively. They are useful as a means of breaking down the simulation error into its characteristic. (Note that $U^m + U^s + U^c = 1$)

The bias proportion U^m is an indication of systematic error, measuring the extent of deviation between the average values of the forecast and actual series. What we wish is the U^m close to zero. A large value of U^m (above 0.1) would mean that a systematic bias is present, so that the revision of the model is necessary.

The variance proportion U^s indicates the ability of the model to replicate the degree of the variability in the variable of interest. A large U^s means that the actual series has fluctuated considerably while the simulated series shows little fluctuation, or vice versa. Again this will be an indicator that the model should be revised.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Finally, the covariance proportion U^c measures unsystematic error i.e., it represents the remaining error after deviations from average values have been accounted for. Since it is unreasonable to expect prediction to be perfectly correlated with actual outcomes, this component of error is less worrisome than the other two. Indeed, for any value of U > 0, the idea distribution of inequality over the three sources is $U^m = U^s = 0$ and $U^c = 1$.

6. Preliminary in-sample causality analysis

To examine the predictive ability of various indicators in the industrial production index, we should investigate the in-sample causality of our variables in order to see whether it can be interpreted in an out-of-sample forecast. This examination will be done using Granger Causality test and the Eviews.

6.1 Granger Causality Test

Correlation does not necessarily imply causation in any meaningful sense of that word. The econometric graveyard is full of magnificent correlations, which are simply spurious or meaningless.

The Granger causality test is a statistical hypothesis test for determining whether one time series is useful in forecasting another. A time series X is said to Granger-cause Y if it can be shown, usually through a series of t-tests and F-tests on lagged values of X (and with lagged values of Y also included), that those X values provide statistically significant information about future values of Y.

The Granger (1996) approach to the question of whether X causes Y is to see how much of the current Y can be explained by past values of Y and then to see whether adding lagged values of X can improve the explanation. Y is said to be Granger-caused by X if X helps in the prediction of Y. To put it differently, if the coefficient's of the lagged X's are statistically significant.

We should note that the statement X Granger causes Y does not imply that Y is the effect or the result of X. The Granger Causality test is based on the following equations: $\mathrm{Y}_t = \beta_0 + \beta_1 \mathrm{Y}_{t-1} + \beta_2 Y_{t-2} + \beta_i Y_{t-i} + \gamma_1 X_{t-1} + \gamma_2 X_{t-2} + \gamma_i X_{t-i} + U_t$ (1)

$$\mathrm{X}_t = \beta_0 + \beta_1 \mathrm{X}_{t-1} + \beta_2 \mathrm{X}_{t-2} + \beta_i \mathrm{X}_{t-i} + \gamma_1 \mathrm{Y}_{t-1} + \gamma_2 \mathrm{Y}_{t-2} + \gamma_i \mathrm{Y}_{t-i} + U_t \quad (2)$$

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

If $\gamma_1, \gamma_2 \gamma_i \neq 0$ and statistically significant then we say that X granger causes Y in regression (1) and Y granger causes X in regression (2).

6.2 Empirical Analysis

In proving the Granger causality relationship we follow the above procedure:

- ✓ First, we run the Augmented Dickey Fuller (ADF) and the Phillips-Perron unit root tests in order to ensure that all time series are stationary. We conclude that except the term spreads that are stationary, all variables have unit root and therefore they transformed into first differences.
- ✓ Second, for each one of the variables we test for Granger Causality between the specific variable and the economic activity (measured by the industrial production) and we select the lag order of the VAR using the Akaike information criterion (AIC) and Final Predictor Error (FPE).
- ✓ Then, we construct bivariate VAR models consisting of the growth of industrial production and one financial variable each time. Finally, we construct a VAR consisting of all variables in order to test for the predictive power of all financial variables concerning the economic activity (industrial production).

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 1

Pairwise Granger Causality Tests
Sample: 1968M02 2013M07
Lags: 4 (Optimal Lag according to Akaike)

Null Hypothesis:	Obs	F-Statistic	Prob.
3m T-BILL does not Granger Cause IP GROWTH	541	1.43243	0.2219
IP GROWTH does not Granger Cause 3MONTH		7.80985	4.E-06

Table 2

Pairwise Granger Causality Tests
Sample: 1968M02 2013M07
Lags: 4 (Optimal Lag according to Akaike)

Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
CPI does not Granger Cause IP GROWTH	541	3.12078	**0.0149**
IP GROWTH does not Granger Cause CPI		2.56422	0.0375

Table 3

Pairwise Granger Causality Tests
Sample: 1968M02 2013M07
Lags: 3 (Optimal Lag according to Akaike)

Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
GOLD does not Granger Cause IP GROWTH	542	1.59262	0.1902
IP GROWTH does not Granger Cause GOLD		1.34185	0.2599

Table 4

Pairwise Granger Causality Tests
Sample: 1968M02 2013M07
Lags: 4 (Optimal Lag according to Akaike)

Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
HOUSE does not Granger Cause IP GROWTH	541	13.1825	**3.E-10**
IP GROWTH does not Granger Cause HOUSE		2.23098	0.0645

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 5

Pairwise Granger Causality Tests
Sample: 1968M02 2013M07
Lags: 5 (Optimal Lag according to Akaike)

Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
M2 does not Granger Cause IP GROWTH	540	1.10519	0.3565
IP GROWTH does not Granger Cause M2		3.28958	0.0062

Table 6

Pairwise Granger Causality Tests
Sample: 1968M02 2013M07
Lags: 3 (Optimal Lag according to Akaike)

Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
OIL does not Granger Cause IP GROWTH	542	0.44014	0.7244
IP GROWTH does not Granger Cause OIL		1.24978	0.2910

Table 7

Pairwise Granger Causality Tests
Sample: 1968M02 2013M07
Lags: 3 (Optimal Lag according to Akaike)

Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
S&P does not Granger Cause IP GROWTH	542	14.7466	**3.E-09**
IP GROWTH does not Granger Cause S&P		0.75000	0.5227

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 8

Pairwise Granger Causality Tests
Sample: 1968M02 2013M07
Lags: 4 (Optimal Lag according to Akaike)

Null Hypothesis:	Obs	F-Statistic	Prob.
TERM SPREAD does not Granger Cause IP GROWTH	541	3.88887	**0.0040**
IP GROWTH does not Granger Cause TERM SPREAD		4.50514	0.0014

According to the above statistical tables, for period M02 1968 to M07 2013 short-term interest rates, oil and gold prices as well as the money supply seems to not granger cause Industrial Production. The null hypothesis of the above test is that IP growth does not Granger Cause short-term interest rates, oil, gold prices and money supply respectively; and that short-term interest rates, oil, gold prices and money supply does not Granger Cause IP growth. In the first case whatever of the above mentioned variable we examine, we find the Probability higher than 10% which supports the null hypothesis. Nevertheless, we can observe that in money supply and 3 month rates, the Probabilities are 0.0062 and 4.E-06 respectively which does not support the null hypothesis. Therefore, the null hypothesis can be rejected indicating that money supply and 3 month rates cause IP but not the opposite direction. As far as the oil and gold prices we can conclude that they do not present any cause relationship with IP growth due to the high probabilities that support the null hypothesis in both directions.

Tables 2, 4, 7, 8 shows that the null hypothesis for granger cause relationships among IP growth and cpi, house, S&P, term spread respectively and in the opposite direction is not supported. For instance, the S&P and the term spread have Probability 3.E-09 and 0.0040 respectively which is no support to the null hypothesis, proving the granger causality between IP growth and S&P. Similarly, the IP growth and term spread have granger cause relationship.

Finally, table 10 demonstrates the Var Granger Causality Test of all variables from which we can see the relationship between them. This way we can link in a chain the direction with which each variable affects the other, resulting in the

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

industrial production growth. We should note that we observe indirect links between the variables that conclude to the IP growth. We can indicate it in the following section, where we will study whether the granger causality can be reliable in proving the predictive power of a variable.

7. Out-of-sample forecasting evaluation

Our goal in this section is to examine the predictive ability of various indicators in the industrial production index. First, we start with the base model that consists of stock prices and short-term interest rates with which we gain a satisfactory out-of-sample forecasts. Then, we will try to investigate the marginal forecasting information putting other financial variables and generally examining which asset prices or other channels of monetary transmission are useful indicators for predicting industrial production (defined as a measure of output growth).

