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THE EVOLVING PREDICTIVE POWER OF SPREADS ON GDP DYNAMICS

by Giulio Nicoletti and Raffaele Passaro

In 2012 all ECB publications feature a motif taken from the €50 banknote.

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Abstract

We investigate the predictive content of credit and government interest spreads with respect to the Italian GDP growth. Our analysis with Dynamic Model Averaging identifies when interest spreads were more useful predictors of economic activity: these periods are not limited to the Great Recession. For credit spreads we gather information from both bank loans and corporate bonds and we compare their predictive role over time and over different forecasting horizons.
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Non technical summary

After financial markets froze in 2008, interest rate spreads surged and global economic activity fell with a momentum unprecedented since the years of the Great Depression. This confirmed a widespread consensus: sudden disruptions in the credit sector can be the onset of large drops of real activity. Beside extreme events, economic research investigated whether interest rate conditions matter also for regular business cycles. Specifically, the forecasting literature investigated whether interest rate spreads on both government and corporate debt can predict real economic activity. Overall, the main empirical findings suggest that interest rate spreads can predict business cycle fluctuations, but their forecasting power considerably changes according to the considered data sample.

Our first contribution to the literature is to explicitly quantify the amount of time variation that characterizes the predictive ability of interest rate spreads with respect to economic activity. In particular, we focus on the difference in the forecasting performance between the Great Recession period and the previous one. In order to do that, we employ a Bayesian technique, namely Dynamic Model Averaging, which is tailored to tackle the question of how forecasting performance of different variables changes over time.

Our second contribution relates to the type of credit data to be used. Most of the literature focuses on credit spread information provided by corporate bonds exchanged in markets: while this is a natural choice for the US economy it is less so for countries in which firms mostly rely on banking finance, such as those in the Euro Area. This paper explicitly compares the forecasting performance of market credit spreads with respect to banking credit spreads in forecasting the GDP in Italy, a country for which corporate bonds markets are particularly underdeveloped.

We conclude that credit spreads were relevant not only in the Great Recession period, but their forecasting ability also peaked in previous crisis episodes such as 1992 and 2001. In this respect, we can say that credit spreads help in forecasting, but sometimes they do so more. Concerning government spreads, the slope of the term structure in Italy does not have a large forecasting ability with respect to GDP growth: better forecasting power is displayed by the spread between the 12 and 3 months government bond yields; its forecasting contribution is high and stable over the whole period after the entrance of Italy in the Euro Area. We also show that credit information from both markets and banks can be important and, in particular, market information is more useful in assessing current conditions (‘nowcasting’), while banks information helps more in assessing future conditions (‘forecasting’).

1 Introduction[1]

After financial markets froze in 2008, global economic activity fell briskly with a momentum unprecedented since the years of the Great Depression. The pattern confirmed a widespread consensus: large and sudden disruptions in the financial sector which result in surges in interest rate spreads can be the onset of large drops in economic activity. Besides black swans, economic research investigated whether interest rate spreads matter for regular business cycles. Specifically, the forecasting literature investigated whether interest rate spreads on both government debt (i.e. yield curve or term spread) and on non-financial firms debt (i.e. credit spreads) can timely predict future real economic activity.

Concerning interest rates on government debt, a remarkable body of evidence on US data found the slope of the yield curve, i.e. the difference between the long and short term rates on government debt, as a good leading indicator for GDP dynamics (Harvey (1989); Estrella and Hardouvelis (1991); Plosser and Rouwenhorst (2003) Stock and Watson (1989)). Stock and Watson (2003) found an attenuation of the nexus between real growth and the slope, while Adrian, Estrella, and Shin (2010) found positive results and offered a theoretical interpretation. Overall, the empirical literature suggests that government rate spreads can predict business cycle fluctuations, but their forecasting power considerably changes according to the considered data sample, as documented by the survey of Wheelock and Wohar (2009). For credit spreads , Stock and Watson (2003) found mixed evidence about its predictive ability on GDP dynamics, while Gilchrist, Yankov, and Zakrajsek (2009) (GYZ hereafter) showed that credit spreads can have a strong predictive content on US real activity.

This paper investigates how the predictive power of interest rate spreads over GDP dynamics evolved over time. We consider both government debt and credit spreads faced by non-financial firms. Results suggest that credit spreads have a more prominent role in GDP forecasting in periods of financial distress. A further value added of the paper is that we evaluate credit spreads derived from both corporate bonds and from banking loans. Most of the available literature focuses only on credit spread information provided by corporate bonds exchanged in markets. While this is a natural choice for the US economy it is less so for countries in which firms mostly rely on banking finance, as for example in the

[1]We thank Dimitris Korobilis for providing us with its original matlab code of DMA; we thank Antonello d'Agostino, Michael Ehrmann, Juri Marcucci, Fabio Busetti, Alessandro Carboni, Marco J. Lombardi, Fabio Fornari, Stefano Siviero and an anonymous referee for useful comments. Thanks to Lorenzo Bencivelli for providing Eurocoin data. For insightful comments we also thank Monica Billio, Marta Banbura, Hashem Pesaran, Neil Ericsson and participants at the 2010 CFE conference, ECB workshop and internal seminar at both ECB and at the Bank of Italy.

Euro Area.[2] The paper explicitly compares the forecasting performance of market credit spreads against banking credit spreads in forecasting the GDP in Italy, a country for which corporate bonds markets are particularly underdeveloped. Our results show that credit spreads, both from markets and banks play a relevant role in predicting real activity.[3]

We discuss the predictive contribution of interest rate spreads at different horizons, including both nowcasting and forecasting applications (up to one year ahead). From a methodological perspective, our contribution uses a bayesian method, Dynamic Model Averaging (DMA heretofore) as in Koop and Korobilis (2011), which is taylored to tackle the question of how the predictive content of explanatory variables evolves over time. Close to the spirit of Stock and Watson (2003), we use a direct forecasting approach, as also in Marcellino, Stock, and Watson (2006), with the value added that DMA allows to track how the predictive contribution of variables changes over time. As we describe in section 2, DMA extends Bayesian Model Averaging (BMA) by allowing for time variation in both model parameters and weights: in this respect it represents a good framework to assess how the forecasting contribution of interest spreads varies over time, even over short periods, such as the one following the Great Recession.

In section 2 we provide some details of Bayesian DMA. In section 3 we describe our dataset and our experiments. Section 4 discusses our results for nowcasting, one quarter ahead and one year ahead forecasting. In section 5 we check the robustness of our results, to the inclusion of different control variables as well as to the use of a different methodology, namely BMA on rolling samples. Some conclusions follow.

2 Empirical methodology

To evaluate how the predictive content of interest rate spreads evolves over time, we use Dynamic Model Averaging (DMA), introduced by Raftery, Karny, and Ettler (2010) and then used by Koop and Korobilis (2011) for inflation forecasting. The rationale behind choosing DMA as our main tool of inquiry is well-rooted in our research question. As we are mostly concerned with the time-variation of the predictive power of *interest rates spreads*, DMA allows to track it by displaying how model weights evolve over time. As highlighted by the previous literature

[2] Papers which focus on predicting Euro Area GDP with financial variables are Ciccarelli, Maddaloni, and Peydro (2010), Espinoza, Fornari, and Lombardi (2009), Forni, Hallin, Lippi, and Reichlin (2003) and Buchmann (2011).

[3] Previous research (Buchmann (2011)) showed that market information on corporate bonds can be an important predictor of real activity for the EA as a whole, but, up to our knowledge no previous research has tried to assess also the forecasting contribution of banking spreads.

(both Raftery, Karny, and Ettler (2010) and Koop and Korobilis (2011)) and we shortly explain below, DMA does so more efficiently than standard BMA. Compared to other Bayesian methodologies used in the literature, DMA has several further advantages. Pace (2011) and Benati and Goodhart (2007) use Time Varying Parameter models to assess time variation of predictive ability of yield spreads against GDP. In particular, Benati and Goodhart (2007) evaluate how the R^2 implied by a time varying VAR, which includes the term spread, evolves over time. Compared to this latter methodology, DMA has the advantage of being able to include many more variables in a parsimonious way and in not being restricted only to the in-sample (R^2) analysis. Finally, for what concerns the choice of Bayesian techniques, classical econometrics -at the present stage- does not allow to formally discuss how predictive ability changes over time. In particular, even if important techniques are available within a frequentist framework (e.g. the Model Confidence Set by Hansen, Lunde, and Nason (2011)), they are mostly based on the asymptotic assumption that the numerosity of the out-of-sample tends towards infinity, not allowing for predictive ability to change over time.

In our simple DMA application, a representative model k is a direct forecasting regression:[4]

$$y^k_{t+j} = \beta^k_t x^k_t + \epsilon^k_{t+j}, E(\epsilon^k_t \epsilon^k_t) = V^k$$

$$y^k_{t+j} \equiv \frac{400}{j} \log \frac{GDP_{t+j}}{GDP_t}.$$

Regression coefficients β^k_t are time–varying and their law of motion is a random walk, as in the Time Varying BVAR literature (see Cogley and Sargent (2005)). The state space representation for model k:

$$y^k_{t+j} = \beta^k_t x^k_t + \epsilon_{t+j}, E(\epsilon_t \epsilon_t) = V^k, \forall t \quad (1)$$

$$\beta^k_t = \beta^k_{t-1} + \eta_t, E(\eta_t \eta_t) = Q^k, \forall t. \quad (2)$$

To project β^k_t over time, the standard Kalman filter recursions are used: in order to estimate Q^k and V^k, rather than the computationally intensive Gibbs sampler (as in Cogley and Sargent (2005)), we use the so called *forgetting approach.* In the *forgetting* approach the projection equation of the variance-covariance matrix of parameters ($\Sigma^k_{t|t-1}$)

$$\Sigma^k_{t|t-1} = \Sigma^k_{t-1|t-1} + Q^k,$$

is replaced by:

$$\Sigma^k_{t|t-1} = \frac{1}{\lambda} \Sigma^k_{t-1|t-1},$$

[4]A generalization to a VAR case is provided by Koop and Onorante (2011).

which basically avoids the use of Gibbs sampling for Q once $\Sigma^k_{0|0}$ is initialized. λ is called *forgetting factor* (see Koop and Korobilis (2011) for references) and it is a calibrated hyperparameter which regulates how quickly regression coefficients incorporate new information. $\lambda = 1$ is equivalent to estimating parameters with an expanding window, while $\lambda < 1$ corresponds to rolling window estimation: more precisely one can consider the term $\frac{1}{1-\lambda}$ as the effective window size of the estimation. For example with $\lambda = 0.95$ and quarterly data, the observations 5 years ago receive roughly 35% as much weight as last period's observations.