Therefore, we organize the data into three blocks:

- Block 1 (base model): financial variables (interest rates, stock prices)
- Block 2: housing, oil and gold prices
- Block 3: CPI and money supply

7.1. Forecasting Strategy

Our iterated multistep approach consists of first estimating a dynamic model for the monthly growth rates, and then using the chain rule to compute *h*-step-ahead forecasts of the series. In particular, our forecasting multivariate regression model is

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{7} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t \qquad (1)$$

where y_t represent the growth rates of industrial production (denoted as IP_t), and x_{it} denote the indicators short-term interest rates (denoted as SI_t), term spread (denoted as TS_t), stock prices (denoted as SP_t), housing prices (denoted as HP_t), oil prices (denoted as OP_t), precious metal: gold (denoted as GD_t), consumer price index for all urban consumers: all items (denoted as CPI_t) and money supply (denoted as MS_t) for each case. The parameters α, β_k , γ_{ik} , k = 1,….p, i = 1,..,7 are estimated by

OLS. By iterating forward one-period ahead h times we are able to compute the forecasts recursively, $\tilde{y}_{t+h} = \hat{\alpha} + \sum_{k=1}^{p} \hat{\beta}_k \tilde{y}_{t+h-k} + \sum_{i=1}^{7} \sum_{k=1}^{p} \hat{\gamma}_{ik} \tilde{x}_{it+h-k}$ (2)

based only on values of the series up to the date on which the forecast is made.
Long horizon iterated forecasts of the industrial production growth rates are computed as $y_{t+h} = y_t^0 + \sum_{j=1}^{h} \tilde{y}_{t+j}$ (3)

where y_t^0 is the log of the industrial production level at time t.

To compute the forecasts, the models are estimated, lag lengths are selected using observations from date 1 through date q (the length of the estimation window). The lag length selection is based on Akaike Information Criterion (AIC) with maximum lag order set to five lags. Moving forward by one month, the models are reestimated (and information criteria computed) using data from date 2 through date q + 1. This sequence of actions is repeated T - q - h times through the sample. Hence, sequences of h-step-ahead forecasts of the growth in industrial production are formed, and as a consequence the corresponding forecast errors, allowing us to compute the root mean squared forecast error (RMSFE), the Theil inequality criterion (Theil), the bias (bias) and variance (Var) components of the Theil inequality decomposition that we have defined in previous section. We choose to set $q = 0.70T$ and $0.60T$ so that we form series of forecast errors with minimum length 150 to 190 observations.

Clark and McCracken (2005) showed that lack of parameter constancy of the regression model used for forecasting economic series, has a substantial impact on its out-of-sample performance. Recent econometric advances in forecasting economic series present methods whose implementation does not require testing for heterogeneity of a stochastic process or parameter instability of a regression model. **Pesaran and Timmermann (2007)** showed that averaging forecasts obtained from in-sample model estimation windows of different lengths ensures a satisfactory finite sample performance, especially in the presence of neglected structural breaks of small size.

Therefore, concerning the standard rolling window approach, we implement forecast combination across observation windows of different lengths, as proposed by Pesaran and Timmerman (2007) and Pesaran and Pick (2009). The starting point of

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

the in-sample window is changed removing one observation. The forecasts are calculated based on the parameters of the predicting model estimated on these observation windows. Then the corresponding to the different starting point data windows forecasts are averaged. The forecast averages of the rolling window are used for the computation of the root mean square forecast error (hereafter denoted as RMSFE), Theil inequality criterion, bias and variance decomposition based on the Theil inequality.

For each observation window and in order to estimate multiple structural breaks on output growth dynamics, we use the sequential procedure of Bai and Perron (1998, 2003) equaling then the starting points of each sub-window to these break points. Five breakpoints are considered within each rolling window (either 60%T or 70%T). The size and location of the multiple change-points can be consistently estimated by this procedure.

The empirical analysis is performed using the MATLAB programming language.

7.2. Forecast Results

7.2.1. Without structural breaks

To examine whether financial variables mentioned above have forecasting information, it is essential to investigate both the stability and the accuracy of our models before implementing the five break points. The loss forecasting stability can be indicated by the high bias which is an indication of systematic error. By the notion systematic error we refer to a high deviation between the average values of the forecast and the actual series. We first estimate the block 1 (base model) and then we examine block one in conjunction with others in order to not only conclude about the accuracy and stability but also take few indications of which variables predict better the industrial production. We, also, compare the forecast performance of short-term model with the term spread. Finally, our estimations done with estimation window 70%T (q=400). The conclusions can be summarized below.

Table 11 demonstrates the estimation of the base model (stock prices and short-term interest rates) and we see that these two variables appear a satisfactory out-

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

of sample forecast since Theil coefficient is below 1, although it increases with horizon. However, the bias raise as horizon increases. In addition, when we repeat our estimations putting the spread in the place of short-term rates we saw that both RMSFE and Theil improved more significant than short-term rate model, but bias remain high as horizon increases.

Table 12 presents the marginal predictive information of the money supply and CPI by repeating the above estimations. Again, we can observe a forecasting ability of these variables. However, as for the bias it remains high as horizon increases but in the case of short-term rate is significantly lower than in the model which includes the term spread. For instance, for h=60 in the first model it is 0.3721 and in the second 1.2346. In addition, it is obvious that with the spread in our estimations the forecast accuracy improved significantly as horizon increases compared to the model with short-term interest rates in which Theil appears to increase with horizon.

Then, examining the marginal predictive information of the housing, oil and gold prices in the base model we reach the results of the table 13, which are similar to the previous as for the bias. As far as the short-term interest rate model is concerned, we can see that its forecast ability is better than the spread model. However, as the horizon increases we see an improvement for RMSFE and Theil in the spread model whereas in the short-term it increases. It is worth mention that comparing tables 11 and 13 we can observe that our results are roughly the same. This may indicate that block 2 has no significant forecasting ability in the base model.

Table 14 demonstrates the estimations when we include in our model all the examined variables (base model, housing, oil, gold, cpi and money supply). We see a satisfactory RMSFE and Theil although in the short-term model they increase in a higher rate as horizon grows. In fact, we can again take some indications that housing, oil and gold prices have not predictive content for industrial production since our results are roughly close to these in table 12 (where we estimate with short-term interest rates, stock prices, cpi and money supply). In addition, we can observe that in the term spread model our results are significantly better than in the short-term model. As for the bias, it remains high when horizon increases.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Finally, for robustness purposes we create table 15 that presents results when we replace money supply with term spread. In fact, what we wish to see is whether excluding one financial market variable we can gain in forecasting performance. What we observe is that model loses significantly its forecasting accuracy as horizon increases, not to mention the forecasting ability due to high bias. By this result we can conclude that excluding money supply from our estimations we have significant loss in model's forecast ability.

In sum, we can conclude that our estimations present forecast accuracy but there is no forecast stability, due to high bias (above 0.1). For short horizon, all models that neglect structural breaks produces satisfactory forecast accuracy and stability. However, as horizon increases we can observe significant forecasting loss in all models including those with term spread. Therefore, further investigation is of importance so as to reach safe conclusions of which variables predict better the industrial production in a long horizon.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

7.2.2. With structural breaks

In this section we will present the forecasting performance of financial variables in an out of sample forecast exercise for US growth rates of industrial production taking into consideration the structural breaks. This way we may prove the forecast ability in long horizons. In fact, we will create tables for seven horizons ahead and two different estimation windows. In addition, we may examine which combination of variables provides us with the best forecasting performance.

Table 16 demonstrates results for the base model (short-term interest rates and stock prices). This model is found to have a satisfactory forecasting ability regarding Theil and RMSFE. Indeed, although Theil is close to one, significantly higher than in estimations neglected the structural breaks, in long horizons we take lower estimations. In fact, RMSFE reduces from 0.0875 to 0.0720 and Theil from 0.8758 to 0.8726 for horizon 48 and 60 months ahead respectively. These indicate forecasting accuracy. As far as the bias is concerned, we can also conclude that there is no systematic error since it decreases significantly as horizon increases. In fact, for horizon 48 and 60 months we see bias 0.0227 and 0.0021 respectively which means greater stability for long horizons. These results, compared with the previous that we do not include the break points, prove that our model has not only forecast accuracy due to low Theil and RMSFE but also forecast stability since bias decreases.

On the other hand, for estimation window 60%T we observe a significant increase in the RMSFE but the Theil seems to decrease compared with higher estimation window. The bias, however, increases whereas variance decreases as h grows. The latter can be justified by the fact that as long as we reduce the estimation window there is lower sample period, resulting in higher bias.

Then, indicating the satisfactory forecasting ability of financial variables (short-term interest rates and stock prices), we will move on investigating whether there are other financial variables that may improve our results. We will examine first the forecasting information that gives in the base model prices such as housing, oil, gold, second inflation (consumer price index) and money supply and last but not least both of them. This way, we can take indications of which block provide us with better results.

Table 17 demonstrates the forecasting performance of housing, oil and gold prices in the base model. We reach the same conclusion with these in the previous section (in the absence of the structural breaks). Indeed, we observe that in both the estimation windows our results are the same.

Following the previous table and in order to investigate further the forecasting performance of prices for predicting US growth rates of industrial production we develop Table 18. This table presents the results for forecasting ability of block 2 (housing, oil and gold prices) for US growth rates. We see that both the RMSFE and Theil criterion appears to increase until the 36 months ahead. However, for h = 48 months seems to decrease, which indicates an improvement of the predictive ability in long horizon. The bias decreases as h increases; on the other hand, the variance increases as h grows. Therefore, we can conclude that they have predictive ability but it is not high enough to affect our estimations when other variables (such as short-term interest rates and stock prices) are included.

As far as the estimation window of 60%T is concerned, we observe a significant increase in the RMSFE but the Theil seems to decrease compared with higher estimation window. The bias, however, increases whereas variance decreases as h grows. For example, for horizon 60 months the bias is 0.2149 and the variance 0.7892, whereas in the 70%T estimation window they are 0.0023 and 1.0091 respectively.

Table 19 reports the forecast results when all variables are included. What we observe is that the forecasting performance improved significantly compared with the previous estimations. For instance, for horizon 60 months in the base model yields Theil 0.8726 whereas in all variables it is 0.8651. As in the previous estimations, we can again indicate a gain in the forecasting ability in long horizon due to the improvement of both RMSFE and Theil as horizon increases. As for the bias it decreases; whereas the variance increases with horizon.

On the other hand, for estimation window 60%T, we observe higher predictive ability of these indicators since although RMSFE increases, the Theil seems to decrease compared with higher estimation window. The bias, however, increases whereas variance decreases as h grows.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 20 reports the forecast results of seven forecasting models that we make in order to examine thoroughly which variables have the major predictive power for industrial production growth rates. From the previous estimations we have seen that the model with all variables confirms the most satisfactory forecasting performance as horizon increases. Nevertheless, what are exactly the variables with the best marginal information?

Models 1 and 2 confirm that whether CPI or money supply are excluded from our estimations we lose in the forecasting accuracy. In fact, they produces the same results either including CPI or money supply, which indicates that both these variables have significant forecasting ability for industrial production growth rates. In addition, although RMSFE is stable until 60 months ahead, these models yields Theil coefficient 0,8742 from 0,8651 when all variables included.

After proving the significance of CPI and money supply in our estimations we continue examining the predictive ability of prices (such as housing, oil and gold). By this we mean that we will estimate model 3 including housing prices and model 4 with oil and gold prices instead of housing prices. What we observe is that none of these prices have marginal predictive information since they yield the same results with the model of all variables included with slight differences in the Theil coefficient.

Then, we repeat our estimations without prices (block 2) and the results (model 5) confirm that when other variables are included housing, oil and gold prices lose their forecasting ability. However, it still remains to be seen whether block 1 or block 3 produces the major marginal predictive information. Hence, model 6 reports the forecasting ability of cpi and money supply for industrial production. Indeed, we confirm that block 3 produces sizeable gains not only in the base model but also when all variables included. Nevertheless, we should note that as horizon raises Theil coefficient for the model 6 reduces with lower rate than in the model 5. For instance, for horizons 48 and 60, model 6 yields Theil coefficient 0.8681 and 0.8639 respectively; on the other hand, model 5 yields Theil coefficient with 0.8706 and 0.8651 respectively. Finally, proving the major predictive ability of cpi and money supply we estimate our model excluding stock prices in order to conclude in the best combination of variables. Thus, we create table 8 which confirm that the only short-term interest rates, cpi and money supply are those variables with the best forecasting ability for predicting the US growth of industrial production.

As far as the 60% estimation window is concerned, we see again, for all models examined, higher predictive ability of these indicators since although RMSFE increases, the Theil seems to decrease compared with higher estimation window. The bias, however, increases whereas variance decreases as h grows. Moreover, it is worth mentioned that when both cpi and money supply are included in our estimations Theil coefficient decreases in a higher rate something that support the conclusion that they produces significant forecasting ability for industrial production as well as they give marginal information in the base model.

In sum, we can conclude that the estimations when all variables included indicate better forecasting ability than the base model since Theil coefficient seems to be low as horizon increases. However, having proved that block 2 do not give us marginal predictive information, another questions arise. For instance, is the base model that have the better predictive ability or the money supply and CPI? In other words is the financial variables, the money supply, the CPI alone or all these variables that improve our estimations? Hence, we confirm that not only short-term interest rates, cpi and money supply have the best forecasting performance in long horizon but also cpi and money supply give the major predictive power in our estimations compared to all variables examined. In addition, with the presence of the structural breaks we have significant gains in long horizons compared with the estimations in their absence.

Moreover, the variance proportion is smaller over the recession period, whereas the bias proportion increases during recession. The small variance indicates that the forecast series become more volatile and thus is able to capture more of the variance of the series. Therefore, in all tables we can observe that as estimation window and horizon increases the bias decreases; whereas the variance raises. By this we can conclude that our forecast series are more volatile in lower windows; but they loses their stability due to higher bias.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

7.3 Robustness Analysis

To examine the marginal forecasting information of the term spread in the base model we create Table 21. In both estimation windows as horizon increases there are sizeable gains for Theil coefficient when using it to measure forecasting accuracy. For instance, for horizon 60 months (5 years) Theil yields 0.6783 when q=70% and 0.6274 when q=60%. As for the forecast bias of the q=70% seems more volatile than for the lower window.

In this framework, so as to see whether short-term rates or term spread have the most predictive content, we repeat the above estimations but excluding the short-term interest rates. The results are presented in table 22. They are roughly the same with the previous model, supporting the high forecasting ability of the term spread in the base model.

Moreover, table 23 reports our results when all variables included. What we observe is that whatever the variables included in our model the term spread has additional information which can be exploited for improving forecasts of future economic activity. The above can also be resulted by looking tables 21 through 23.

Finally, in table 24 we indicate that prices (such as housing, oil, gold) do have forecasting ability for predicting US growth rates of industrial production but they do not provide significant gain in our estimations. Therefore, for further investigation we replace the housing starts with CPI: Housing as well as spot oil prices with crude oil WTI. What we observe is that housing prices have no marginal information since the results are the same with those in model 7 table 20. Additionally, in the second estimation with crude oil we observe that until 48 months horizon, RMSFE and Theil increase in a higher rate than the models that have previously estimated. However, in 60 months ahead we see a surprising reduction of the Theil; on the other hand RMSFE and bias increase. Hence, we can support our indication from preliminary in-sample causality analysis that oil prices have not cause relationship with IP growth as well as they do not produce any marginal forecasting information to the output growth.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

8. Predicting the financial crisis of 2007

In this section we wish to investigate the forecasting performance of all the variables that used in the previous estimations over the period 2007 until 2013.

After the Great Depression of the 1930s the world economy faced its most dangerous crisis in 2008. The contagion began when the high home prices in the United States finally turned decisively downward, spread quickly, first to the U.S. financial sector ant then to financial markets internationally. What affected most in the United States was

- ✓ the entire investment banking industry,
- ✓ the biggest insurance company,
- ✓ the two enterprises chartered by the government to facilitate mortgage lending,
- ✓ the largest mortgage lender,
- ✓ the largest savings and loan, and
- ✓ two of the largest commercial banks.

However, it is not only the financial sector that affected most. Companies also were suffered casualties since they normally rely on credit which diminished due to crisis. For instance, the American auto industry pleaded for a federal bailout in vain as well as banks, trusting no one to pay them back, simply stopped making the loans that are crucial for most businesses to regulate their cash flows. Share prices, additionally, plunged throughout the world. Indeed, the Dow Jones Industrial Average in the U.S. lost 33.8% of its value in 2008. Finally, it is worth mention that the National Bureau of Economic Research, determined that a recession had begun in the United States in December 2007, making this already the third longest recession in the U.S. since World War II.

We decide to include all variables, although there are some that they do not have marginal predictive information, since we wish to examine whether the above results will change significantly during crisis and before the crisis period.

Therefore, we retain the same estimation window q=400 and we reduce the number of sample period from 1974 until 2013 so as to obtain the forecast ability of these variables for the period of the financial crisis (2008 until 2013).