Sampling of V^k is also replaced by its recursive estimate:

$$V^k_t = \kappa V^k_{t-1} + (1-\kappa)\left(\epsilon^k_t\right)^2,$$

with κ calibrated to 0.95.[5]

We now turn to describe how model weights are formed and how they are updated over time. Let $\pi^k_{t|t-1}$ denote the probability that at time t and given information up to $t-1$, model k is the best forecasting model: when time t information arrives, the model weight can be updated using Bayes' theorem as follows. Consider a state indicator of the best model l so that $\pi^k_{t|t-1}$ denotes the probability of the event $l = k$, best model is k. When time t information arrives, a straighforward application of Bayes' theorem implies:

$$\pi^k_{t|t} = \frac{\pi^k_{t|t-1} f^k_l}{\sum_k \pi^k_{t|t-1} f^k_l}, \tag{3}$$

where $f^k_l = p(y_{t+j} \mid x^k_t, l = k)$ is the probability at time t of output being y_{t+j}, conditional on the state being $l = k$. f^k_l corresponds to the *predictive density* of model k and under the assumption of normal errors, it is computed as:

$$\begin{aligned} f^k_l &= \left(\frac{1}{(2\pi var^k_t)^{-0.5}}\right)\exp\left(-\frac{(y_t - \mu^k_{t|t-1})^2}{2var^k_t}\right), && (4)\\ \mu^k_{t|t-1} &= x^k_t \beta^k_{t|t-1}, && (5)\\ var^k_t &= V^k_{t|t-1} + x^k_t \Sigma^k_{t|t-1} x'^k_t. && (6) \end{aligned}$$

$\pi^k_{t|t}$ is then projected forward in time using again a *forgetting approach* (see Raftery, Karny, and Ettler (2010) for further details) as follows:

$$\pi^k_{t+1|t} = \frac{(\pi^k_{t|t})^\alpha}{\sum_{k=1}^K (\pi^k_{t|t})^\alpha}, \tag{7}$$

[5] Results are not sensitive to this calibration.

where $K = 2^N$ is the number of possible model combinations given by the N variables in the dataset.

DMA makes also use of prior knowledge: priors on α and λ are dogmatic as they are calibrated; model weights are initialized at the equal weight starting condition. For regression coefficients and the variance of their innovation we follow Koop and Korobilis (2011) by setting them respectively to zero and to a high value (100).

The Dynamic Model Average forecast is constructed as a weighted average ($\hat{y}^k$) over the different $K = 2^N$ model forecasts:

$$(\hat{y}_{t+j})^{DMA} = \sum_{k=1}^{K} \pi^k_{t|t-1} \hat{y}^k_{t+j},$$

in order to assess the contribution of the single indicators (in number N), we follow the approach in Koop and Korobilis (2011), so that the predictive contribution of each single variable x is obtained by summing the weights of each model k which contains x among its explanatory variables.

It is possible to relate DMA to BMA: following the discussion in Raftery, Karny, and Ettler (2010), combining equations 7 and 3 one can compute model weights as a function of the past predictive densities only:

$$\pi^k_{t|t-1} \propto \prod_{i=1}^{t-1} \left[p(y_{t+j-i} \mid x^k_{t-i}, l = k)\right]^{\alpha^i} . \tag{8}$$

Equation 8 shows how the decaying parameter α operates in forming model weights. If $\alpha = 1$ (and $\lambda = 1$) DMA is equivalent to BMA with an expanding estimation window. When $\alpha < 1$, good model performance receives less and less weight as time elapses, in an exponentially decaying manner. Model performance is measured by the predictive density and it is forgotten at a rate α, so that, if for example α is 0.99 and data are quarterly, the predictive density of five years ago contributes to the time t model weight by only 80% as compared to previous period predictive density. By decreasing the term α the researcher tunes the forgetting rate in order to assess which variables were good predictors even over a very restricted time span, as it is when we assess which predictors were relevant in the Great Recession period and immediately afterwards.

3 Data descriprion

Here we detail only the set of interest rate spreads used in the analysis and we describe briefly the remaining indicators of our dataset, referring to Appendix 2 for a more complete list of indicators and metadata.

For credit spreads we use use both information from banks (denoted with b below) and from markets (m), in particular

b For bank credit spreads, we use the spread between the average rate on outstanding loans to non-financial firms and the prime rate, the rate applied to firms in the 10th percentile of credit rating as evaluated by banks (source: Bank of Italy).[6]

m As no corporate bond yield index is avaiable for Italy[7] we rely on information from the Euro Area and at the global level. For the Euro Area level we use the BAA-AAA spread index available from Merrill Lynch for non financial corporations, the same described in Buchmann (2011). At the global level we use the KFC index of financial conditions as described in Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010).[8]

Concerning government bonds, we construct spreads as the difference between the yields on 3-months government bonds and the yields on, respectively 6, 12 months government bonds and the average yield on outstanding long term debt, i.e. whose residual maturity is higher than one year (source: Bank of Italy).[9]

The remaining control variables in our dataset mainly resemble those in Stock and Watson (2003), with few modifications:

- Real variables: industrial production, unemployment rate, employment, retail sales, manufacturing capacity utilization.
- Prices: Headline CPI and PPI index.
- Survey indicators: business and households confidence from Istat, PMI manufacturing index.
- Foreign indicators: IFO, both consumer and business indicators for Germany, Eurocoin as predictor for the Euro Area business cycle; the Baltic Dry index, as proxy for global acticity; the US real GDP.

[6]Using the prime rate allows to be at least partially consistent with the results by Gilchrist, Yankov, and Zakrajsek (2009), suggesting that a timely sorting of spreads by risk is an important issue.