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

To examine the forecasting accuracy and indicate the variables that have the most significant forecasting performance we create table 25. It demonstrates the forecasting accuracy of the base model (stock prices and short-term interest rates), proving that as horizon increases Theil coefficient reduces, although RMSFE shows an insignificant increase. For instance, Theil is 0.8818 and 0.8770 for horizon 12 and 24 respectively. Then, models 2 demonstrates the results when all variables are included and model 3 the base model with consumer price index and money supply. What we observe is that whether housing, oil and gold prices included in conjunction with cpi and money supply our results remain the same. Therefore, we can suggest that stock prices and short-term interest rates have the best forecasting ability. Finally, model 4 and 5 shows the term spread that seems to have the marginal predictive information since either with short-term or the sock prices there are significant improvements in long horizons

Then, we will present the results for the pre-crisis period and especially in estimating the period of 2006 until 2008. We should note that again we keep the same estimation window (q=400). We can conclude that our results are the same with those with all sample period. In fact, we observe that the marginal forecasting performance seems with short-term interest rates, stock prices, cpi and money supply. In addition, we see that term spread has the most predictive power whether prices (such as housing, oil and gold) or cpi and money supply are included.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 25.
Measuring the forecasting ability of various monthly indicators during financial crisis

h: *Steps Ahead* **q=400**	**rmsfe**	**Theil**	**bias**	**Var**
1. IP_t, SI_t, SP_t				
1	0.0098	0.9000	0.0246	0.8968
2	0.0162	0.9357	0.0112	0.9497
4	0.0286	0.9619	0.0047	0.9843
12	0.0704	0.8818	0.0012	1.0145
24	0.0782	0.8770	0.1991	0.8194
2. IP_t, SI_t, SP_t, HP_t OP_t, $GD_{t,}$, CPI_t, MS_t				
1	0.0100	0.9593	0.0014	0.7531
2	0.0165	0.9758	0.0011	0.8594
4	0.0290	0.9871	0.0011	0.9358
12	0.0711	0.8944	0.0025	1.0133
24	0.0793	0.8973	0.2055	0.8127
3. IP_t, SI_t, SP_t, CPI_t, MS_t				
1	0.0100	0.9593	0.0014	0.7531
2	0.0165	0.9758	0.0011	0.8594
4	0.0290	0.9871	0.0011	0.9358
12	0.0711	0.8944	0.0025	1.0133
24	0.0793	0.8973	0.2055	0.8127
4. IP_t, SP_t, SI_t, TS_t				
1	0.0093	0.7962	0.0093	0.6488
2	0.0155	0.8220	0.0126	0.7488
4	0.0278	0.8591	0.0133	0.8403
12	0.0701	0.8828	0.0022	0.8452
24	0.0712	0.7513	0.1274	0.6652
36	0.0813	0.6847	0.3498	0.5568
5. IP_t, SP_t, TS_t				
1	0.0093	0.7962	0.0093	0.6488
2	0.0155	0.8219	0.0126	0.7487
4	0.0278	0.8590	0.0133	0.8404
12	0.0701	0.8828	0.0022	0.8451
24	0.0712	0.7514	0.1273	0.6648
36	0.0814	0.6848	0.3496	0.5563

Table 26.
Measuring the forecasting ability of various monthly indicators pre-crisis period

h: *Steps Ahead* **q=400**	**rmsfe**	**Theil**	**bias**	**Var**
1. IP_t, SI_t, SP_t				
1	0.0108	0.8810	0.1511	0.8565
2	0.0157	0.9132	0.1338	0.8849
4	0.0260	0.9447	0.1169	0.9088
12	0.0437	0.8587	0.0274	1.0134
24	0.0437	0.8630	0.0804	1.0020
2. IP_t, SI_t, SP_t, HP_t OP_t, $GD_{t,}$, CPI_t, MS_t				
1	0.0109	0.8696	0.1685	0.8215
2	0.0158	0.9023	0.1459	0.8646
4	0.0261	0.9361	0.1243	0.8991
12	0.0437	0.8521	0.0298	1.0095
24	0.0438	0.8587	0.0841	0.9953
3. IP_t, SI_t, SP_t, CPI_t, MS_t				
1	0.0109	0.8696	0.1685	0.8215
2	0.0158	0.9023	0.1459	0.8646
4	0.0261	0.9361	0.1243	0.8991
12	0.0437	0.8521	0.0298	1.0095
24	0.0438	0.8587	0.0841	0.9953
4. IP_t, SP_t, SI_t, HP_t OP_t, $GD_{t,}$, CPI_t, MS_t TS_t				
1	0.0106	0.8698	0.0675	0.6376
2	0.0156	0.8793	0.1061	0.6651
4	0.0264	0.9014	0.1422	0.7208
12	0.0471	0.8607	0.1158	0.7559
24	0.0510	0.7754	0.3856	0.6009
5. IP_t, SP_t, HP_t OP_t, $GD_{t,}$, CPI_t, MS_t TS_t				
1	0.0106	0.8698	0.0675	0.6376
2	0.0156	0.8793	0.1061	0.6651
4	0.0264	0.9014	0.1422	0.7208
12	0.0471	0.8607	0.1158	0.7559
24	0.0510	0.7754	0.3856	0.6009

Conclusions

Our interest is on whether financial variables that are often associated with future output growth have powerful role in predicting economic activity in a long horizon. Our focus investigation is on the US and we employ the rolling window approach, estimating the different lengths of observation windows with Bai and Perron procedure (1998, 2003).

We start our study by making an in-sample causality test in the under investigation variables. We observe in our analysis that variables such as oil and gold prices do not have cause relationship with IP growth and therefore they do not produce any marginal forecasting information for the IP growth. However, it is evidenced that oil prices have an impact in US economy. Higher oil prices directly affect gasoline, home heating oil, manufacturing and electric power generation. Additionally, gold prices are usually a good indicator of how healthy the U.S. economy is.

Second, in sample causality test suggests a cause relationship between house and S&P composite index. Nevertheless, the out of sample forecast proved that there is forecast ability; but they do not provide any marginal predictive power for IP growth when other variables are included (such as cpi, money supply). This finding is in accordance with Stock and Watson (2003) who indicated that a significant Granger causality statistic contain little or no information about the predictive content of an indicator.

Third, we can see that 3month T-BILL and money supply seem to have not any cause relationship with IP growth, whereas the out of sample forecast measure indicate that these variables have the most powerful predictive information for the IP as horizon increases. This can be justified by the indirect link between money supply and cpi. By this I mean that from the joint causality tests we observe a cause model between cpi, 3m T-BILL, the term spread and oil prices. The intuition behind this is also justified by the economic theory. Governments usually start thinking the possibility of an interest rate rise so as to avoid the phenomenon of hyper-inflation. The most common way to sustain inflation is the rise of the short-term interest rates. The latter rise bring a reduction in the consumption and people's preference for

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

saving money due to high yields offered for their deposits. Simultaneously, a shock in inflation combined with the rise in interest rates send vague signs concerning the direction of stock market with significant effects for the output growth.

Following our analysis, we examine the forecasting ability of all these variables, employing the out of sample forecasting exercise. First we neglect the structural breaks and then we take them into consideration. We indicate that without structural breaks we lose in the forecast stability although in short horizon we observe significant improvements. On the other hand, considering the structural breaks we confirm sizeable gains for both forecast accuracy and forecast stability of our models in long horizons. We also conclude that the major forecasting performance have the short-term interest rates, consumer price index and money supply (M2). Moreover, we should emphasized the high predictive content that gives the term spread in any model that we estimate.

Finally, to investigate whether these variables remain stable in their satisfactory forecasting performance we repeat our estimation but only in the period during the financial crisis of 2007 and the pre-crisis period i.e. from 2006 until 2008 where is the year that the crisis is recognized in the U.S. The picture changes instead during the crisis period. We conclude that only short-term interest rates and stock prices have the best predictive ability, not to mention the term spread that reflects the major marginal predictive information. For the pre-crisis period we take the same results as in the previous estimations. Therefore, we indicate that during crisis there are few structural breaks as well as sudden shocks in the prices and therefore the forecasting performances of variables that are previously satisfactory now differ.

As a concluding remark, we should mention that financial market variables contain considerable information about future economy. In addition, the fact that short-term interest rates, consumer price index and money supply produce marginal predictive information indicates the significant role of monetary policy in taking economic decisions and then affecting the output growth in long horizon.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

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ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Appendix 1

(Table of Data)

Series Description		
Series Label	Source	Series Frequency Monthly
		Asset Prices
DTB3	Federal Reserve Bank of St. Louis	Interest rate: 3-Month Treasury Bill: Secondary Market Rate (Discount Basis)
FRTCM10(IR)	Federal Reserve Bank of St. Louis	Treasury Constant Maturity 10 YEAR (D) – Middle rate
S&PCOMP(RI)	Datastream	S&P 500 Composite - Price Index
GOLDBLN	Datastream	Precious Metal: Gold Bullion LBM U$/Troy Ounce
USHOUSE.O	Datastream	New Private Housing Units Started (AR) Volume Index, seasonally adjusted
		Activity
USIPTOT.G	Datastream	Industrial Production - Total Index Volume Index, seasonally adjusted
USIPMAN.G	Datastream	Industrial Production - Manufasturing (NAICS) Volume Index, seasonally adjusted
		Commodity Prices
OILPRICE	Federal Reserve Bank of St. Louis	Spot Oil Price: West Texas Intermediate (Discontinued series)
OILWTIN	Datastream	Crude Oil WTI Cushing U$/BBL
CPIAUCSL	Federal Reserve Bank of St. Louis	Consumer Price Index for All Urban Consumers: All Items (seasonally adjusted)
CPIHOSSL	Federal Reserve Bank of St. Louis	Consumer Price Index for All Urban Consumers: Housing (seasonally adjusted)
		Money
USM2....B	Datastream	Money Supply M2

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Appendix 2

(Unit Root tests)

Null Hypothesis: SP 500 COMPOSITE has a unit root			
Exogenous: None			
Lag Length: 0 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-21.71730	0.0000
Test critical values:	1% level	-3.442142	
	5% level	-2.866634	
	10% level	-2.569543	
*MacKinnon (1996) one-sided p-values.			
Exogenous: Constant, Linear Trend			
Lag Length: 0 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-21.75020	0.0000
Test critical values:	1% level	-3.975015	
	5% level	-3.418102	
	10% level	-3.131521	
*MacKinnon (1996) one-sided p-values.			
Exogenous: Constant			
Lag Length: 0 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		21.60227	0.0000
Test critical values:	1% level	-2.569220	
	5% level	-1.941406	
	10% level	-1.616308	
*MacKinnon (1996) one-sided p-values.			

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Null Hypothesis: OIL PRICE has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-15.36517	0.0000
Test critical values:	1% level	-3.442142	
	5% level	-2.866634	
	10% level	-2.569543	
*MacKinnon (1996) one-sided p-values.			
Exogenous: Constant, Linear Trend			
Lag Length: 0 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-15.37742	0.0000
Test critical values:	1% level	-3.975015	
	5% level	-3.418102	
	10% level	-3.131521	
*MacKinnon (1996) one-sided p-values.			
Exogenous: None			
Lag Length: 0 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-15.33949	0.0000
Test critical values:	1% level	-2.569220	
	5% level	-1.941406	
	10% level	-1.616308	
*MacKinnon (1996) one-sided p-values.			

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Null Hypothesis: MONEY SUPPLY M2 has a unit root			
Exogenous: Constant			
Lag Length: 4 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-5.044200	0.0000
Test critical values:	1% level	-3.442231	
	5% level	-2.866673	
	10% level	-2.569564	
*MacKinnon (1996) one-sided p-values.			
Exogenous: Constant, Linear Trend			
Lag Length: 4 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-7.332617	0.0000
Test critical values:	1% level	-3.975141	
	5% level	-3.418164	
	10% level	-3.131557	
*MacKinnon (1996) one-sided p-values.			
Exogenous: None			
Lag Length: 8 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-1.672925	0.0893
Test critical values:	1% level	-2.569283	
	5% level	-1.941415	
	10% level	-1.616302	
*MacKinnon (1996) one-sided p-values.			

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Null Hypothesis: HOUSING UNITS has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-32.15288	0.0000
Test critical values:	1% level	-3.442142	
	5% level	-2.866634	
	10% level	-2.569543	
*MacKinnon (1996) one-sided p-values.			
Exogenous: Constant, Linear Trend			
Lag Length: 1 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-32.13609	0.0000
Test critical values:	1% level	-3.975015	
	5% level	-3.418102	
	10% level	-3.131521	
*MacKinnon (1996) one-sided p-values.			
Exogenous: None			
Lag Length: 1 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-32.17812	0.0000
Test critical values:	1% level	-2.569220	
	5% level	-1.941406	
	10% level	-1.616308	
*MacKinnon (1996) one-sided p-values.			

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Null Hypothesis: GOLD BLN has a unit root

Exogenous: Constant			
Lag Length: 0 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-24.91462	0.0000
Test critical values:	1% level	-3.442142	
	5% level	-2.866634	
	10% level	-2.569543	
*MacKinnon (1996) one-sided p-values.			

Exogenous: Constant, Linear Trend			
Lag Length: 0 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-24.93564	0.0000
Test critical values:	1% level	-3.975015	
	5% level	-3.418102	
	10% level	-3.131512	
*MacKinnon (1996) one-sided p-values.			

Exogenous: None			
Lag Length: 0 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-24.81543	0.0000
Test critical values:	1% level	-2.569220	
	5% level	-1.941406	
	10% level	-1.616308	
*MacKinnon (1996) one-sided p-values.			

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Null Hypothesis: CONSUMER PRICE INDEX has a unit root			
Exogenous: Constant			
Lag Length: 1 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-14.39846	0.0000
Test critical values:	1% level	-3.442164	
	5% level	-2.866643	
	10% level	-2.569548	
*MacKinnon (1996) one-sided p-values.			

Exogenous: Constant, Linear Trend			
Lag Length: 1 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-14.43724	0.0000
Test critical values:	1% level	-3.975046	
	5% level	-3.418117	
	10% level	-3.131530	
*MacKinnon (1996) one-sided p-values.			

Exogenous: None			
Lag Length: 14 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-1.792151	0.0696
Test critical values:	1% level	-2.569332	
	5% level	-1.941422	
	10% level	-1.616298	
*MacKinnon (1996) one-sided p-values.			

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Null Hypothesis: 3 MONTH TREASURY BILL has a unit root			
Exogenous: Constant			
Lag Length: 12 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-5.677207	0.0000
Test critical values:	1% level	-3.442413	
	5% level	-2.866753	
	10% level	-2.569607	
*MacKinnon (1996) one-sided p-values.			
Exogenous: Constant, Linear Trend			
Lag Length: 12 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-5.699990	0.0000
Test critical values:	1% level	-3.975400	
	5% level	-3.418290	
	10% level	-3.131632	
*MacKinnon (1996) one-sided p-values.			
Exogenous: None			
Lag Length: 12 (Automatic based on SIC, MAXLAG=14)			
		t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-5.665278	0.0000
Test critical values:	1% level	-2.569316	
	5% level	-1.941419	
	10% level	-1.616299	
*MacKinnon (1996) one-sided p-values.			

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 10

VAR Granger Causality/Block Exogeneity Wald Tests
Sample: 1968M02 2013M07
Included observations: 542

Dependent variable: IP GROWTH

Excluded	Chi-sq	df	Prob.
3m T-BILL	1.626129	3	0.6535
CPI	7.140762	3	**0.0675**
GOLD	5.200853	3	0.1577
HOUSE	16.31416	3	**0.0010**
M2	3.494850	3	0.3214
OIL	0.138249	3	0.9869
S&P	26.07476	3	**0.0000**
TERM SPREAD	6.142119	3	**0.1049**
All	99.27544	24	0.0000

Dependent variable: 3m T-BILL

Excluded	Chi-sq	df	Prob.
INDUSTRIAL	19.77075	3	**0.0002**
CPI	26.94292	3	**0.0000**
GOLD	8.445035	3	**0.0377**
HOUSE	9.947486	3	**0.0190**
M2	2.093575	3	0.5532
OIL	1.002219	3	0.8007
S&P	1.611694	3	0.6567
TERM_SPREAD	2.393281	3	0.4949
All	83.65545	24	0.0000

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Dependent variable: CPI

Excluded	Chi-sq	df	Prob.
INDUSTRIAL	5.059662	3	0.1675
3m T-BILL	8.933170	3	**0.0302**
GOLD	0.638278	3	0.8876
HOUSE	2.865599	3	0.4128
M2	4.420971	3	0.2194
OIL	47.13352	3	**0.0000**
S&P	4.443668	3	0.2174
TERM_SPREAD	27.91109	3	**0.0000**
All	103.5529	24	0.0000

Dependent variable: GOLD

Excluded	Chi-sq	df	Prob.
INDUSTRIAL	2.816722	3	0.4208
3m T-BILL	4.718924	3	0.1936
CPI	0.890815	3	0.8276
HOUSE	5.182522	3	0.1589
M2	16.48940	3	**0.0009**
OIL	19.22465	3	**0.0002**
S&P	1.449662	3	0.6939
TERM_SPREAD	1.186579	3	0.7562
All	61.15583	24	0.0000

Dependent variable: HOUSE

Excluded	Chi-sq	df	Prob.
INDUSTRIAL	4.441850	3	0.2175
3m T-BILL	8.576189	3	**0.0355**
CPI	4.344240	3	0.2266
GOLD	2.073433	3	0.5573
M2	11.96586	3	**0.0075**
OIL	3.561529	3	0.3129
S&P	19.41798	3	**0.0002**
TERM_SPREAD	24.81611	3	**0.0000**
All	87.45147	24	0.0000

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Dependent variable: M2

Excluded	Chi-sq	df	Prob.
INDUSTRIAL	6.905285	3	**0.0750**
3m T-BILL	1.468828	3	0.6895
CPI	27.68978	3	**0.0000**
GOLD	3.927093	3	0.2694
HOUSE	3.387632	3	0.3356
OIL	0.444378	3	0.9309
S&P	1.781788	3	0.6189
TERM_SPREAD	9.231706	3	**0.0264**
All	64.50246	24	0.0000