[7]A simple query on Datalogic shows that, looking at the past 15 years, the amount of bond emissions for Italy would not be sufficient to construct any reliable market indicator.

[8]To appraise a forecaster one should reproduce the KFC index using real time information. For simplicity we took the series at it is from Mark Watson's website. When the KFC index is removed from the dataset results do not change significantly.

[9]We also exploited both the IFS dataset which has three groups of rates (weighted averages): short medium and long term rates and the harmonized dataset available from the BIS to gather information on the whole term structure. Results are comparable, but the sample span of the BIS dataset is much more limited, starting from 1998. Results are not shown to save space.

- Commodity prices: commodity price index, silver, gold and the crude oil brent.
- Money and Credit: M1–M3, the stock of credit allocated to productive uses and to mortgages.[10]
- Exchange rates: nominal effective exchange rate.
- Stock market returns from MIB30.

All the reported indicators are available at a monthly frequency or higher.[11]

We apply some linear transformations to each generic variables X_t in our dataset:

$$
\begin{aligned}
X_t^d &= (1-L)X_t, \\
X_t^{dl} &= (1-L)\log X_t, \\
X_t^{d2} &= (1-L)^2 X_t, \\
X_t^{d12} &= (1-L^{12})X_t,
\end{aligned}
$$

where L denotes the lag operator at monthly frequency.[12]

Since a proper real time dataset for our real variables is not available we mainly use ex-post revised data, consistently with the 2010 December information; for robustness purposes we collected a partial real time dataset which only includes vintages for GDP and Industrial Production.[13]

4 Results

4.1 Some OLS reference background

Some very preliminary evidence on the predictive ability of interest rates spreads over our full sample can be obtained by using simple OLS rolling regressions. We do so in order to give the reader a rough mental background of the predicting power of interest rate spreads and some reference variables for the Italian GDP, using the full sample. As this part is not intended to be a full-blown analysis, we

[10]This denomination as according to uses is consistent with the Bank of Italy credit statistics.

[11]The nominal effective exchange rate is quarterly and we interpolate it at a monthly frequency.

[12]For quarterly frequency we use the same definitions with obvious modifications.

[13]Real time IP data are from the OECD MEI dataset, which only start from the 1999 vintage. We used the 1999M1 raw series –which are less subject to revisions– and we recursively applied the TRAMO-SEATS seasonal adjustment procedure to reconstruct vintages backwards. Real time vintages for the GDP are available from 1994, after filling one partially missing vintage in 1998Q1 with values from the 1998Q2 release.

Variable	Nowcasting	1-q-ahead	4-q-ahead
ip_{d12}	1.08	1.06	1.00
Unempl	0.97	0.97	0.84
GDP_{us}	0.92	0.97	0.87
IFO_b	0.85	1.00	1.03
$spre$	1.07	1.07	1.02
$spre_{12-3}$	1.04	1.06	1.01
$spre_{6-3}$	1.02	1.05	1.03
$spre_b$	0.98	0.90	0.76
$spre_{BA}$	0.97	1.02	1.00
KFC	0.89	1.03	0.97

Table 1: Ratio of bivariate models' Mean Square Forecast Error compared to univariate AR's MSFE (nowcasting, 1-q-ahead) or random walk (4-q-ahead).

use simple regressions in which, as in Stock and Watson (2003), a simple AR is augmented with one regressor at the time.[14]

Table 1 shows results with some of our indicators, the year on year growth rate of non SA industrial production (ip_{d12}), the unemployment rate, the US GDP growth rate and the IFO business indicator (IFO_b). Government bond spreads are denoted with *spre*, for the difference between long term rates and 3 months and with *spre* and a number reporting the maturity (e.g. $12-3$ for the difference between 12 and 3 months). Credit spreads are denoted with, respectively $spre_b$ and $spre_{BA}$, for banking and markets credit spreads.

4.2 Using DMA

In order to assess the relevance of all the models implied in our dataset, we should run DMA on 34 indicators, producing a minimum of 2^{34} different models, excluding lags, to be evaluated: this would be computationally unfeasible in our set-up. By the same token, our main aim is not in exploring systematically the forecasting power of our complete dataset, but rather to describe whether and when interest rates spreads help in forecasting, even after a reasonable control group of available real and financial indicators is included in the dataset. To reach our goal in the most rigorous, yet computationally feasible manner, we proceed as follows:

1. We always include the lagged dependent variable in the DMA.
2. All credit spreads and the KFC are introduced in the DMA.

[14]We use rolling regressions with a window of 35 observations. Lags of the endogenous and the exogenous variable are chosen at every iteration by the BIC criterion.

3. Government bond spreads enter the DMA, but only the ones which are more strongly linked with GDP, using in-sample selection techniques. (the one or more which appear among the first five predictors chosen by LARS, detailed below).

4. Control variables, both real and financial, we use an in-sample selection technique (LARS).

Concerning the choice of our selection techniques, we follow the literature on factor models (see Bai and Ng (2008) and for Italy Bulligan, Marcellino, and Venditti (2011)) and we preselect variables using a LARS procedure (Efron, Hastie, Johnstone, and Tibshirani (2004)). While pre-selection of control variables (3) seems a choice fully consistent with our goals, pre-selecting government spreads (2) is forced mainly by computational reasons (i.e. it would not be possible to include the whole term structure of government rates in the DMA). We run several robustness checks on the included government spreads in section 5.2.