Dependent variable: OIL

Excluded	Chi-sq	df	Prob.
INDUSTRIAL	6.216902	3	0.1015
3m T-BILL	4.895971	3	0.1796
CPI	2.062637	3	0.5595
GOLD	3.112134	3	0.3747
HOUSE	0.213828	3	0.9753
M2	0.842425	3	0.8393
S&P	6.473088	3	**0.0907**
TERM_SPREAD	9.723768	3	**0.0211**
All	31.62537	24	0.1366

Dependent variable: S&P

Excluded	Chi-sq	df	Prob.
INDUSTRIAL	3.834907	3	0.2799
3m T-BILL	13.52764	3	**0.0036**
CPI	3.713572	3	0.2941
GOLD	5.819306	3	0.1207
HOUSE	9.196438	3	**0.0268**
M2	2.131871	3	0.5455
OIL	0.116097	3	0.9898
TERM SPREAD	2.684447	3	0.4429
All	39.74084	24	0.0228

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Dependent variable: TERM SPREAD			
Excluded	**Chi-sq**	**df**	**Prob.**
INDUSTRIAL	20.05134	3	**0.0002**
3m T-BILL	2.198922	3	0.5322
CPI	5.061063	3	0.1674
GOLD	26.35182	3	**0.0000**
HOUSE	3.988620	3	0.2627
M2	2.083272	3	0.5553
OIL	2.992531	3	0.3928
S&P	3.252317	3	0.3543
All	64.89132	24	0.0000

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Appendix 3

(Estimations without Structural Breaks)

Table 11.
Measuring the forecasting ability of stock prices and either short-term rates or term spread monthly indicators

h: *Steps Ahead*	***Estimation windows of lengths 0.7T (q=400)***							
	Panel A				***Panel B***			
	SR_t and SI_t				***SR_t, SI_t and TS_t***			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0069	0.6769	0.0001	0.5067	0.0071	0.6992	0.0292	0.4874
4	0.0174	0.5865	0.0041	0.5282	0.0184	0.6404	0.1085	0.5030
12	0.0492	0.7118	0.0072	0.6163	0.0535	0.6514	0.1979	0.5611
24	0.0750	0.7044	0.0214	0.6523	0.0863	0.7103	0.3337	0.5297
36	0.0905	0.6859	0.0494	0.6247	0.1090	0.7235	0.4466	0.4561
48	0.1019	0.7188	0.1259	0.4912	0.1196	0.7353	0.5430	0.3630
60	0.1081	0.7906	0.2744	0.2672	0.1127	0.7338	0.7603	0.2395

***Note*:** This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seven forecasting horizons (*h*) based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{j} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

, where j = 2 or 3 respectively

where $y_t = IP_t$ stands for industrial production growth rates and x_{it} are the predictors, i.e. **Panel A**. SI_t and SR_t stand for short-term interest rates and stock returns respectively and **Panel B**. SI_t, TS_t, SR_t stand for short-term interest rates, term spread and stock returns respectively.

ΠΑΝΕΠΙΣΤΗΜΙ

Table 12
Measuring the forecasting ability of block 1 and 3

h: *Steps Ahead*	*Estimation windows of lengths 0.7T (q=400)*							
	Panel A				*Panel B*			
	SR_t, SI_t, MS_t and CPI_t				*SR_t, SI_t, MS_t, CPI_t and TS_t*			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0070	0.6760	0.0096	0.5251	0.0071	0.6911	0.0420	0.4709
4	0.0176	0.5777	0.0381	0.5718	0.0185	0.6228	0.1543	0.4503
12	0.0485	0.6408	0.0621	0.6343	0.0539	0.7170	0.2942	0.4616
24	0.0782	0.6391	0.1167	0.5312	0.0917	0.7200	0.4733	0.3358
36	0.1012	0.6485	0.1820	0.4008	0.1212	0.7124	0.6093	0.2224
48	0.1253	0.7272	0.2698	0.2395	0.1370	0.7259	0.7865	0.1376
60	0.1482	0.8586	0.3721	0.0849	0.1297	0.7252	1.2346	0.0453

Note: This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seven forecasting horizons (*h*) based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{j} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

, where j = 4 or 5 respectively

where $y_t = IP_t$ stands for industrial production growth rates and x_{it} are the predictors, i.e. **Panel A**. SI_t, SR_t, MS_t and CPI_t stand for short-term interest rates, stock returns, money supply and CPI: All urban consumers (all items) respectively and **Panel B**. SI_t, TS_t, SR_t, MS_t and CPI_t, stand for short-term interest rates, term spread, stock returns, money supply and CPI: All urban consumers (all items) respectively.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕ

Table 13
Measuring the forecasting ability of block 1 and 2

h: *Steps Ahead*	***Estimation windows of lengths 0.7T (q=400)***							
	Panel A				***Panel B***			
	SR_t, SI_t, HP_t, OP_t and GD_t				***SR_t, SI_t, HP_t, OP_t, GD_t and TS_t***			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0070	0.6903	0.0025	0.5306	0.0070	0.7012	0.0101	0.5112
4	0.0177	0.6053	0.0116	0.5865	0.0178	0.6538	0.0289	0.6023
12	0.0499	0.7111	0.0207	0.6768	0.0500	0.8370	0.0542	0.6966
24	0.0768	0.6886	0.0529	0.6993	0.0763	0.8386	0.1307	0.6803
36	0.0937	0.6610	0.1129	0.6509	0.0913	0.8460	0.1243	0.6815
48	0.1076	0.6866	0.2368	0.4916	0.0920	0.8537	0.1111	0.6660
60	0.1173	0.7454	0.4458	0.2552	0.0793	0.8175	0.1006	0.5446

***Note*:** This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seven forecasting horizons (h) based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{j} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$, where j = 5 or 6 respectively

where $y_t = IP_t$, stands for industrial production growth rates, and x_{it} are the predictors, i.e. **Panel A**. SI_t, SR_t, HP_t, OP_t and GD_t stand for short-term interest rates, stock returns, housing, spot oil and gold prices respectively and **Panel B**. SI_t, SR_t, HP_t, OP_t, GD_t and TS_t stand for short-term interest rates, stock returns, housing, spot oil, gold prices and term spread respectively.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕ

Table 14
Measuring the forecasting ability of the three blocks

h: Steps Ahead	*Estimation windows of lengths 0.7T (q=400)*							
	Panel A				***Panel B***			
	SR_t, SI_t, HP_t, OP_t, GD_t, MS_t and CPI_t				***SR_t, SI_t, HP_t, OP_t, GD_t, MS_t, CPI_t and TS_t***			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0070	0.6716	0.0177	0.5383	0.0069	0.6822	0.0096	0.4875
4	0.0177	0.5696	0.0652	0.5740	0.0170	0.6215	0.0059	0.6042
12	0.0494	0.6233	0.1085	0.6197	0.0456	0.7245	0.0182	0.6666
24	0.0814	0.6231	0.1941	0.5090	0.0709	0.7835	0.1555	0.4767
36	0.1078	0.6365	0.2863	0.3725	0.0873	0.7666	0.2055	0.3332
48	0.1365	0.7139	0.3907	0.2159	0.0975	0.7196	0.0506	0.3773
60	0.1660	0.8400	0.4957	0.0739	0.0861	0.7063	0.1389	0.1533

***Note*:** This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seven forecasting horizons (h) based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{j} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

, where j = 7 or 8 respectively

where $y_t = IP_t$, stands for industrial production growth rates, and x_{it} are the predictors, i.e. **Panel A**. SI_t, SR_t, HP_t, OP_t, GD_t, MS_t and CPI_t stand for short-term interest rates, stock returns, housing, spot oil and gold prices, money supply and CPI: All urban consumers (all items) respectively and **Panel B**. TS_t, SI_t, SR_t, HP_t, OP_t, GD_t, MS_t and CPI_t stand for term spread, short-term interest-rates, stock returns, housing, spot oil and gold prices, money supply and CPI: All urban consumers (all items) respectively.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙ

Table 15

Measuring the forecasting ability of various monthly indicators replacing money supply with term spread

h: *Steps Ahead*	***Estimation windows of lengths 0.7T (q=400)***			
	rmsfe	**Theil**	**Bias**	**Var**
1	0.0069	0.6830	0.0032	0.5382
4	0.0173	0.5868	0.0125	0.5979
12	0.0466	0.6533	0.0183	0.6522
24	0.0722	0.6363	0.0396	0.5337
36	0.0879	0.6235	0.0680	0.4231
48	0.1104	0.7684	0.0893	0.2923
60	0.1330	0.9740	0.1400	0.0935

***Note*:** This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seven forecasting horizons (*h*) based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{7} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

where $y_t = IP_t$ stands for industrial production growth rates and x_{it} are the predictors, i.e. SI_t, SR_t, HP_t, OP_t, GD_t, CPI_t and TS_t stand for short-term interest rates, stock returns, housing prices, spot oil prices, precious metal: gold, money supply and CPI: All urban consumers (all items) respectively.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙ

Appendix 4

(Estimations with Structural Breaks)

Table 16.
Measuring the forecasting ability of the base model

h: Steps Ahead	*Estimation windows of lengths 0.7T (q=400)*				*Estimation windows of lengths 0.6T (q=330)*			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0076	0.8062	0.0214	0.8302	0.0070	0.7483	0.0082	0.7752
4	0.0205	0.9066	0.0039	0.9497	0.0195	0.8706	0.0377	0.8978
12	0.0508	0.9569	0.0235	0.9670	0.0501	0.9404	0.0896	0.8938
24	0.0753	0.9698	0.0393	0.9604	0.0781	0.9586	0.1392	0.8545
36	0.0882	0.9746	0.0438	0.9600	0.0942	0.9647	0.1624	0.8352
48	0.0875	0.8758	0.0227	0.9844	0.0997	0.8664	0.1746	0.8259
60	0.0720	0.8726	0.0021	1.0092	0.0919	0.8644	0.2140	0.7877

Note**:** This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seven forecasting horizons (*h*) and estimation windows 70%T and 60%T based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{P} \beta_k y_{t-k} + \sum_{i=1}^{2} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

where $y_t = IP_t$ stands for industrial production growth rates and x_{it} are the predictors, i.e. SI_t, and SR_t stand for short-term nominal interest rates and stock returns respectively.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 17.
Measuring the forecasting ability of block 1 and 2

h: *Steps Ahead*	***Estimation windows of lengths 0.7T (q=400)***				***Estimation windows of lengths 0.6T (q=330)***			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0076	0.8062	0.0214	0.8302	0.0070	0.7483	0.0082	0.7752
4	0.0205	0.9066	0.0039	0.9497	0.0195	0.8706	0.0377	0.8978
12	0.0508	0.9569	0.0235	0.9670	0.0501	0.9404	0.0895	0.8963
24	0.0753	0.9698	0.0393	0.9604	0.0781	0.9585	0.1391	0.8563
36	0.0882	0.9746	0.0438	0.9600	0.0942	0.9647	0.1624	0.8352
48	0.0875	0.8758	0.0227	0.9844	0.0997	0.8665	0.1745	0.8271
60	0.0720	0.8726	0.0021	1.0092	0.0919	0.8644	0.2140	0.7877

Note**:** This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seven forecasting horizons (*h*) and estimation windows 70%T and 60%T based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{P} \beta_k y_{t-k} + \sum_{i=1}^{5} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

where $y_t = IP_t$ stands for industrial production growth rates and x_{it} are the predictors, i.e. SI_t, SR_t, HP_t, OP_t, GD_t stand for short-term nominal interest rates, stock returns, housing prices, spot oil prices and precious metal: gold respectively.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 18.
Measuring the forecasting ability of block 2

h: *Steps Ahead*	*Estimation windows of lengths 0.7T (q=400)*				*Estimation windows of lengths 0.6T (q=330)*			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0076	0.8229	0.0134	0.8300	0.0070	0.7579	0.0043	0.7819
4	0.0206	0.9162	0.0054	0.9469	0.0195	0.8773	0.0412	0.8966
12	0.0509	0.9613	0.0248	0.9655	0.0502	0.9435	0.0915	0.8934
24	0.0754	0.9725	0.0404	0.9595	0.0782	0.9607	0.1405	0.8551
36	0.0883	0.9763	0.0447	0.9592	0.0943	0.9666	0.1635	0..8360
48	0.0876	0.8772	0.0234	0.9839	0.0998	0.8683	0.1755	0.8271
60	0.0720	0.8742	0.0023	1.0091	0.0920	0.8670	0.2149	0.7892

***Note*:** This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seven forecasting horizons (*h*) and estimation windows 70%T and 60%T based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{3} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

where $y_t = IP_t$ stands for industrial production growth rates and x_{it} are the predictors, i.e. HP_t, OP_t, and GD_t stand for housing prices, spot oil prices and precious metal: gold respectively.

Table 19.
Measuring the forecasting ability of all monthly variables

h: *Steps Ahead*	***Estimation windows of lengths 0.7T (q=400)***				***Estimation windows of lengths 0.6T (q=330)***			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0078	0.8117	0.0097	0.6171	0.0072	0.7316	0.0062	0.5570
4	0.0208	0.9083	0.0060	0.8684	0.0195	0.8572	0.0387	0.8208
12	0.0511	0.9552	0.0248	0.9392	0.0502	0.9323	0.0895	0.8714
24	0.0757	0.9674	0.0397	0.9459	0.0781	0.9521	0.1383	0.8458
36	0.0886	0.9712	0.0435	0.9505	0.0941	0.9601	0.1609	0.8311
48	0.0878	0.8706	0.0220	0.9791	0.0995	0.8618	0.1725	0.8256
60	0.0719	0.8651	0.0017	1.0088	0.0914	0.8586	0.2114	0.7912

***Note*:** This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seven forecasting horizons (*h*) and estimation windows 70%T and 60%T based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{7} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

where $y_t = IP_t$ stands for industrial production growth rates and x_{it} are the predictors, i.e. SI_t, SR_t, HP_t, OP_t, GD_t, CPI_t, MS_t stand for short-term interest rates, stock returns, housing prices, spot oil prices, precious metal: gold, money supply and CPI: All urban consumers (all items) respectively.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 20.
Measuring the forecasting ability of various monthly indicators when some are excluded

h: *Steps Ahead*	**rmsfe**		**Theil**		**Bias**		**Var**	
	0,7T (400)	*0,6T (330)*	*0,7T (400)*	*0,6T (330)*	*0,7T (400)*	*0,6T (330)*	*0,7T (400)*	*0,6T (330)*
1. SI_t, SR_t, HP_t, OP_t, GD_t, CPI_t								
4	0.0206	0.0195	0.9162	0.8773	0.0054	0.0412	0.9469	0.8966
24	0.0754	0.0782	0.9725	0.9607	0.0404	0.1405	0.9595	0.8551
36	0.0883	0.0943	0.9763	0.9666	0.0447	0.1635	0.9592	0.8360
48	0.0876	0.0998	0.8772	0.8683	0.0234	0.1755	0.9839	0.8271
60	0.0720	0.0920	0.8742	0.8670	0.0023	0.2149	1.0091	0.7892
2. ***SI_t, SR_t, HP_t, OP_t, GD_t, MS_t***								
4	0.0206	0.0195	0.9162	0.8773	0.0054	0.0412	0.9469	0.8966
24	0.0754	0.0782	0.9725	0.9607	0.0404	0.1405	0.9595	0.8551
36	0.0883	0.0943	0.9763	0.9666	0.0447	0.1635	0.9592	0.8360
48	0.0876	0.0998	0.8772	0.8683	0.0234	0.1755	0.9839	0.8271
60	0.0720	0.0920	0.8742	0.8670	0.0023	0.2149	1.0091	0.7892
3. SI_t, SR_t, CPI_t, MS_t HP_t								
4	0.0206	0.0195	0.9119	0.8748	0.0046	0.0393	0.9566	0.9080
24	0.0754	0.0782	0.9714	0.9601	0.0398	0.1398	0.9610	0.8568
36	0.0883	0.0943	0.9755	0.9662	0.0443	0.1630	0.9598	0.8371
48	0.0876	0.0998	0.8763	0.8679	0.0231	0.1752	0.9841	0.8278
60	0.0720	0.0920	0.8732	0.8665	0.0023	0.2146	1.0090	0.7898
4. SI_t, SR_t, CPI_t, MS_t, OP_t, GD_t								
4	0.0206	0.0195	0.9162	0.8782	0.0054	0.0395	0.9469	0.9080
24	0.0754	0.0782	0.9725	0.9605	0.0404	0.1398	0.9595	0.8572
36	0.0883	0.0943	0.9763	0.9666	0.0447	0.1640	0.9592	0.8377
48	0.0876	0.0998	0.8772	0.8683	0.0234	0.1755	0.9839	0.8280
60	0.0720	0.0920	0.8742	0.8680	0.0023	0.2149	1.0091	0.7890
5. ***SI_t, SR_t, CPI_t, MS_t***								
4	0.0208	0.0195	0.9083	0.8572	0.0060	0.0387	0.8648	0.8208
24	0.0757	0.0781	0.9674	0.9521	0.0397	0.1383	0.9459	0.8458
36	0.0886	0.0941	0.9712	0.9601	0.0435	0.1609	0.9505	0.8311
48	0.0876	0.0995	0.8706	0.8618	0.0220	0.1725	0.9791	0.8256
60	0.0720	0.0914	0.8651	0.8586	0.0017	0.2114	1.0088	0.7912