All models include a constant term,[15] nesting the random walk model, a usual benchmark in the forecasting literature. Concerning the choice of lags of explanatory variables we use the same strategy as in Buchmann (2011) and we include the lagged endogenous variable but not any lagged explanatory variables. This strategy reduces the number of models to be evaluated and it considerably simplifies the exposition of results.[16]

In order to fully reproduce real time forecasting conditions we run LARS in a recursive manner, rerunning it at each forecast by expanding the time window and reselecting the best explanatory variables.[17] As our main objective is to track credit spreads forecasting performance before and after large recessions we run LARS until 2007Q4, starting from 1993, right after the 1992 currency crisis.

By running LARS in this recursive manner, we noticed that the variables included as the first five preditors by LARS in a time frame from 1993 till 2007[18] did not change much over time, but they exhibited considerable variation in ordering. To further ease exposition we then present results obtained by running LARS on the period 1993-2007. This procedure makes our results easier to read and, as we check, it does not produce a substantial bias in the results.

[15]We check that this is not a critical assumption for our results.

[16]The main results are robust to using also one lag for the explanatory variables.

[17]The spirit of running LARS by expanding the window is consistent only with using DMA at $\alpha = 1$, this is a further reason for not using it more extensively, and, in particular, not in the Great Recession period.

[18]For some of our indicators such as PMI the span of data availability is slightly shorter, we rerun the LARS accordingly. Table 2 reports the variables which are selected in most of the samples.

Variables	Nowcasting	1-step-ahead	4-steps-ahead
ip_{d12}	$\times$		
IFO_b	$\times$	$\times$	
$spre_{12-3}$	$\times$	$\times$	$\times$
$spre$			$\times$
$Stockp$	$\times$	$\times$	$\times$
PMI	$\times$		
$Unempl$		$\times$	$\times$
$R_{ovnight}$			$\times$
ip_{dl}		$\times$	
y_{t-1}	$\times$	$\times$	$\times$
$spre_b$	$\times$	$\times$	$\times$
$spre_{BA}$	$\times$	$\times$	$\times$
KFC	$\times$	$\times$	$\times$

Table 2: Selected indicators by horizon

Table 2 displays variables selected at different forecasting horizons. LARS selects for nowcasting the year-on-year growth rate of non seasonally adjusted industrial production (ip_{d12}), the government term spread between 12 and 3 months ($spre_{12-3}$), the returns from MIB ($Stockp$), the IFO business indicator (ifo_b) and the PMI manufacturing output index (PMI). For for one quarter ahead forecasts, LARS features the quarterly growth rate of industrial production (ip_{dl}), the IFO business indicator, MIB stock returns, the 12-3 government bond spread ($spre_{12-3}$) and the unemployment rate ($unempl$). The overnight rate ($R_{ovnight}$), and the spread between long and short end of the yield curve ($spre$) are relevant only for one year ahead forecasts, for which also unemployment is selected, together with the 12-3 months government bond spread. Below the line we report variables which are always included in the DMA: credit spreads variables ($spre_b$ is the banking credit spread, while $spre_{BA}$ is the Merril Lynch spread) and the lagged GDP (y_{t-1}).

4.3 Nowcasting

For nowcasting we take into account the existing publication lags of Italian macroeconomic indicators, assuming that forecasts are produced at the end of each month:

- In the second month of each quarter (45 days), GDP growth of the previous quarter becomes known.
- Industrial production is known one month after its reference period.

- Survey, Financial and Credit indicators are known in the same month as their reference one.

If anything, the choice of producing end-of-month forecasts is conservative with respect to the evaluation of the interest rate spreads which are more timely available than most of the variables: in other words, if any bias has to be expected from this choice, it should not advantage the variables we are putting under scrutiny.

We proceed as follows in order to bridge monthly indicators into a quarterly frequency:

1. Lagged GDP growth is shifted in the monthly dataset by one month, consistently with its publication lag.

2. Monthly indicators are bridged to quarterly frequency by taking their cumulative mean:

$$PMI^*_{t,m=1} = PMI_{t,m=1}, \tag{9}$$

$$PMI^*_{t,m=2} = \sum_{j=1,2} \frac{PMI_{t,m=j}}{2}, \tag{10}$$

$$PMI^*_{t,m=3} = \sum_{j=1,2,3} \frac{PMI_{t,m=j}}{3}. \tag{11}$$

3. For financial data available at daily frequency, e.g. the stock returns, we take monthly averages and then we use the bridge aggregation in (9–11).[19]

4. Industrial Production is shifted by one month in the dataset, consistently with its publication lag. In order to be consistent with the quarterly aggregation proposed above we adopt year on year growth rates: results are not significantly affected by using quarter on quarter growth rates, or month-on-month.

Our strategy to bridge variables is consistent with direct forecasting methods, where exogenous variables are not iterated forward in order to reach the desired forecasting horizon. While this strategy is easier to follow when using DMA methods, it has also the advantage of treating equally all variables both real and financial. The typical strategy adopted in nowcasting would be to use an autoregressive process in order to have a forecast for the exogenous variable in each single quarter. Besides being more complex to implement within the DMA framework, this would shift part of our research question to how to efficiently predict financial variables.

[19] There is no significant difference when using end of month realizations of the indicators available at a daily frequency.

Consistently with the literature on direct forecasting, we leave this extension for future research.

In order to better disentangle the contribution of variables over time, we analyze model weights as produced under the calibration $\alpha = 0.9$. Model weights do not change substantially over the calibration of the λ, the effective size of the estimation window, we show results for $\lambda = 0.95$, which has also a good forecasting performance with respect to the benchmark (see table 3).

Figure 1 shows probability weights associated to respectively from above-left, lagged GDP growth, industrial production, IFO business and bank credit spreads, over the period 1997M1 to 2009M12.[20]

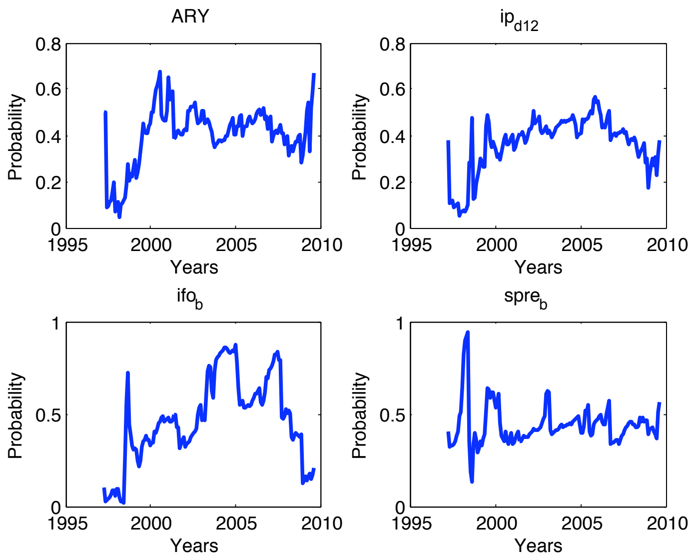

Figure 1: Nowcasting probability weights: $\alpha = 0.9$, $\lambda = 0.95$

The contribution of the lagged GDP growth (ARY) and the industrial production is roughly constant and below the level of 0.5; the ifo business indicator has only a slightly better performance. We do not find a high probability of banking credit spreads being the best forecasting variable in the whole sample.

Figure 2 reports results from market variables. From above-left, we have the government term spread, the KFC index, the stock returns and finally the Merril Lynch spread. All market credit spreads, in particular the KFC and the Merrill Lynch indicator are responsive to the Great Recession period, during which they

[20]We start from 1997 as both PMI and Merril Lynch indicators start in 1995, at any rate 2 years of data are a much safe amount of time to be used as a burn-in period for DMA.

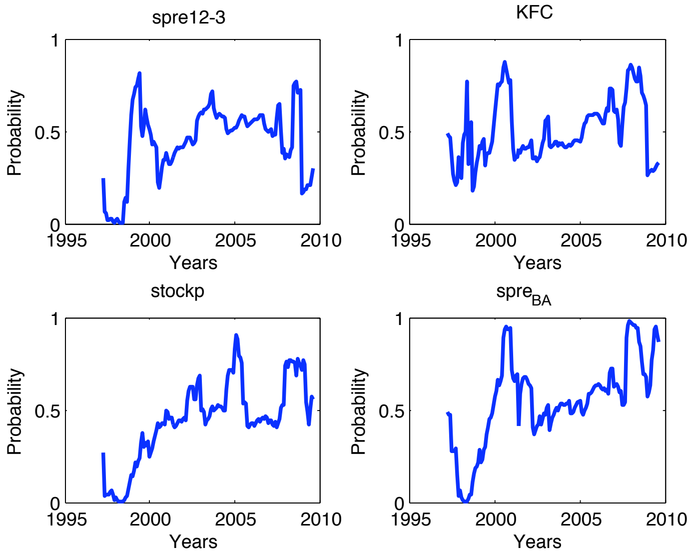

Figure 2: Nowcasting weights on variables: $\alpha = 0.9$, $\lambda = 0.95$

reach a higher weight than in the remaining part of the sample. They also both peak in other moments of financial distress, in particular the 2001 recession: in this respect, credit indicators help forecasting more, sometimes. The same is also partially true for the stock returns, which, beside the Great Recession period, they also capture GDP movements in late 2004. The government term spread instead appears as having a more limited contribution to forecasting, remaining rather stable in the sample and above 0.5.

Figure 3 shows that the predictor which receives the highest probability over the whole sample is the PMI manufacturing index (PMI), with a large fall in the latest part of the sample, probably due to the fact that Italian GDP dropped at the end of 2009 in spite of positive indications from PMI.

Table 3 compares forecasting performance over the all sample and for different calibration of α and λ, as compared to the random walk benchmark. When we progressively exclude interest rate indicators the forecasting performance deteriorates, albeit slightly when the full sample is considered. The fact that forecasting performance generally improves when model selection is more active (for example, when $\alpha = 0.9$) is an indication that the forecasting contribution of variable tends to differ over the sample.[21]

[21] A higher degree of parameter flexibility (i.e. $\lambda = 0.9$) considerably worsens forecasting performance. This is not new in the literature on time varying parameters, see D'Agostino,