6. CPI_t, MS_t								
4	0.0204	0.0195	0.8847	0.8624	0.0015	0.0315	0.9729	0.9228
24	0.0721	0.0783	0.9639	0.9554	0.0016	0.1361	1.0079	0.8594
36	0.0882	0.0944	0.9674	0.9609	0.0417	0.1598	0.9610	0.8391
48	0.0876	0.1000	0.8681	0.98614	0.0213	0.1722	0.9846	0.8296
60	0.0721	0.0922	0.8639	0.8576	0.0016	0.2108	1.0079	0.7914
7. SI_t, CPI_t, MS_t								
4	0.0208	0.0195	0.9083	0.8572	0.0060	0.0387	0.8648	0.8208
24	0.0757	0.0781	0.9674	0.9521	0.0397	0.1383	0.9459	0.8458
36	0.0886	0.0941	0.9712	0.9601	0.0435	0.1609	0.9505	0.8311
48	0.0876	0.0995	0.8706	0.8618	0.0220	0.1725	0.9791	0.8256
60	0.0720	0.0914	0.8651	0.8586	0.0017	0.2114	1.0088	0.7912

Note**: 1.** SI_t, SR_t, HP_t, OP_t, GD_t, CPI_t model is estimated with short-term interest rates, stock returns, housing, oil and gold prices, consumer price index (as a measure for inflation). **2.** SI_t, SR_t, HP_t, OP_t, GD_t, MS_t model is estimated with short-term interest rates, stock returns, housing, oil and gold prices, and money supply (as an monetary policy indicator) respectively. **3.** SI_t, SR_t, HP_t, CPI_t, MS_t model is estimated with short-term interest rates, stock returns, housing prices, consumer price index (as a measure for inflation) and money supply (as an monetary policy indicator) respectively. **4.** SI_t, SR_t, CPI_t, MS_t model is estimated with short-term interest rates, stock returns, oil and gold prices, consumer price index (as a measure for inflation) and money supply (as an monetary policy indicator) respectively. **5.** SI_t, SR_t, CPI_t, MS_t model is estimated with short-term interest rates, stock returns, consumer price index (as a measure for inflation) and money supply (as an monetary policy indicator) respectively. **6.** CPI_t, MS_t model is estimated with consumer price index (as a measure for inflation) and money supply (as a monetary policy indicator) respectively. **7.** SI_t, CPI_t, MS_t model is estimated with short-term interest rates, consumer price index (as a measure for inflation) and money supply (as a monetary policy indicator) respectively. Estimation windows of lengths 0.6T and 0.7T are used (T is the length of the full sample).

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 21.
Measuring the forecasting ability of term spread, short-term rates and stock returns

h: *Steps Ahead*	*Estimation windows of lengths 0.7T (q=400)*				*Estimation windows of lengths 0.6T (q=330)*			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0074	0.8039	0.0000	0.6523	0.0071	0.7922	0.0025	0.6443
4	0.0200	0.8245	0.0001	0.8277	0.0192	0.7714	0.0117	0.6930
12	0.0505	0.8393	0.0011	0.8167	0.0501	0.7735	0.0157	0.6128
24	0.0754	0.8036	0.0001	0.7357	0.0775	0.7262	0.0169	0.4954
36	0.0872	0.7538	0.0001	0.6814	0.0931	0.6882	0.0126	0.4087
48	0.0872	0.6962	0.0340	0.5822	0.0997	0.6605	0.0061	0.3172
60	0.0819	0.6783	0.0320	0.3109	0.0937	0.6274	0.0033	0.2000

Note: This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seventeen forecasting horizons (h) and estimation windows 70%T and 60%T based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{3} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

where $y_t = IP_t$ stands for industrial production growth rates and x_{it} are the predictors, i.e. SI_t, SR_t, and TS_t stand for short-term interest rates, stock returns and term spread respectively.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 22.
Measuring the forecasting ability of term spread and stock returns

h: *Steps Ahead*	***Estimation windows of lengths 0.7T (q=400)***				***Estimation windows of lengths 0.6T (q=330)***			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0074	0.8038	0.0000	0.6523	0.0071	0.7921	0.0025	0.6443
4	0.0200	0.8244	0.0001	0.8278	0.0192	0.7713	0.0117	0.6931
12	0.0505	0.8393	0.0011	0.8166	0.0501	0.7734	0.0157	0.6128
24	0.0754	0.8036	0.0001	0.7357	0.0775	0.7262	0.0169	0.4953
36	0.0872	0.7538	0.0001	0.6813	0.0931	0.6882	0.0126	0.4086
48	0.0873	0.6964	0.0339	0.5820	0.0997	0.6605	0.0062	0.3171
60	0.0819	0.6784	0.0319	0.3108	0.0937	0.6275	0.0033	0.2000

Note: This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seventeen forecasting horizons (h) and estimation windows 70%T and 60%T based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{2} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

where $y_t = IP_t$ stands for industrial production growth rates and x_{it} are the predictors, i.e. SR_t, and TS_t stand for stock returns and term spread respectively.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 23.
Measuring the forecasting ability of all monthly indicators including the term spread

h: *Steps Ahead*	*Estimation windows of lengths 0.7T (q=400)*				*Estimation windows of lengths 0.6T (q=330)*			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0074	0.8039	0.0000	0.6523	0.0071	0.7922	0.0025	0.6443
4	0.0200	0.8245	0.0001	0.8277	0.0192	0.7714	0.0117	0.6930
12	0.0505	0.8393	0.0011	0.8166	0.0501	0.7735	0.0157	0.6128
24	0.0754	0.8036	0.0001	0.7357	0.0775	0.7262	0.0169	0.4954
36	0.0872	0.7538	0.0001	0.6814	0.0931	0.6882	0.0126	0.4087
48	0.0872	0.6962	0.0340	0.5822	0.0997	0.6605	0.0061	0.3172
60	0.0819	0.6783	0.0320	0.3109	0.0937	0.6274	0.0033	0.2000

Note: This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seventeen forecasting horizons (h) and estimation windows 70%T and 60%T based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{8} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

where $y_t = IP_t$ stand for industrial production growth rates and x_{it} are the predictors, i.e. SI_t, SR_t, HP_t, OP_t, GD_t, CPI_t, MS_t and TS_t short-term interest rates, stock returns, housing prices, spot oil prices, precious metal: gold, consumer price index, money supply and term spread respectively.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Table 24.
Measuring the forecasting ability of various monthly indicators when housing and oil prices replaced with another series

h: *Steps Ahead*	***Estimation windows of lengths 0.7T***							
	Panel A.				***Panel B.***			
	SI_t, SR_t, CPI_t:Housing OP_t, GD_t, CPI_t MS_t				***SI_t, SR_t, HP_t, OP_t:Crude Oil, GD_t, CPI_t, MS_t***			
	rmsfe	**Theil**	**Bias**	**Var**	**rmsfe**	**Theil**	**Bias**	**Var**
1	0.0078	0.8117	0.0097	0.6171	0.0088	0.8764	0.0001	0.6141
4	0.0208	0.9083	0.0060	0.8648	0.0242	0.9405	0.0018	0.8762
12	0.0511	0.9552	0.0248	0.9392	0.0612	0.9698	0.0021	0.9704
24	0.0757	0.9674	0.0397	0.9459	0.0900	0.9774	0.0001	0.9961
36	0.0886	0.9712	0.0435	0.9505	0.1009	0.9797	0.0245	0.9840
48	0.0878	0.8706	0.0220	0.9791	0.0908	0.8776	0.0266	0.8879
60	0.0719	0.8651	0.0017	1.0088	0.0383	0.8608	0.0365	0.1838

***Note*:** This table reports the root mean square forecast error (RMSFE), the Theil criterion (Theil), the bias (bias) and the variance (Var) components of the Theil mean square forecast error decomposition for seventeen forecasting horizons (*h*) and estimation windows 70%T and 60%T based on the forecasting model

$$y_t = \alpha + \sum_{k=1}^{p} \beta_k y_{t-k} + \sum_{i=1}^{7} \sum_{k=1}^{p} \gamma_{ik} x_{it-k} + \varepsilon_t$$

where $y_t = IP_t$ stand for industrial production growth rates and x_{it} are the predictors, i.e. **Panel A**. SI_t, SR_t, CPI_t:Housing OP_t, GD_t, CPI_t, MS_t stand for short-term interest rate, stock returns, housing prices, spot oil prices, precious metal: gold, CPI: Housing and money supply respectively. **Panel B**. SI_t, SR_t, HP_t, OP_t:Crude, GD_t, CPI_t, MS_t stand for industrial production growth rates, short-term interest rates, stock returns, housing prices, crude oil prices, precious metal: gold, CPI: All urban consumers (all items) and money supply respectively.

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