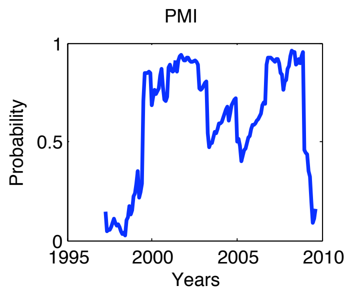

Figure 3: Nowcasting weights on variables: $\alpha = 0.9$, $\lambda = 0.95$

	$\lambda = 1$	$\lambda = 0.99$	$\lambda = 0.95$	$\lambda = 0.9$
All indicators				
$\alpha = 0.99$	0.57	0.56	0.61	0.77
$\alpha = 0.95$	0.55	0.54	0.60	0.73
$\alpha = 0.9$	0.53	0.53	0.56	0.68
Without credit spreads				
$\alpha = 0.99$	0.66	0.65	0.65	0.77
$\alpha = 0.95$	0.66	0.63	0.63	0.75
$\alpha = 0.9$	0.66	0.63	0.62	0.73
Without credit and gov spreads				
$\alpha = 0.99$	0.73	0.71	0.68	0.77
$\alpha = 0.95$	0.71	0.69	0.66	0.74
$\alpha = 0.9$	0.70	0.67	0.64	0.73

Table 3: MSFE nowcasting: DMA compared to RW, different α, λ

The main results above do not change significantly when using our real time dataset: the only relevant difference concerns the Industrial Production, which is subject to statistical revisions. In particular, figure 4 compares the weight of real time IP (blu line) with that obtained using the 2009M12 release (red dashed line of figure 4), showing that in real time industrial production tends to have a larger

Gambetti, and Giannone (2011) on Euro Area data.

predictive content.

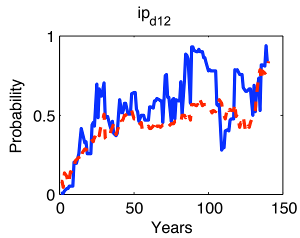

Figure 4: Nowcasting weights on real time IP (blue) vs 2009m12 release (red): $\alpha = 0.9, \lambda = 0.95$

4.4 Forecasting: 1 and 4 quarters ahead

All the indicators selected for forecasting applications[22] are available for a longer time span than for the case nowcasting; we then track the forecasting ability of interest rate spreads over two large recessions in Italy, both the 1992 crisis and the Great Recession.[23]

Figure 5 shows the predictive contribution of, from above-left, the lagged GP growth, the ifo business indicator, the industrial production and the spread computed from bank interest rates.

Differently from the nowcasting case, bank information turns out to be important in the Great Recession period, as shown by a large spike in its weight; a peak in forecasting ability is also observed in the 1992 recession. Industrial production is not very relevant predictor, as this generally considered as more a coincident rather than an anticipatory indicator. The ifo business indicator also peaks during the Great Recession period.[24]

Concerning market information, figure 6 shows the probability of each market variable to be the best forecasting one; from above-left the KFC, stock market returns and the government bond spreads over the 12-3 horizon. KFC is the only market indicator for credit which appears to be mildly responsive to both the Great Recession period and the 1992 crisis. Stock returns play only a limited role

[22]The only exception is the Merril Lynch market credit spread, we set it equal to zero during the period 1990-1995; we proceed in the same way for model weights, by setting to zero weights on all models in which the Merril Lynch indicator appears before 1995.

[23]The MSFE is computed on the same sample as in the nowcasting 1997–2009. Also, none of the results for the post-1997 period hinges upon our decision of exploring a larger time span.

[24]While a thoughly analysis of spillovers to the Italian economy from abroad could be undertaken using DMA, this is outside the scope of this paper.

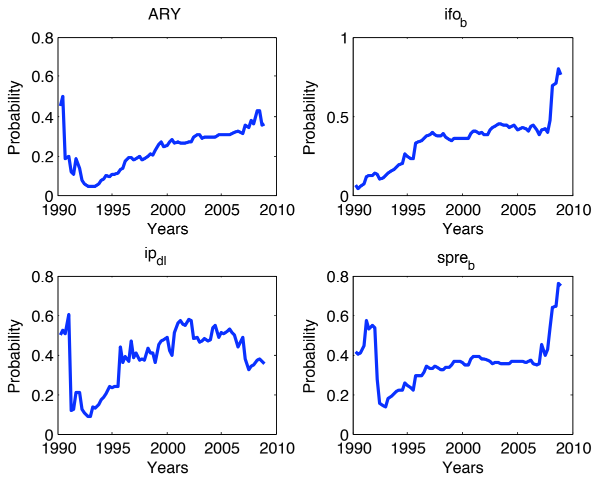

Figure 5: 1-q-ahead weights on variables: $\alpha = 0.9$, $\lambda = 0.95$

in forecasting (by and large its weight is below 0.5), while the government spread has a local peak during the 1992 recession and it gets stable stable and above 0.5 after the run-up of Italy in the Euro. The spike during the period 1992-1993 is to be expected as public debt played a key role for the onset of the 1992 crisis. After 1993 its contribution gets much lower and then peaks again after the entrance of Italy in the Euro Area. Our interpretation is that the run-up to the Euro was characterized by rather high short term interest rates, in order to achieve inflation convergence with the Euro Area, while markets set lower longer term interest rates anticipating the entrance in the Euro Area. The resulting tendency is that of an inverted term spread, this did not actually predict an incoming recession, but it was rather the effect of specific monetary policy actions related to the entrance of Italy in the Euro Area. Finally, the unemployment rate displays a rather low contribution, with a relative peak after 1993, when unemployment peaked and it was absorbed at a very slow pace.

Last figure, 7, shows that the Merril Lynch credit indicator from corporate bonds play a very limited role in forecasting GDP, as weights are much below 0.5 for all the sample period.

The out-of-sample MSFE for different calibrated parameters (α, λ), shows similar results compared to the nowcasting case.

For the case of one year ahead forecasts, we do not find a relevant role for the long term spread, nor for stock returns, once banking spreads are introduced. The KFC index plays a larger role in determining medium term GDP developments

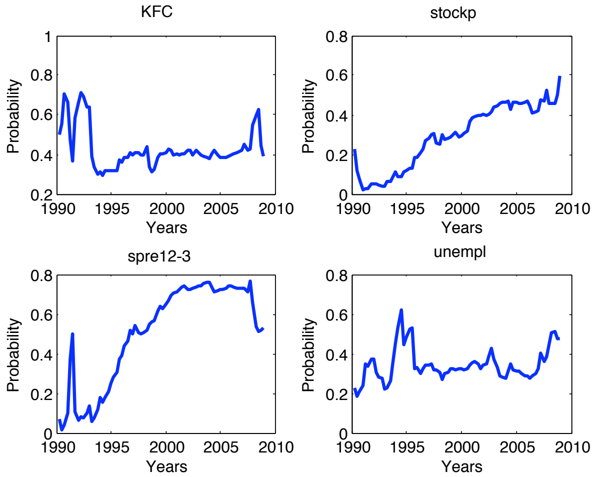

Figure 6: 1-q-ahead weights on variables: $\alpha = 0.9, \lambda = 0.95$

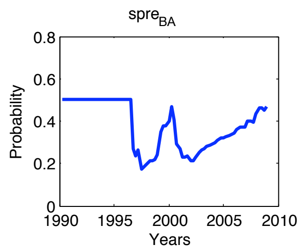

Figure 7: 1-q-ahead weights on Merril Lynch spread: $\alpha = 0.9$, $\lambda = 0.95$

at the onset of the 1992 crisis, while this is more limited during the recent crisis. Banking spreads are a useful predictor for the Italian economy after 2000, but without showing a spike in the Great Recession. The weight on unemployment is highly volatile in the sample but, overall, comparing figures 8 and 7, it better captures the smooth developments in the year on year growth rates rather than the more volatiles q-o-q developments. The weight on unemployment in the Great Recession is lower compared to its peaks in the 1992 crisis and it probably reflects the fact that, also due to specific policy interventions, the rise of unemployment in the Great Recession in Italy was, at least until the beginning of 2010, relatively milder with respect to the 1992 case.

Over the sample, the role of variables in the year-on-year forecasts is quite

	$\lambda = 1$	$\lambda = 0.99$	$\lambda = 0.95$	$\lambda = 0.9$
Benchmark				
$\alpha = 0.99$	0.66	0.65	0.65	0.77
$\alpha = 0.95$	0.66	0.63	0.63	0.75
$\alpha = 0.9$	0.66	0.63	0.62	0.73
Without credit spreads				
$\alpha = 0.99$	0.87	0.85	0.83	0.83
$\alpha = 0.95$	0.82	0.81	0.79	0.79
$\alpha = 0.9$	0.82	0.81	0.79	0.78
Without credit and gov spreads				
$\alpha = 0.99$	0.90	0.90	0.89	0.91
$\alpha = 0.95$	0.87	0.87	0.85	0.85
$\alpha = 0.9$	0.87	0.87	0.85	0.83

Table 4: MSFE 1 quarter ahead forecasts: DMA compared to RW, different α, λ

similar with respect to the one quarter ahead case, with few exceptions. In general, even taking into account the evolving role of predictive ability, including credit and government interest spreads contributes less to forecasting, as we show in table 5.

	$\lambda = 1$	$\lambda = 0.99$	$\lambda = 0.95$	$\lambda = 0.9$
Benchmark				
$\alpha = 0.99$	0.88	0.87	0.84	0.84
$\alpha = 0.95$	0.82	0.81	0.78	0.78
$\alpha = 0.9$	0.81	0.80	0.77	0.75
Without credit spreads				
$\alpha = 0.99$	0.88	0.88	0.89	0.88
$\alpha = 0.95$	0.85	0.85	0.84	0.82
$\alpha = 0.9$	0.83	0.83	0.82	0.80
Without credit and gov spreads				
$\alpha = 0.99$	0.91	0.91	0.91	0.91
$\alpha = 0.95$	0.91	0.91	0.90	0.90
$\alpha = 0.9$	0.88	0.88	0.89	0.87

Table 5: MSFE 1 year ahead forecasts: DMA compared to RW: different α and λ

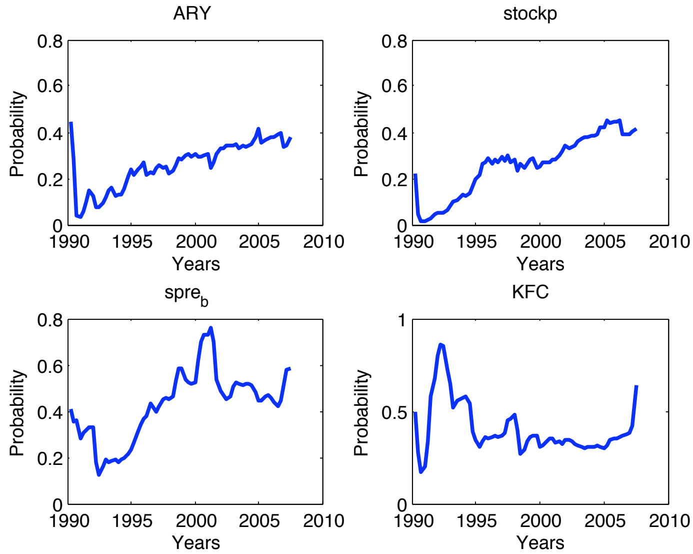

Figure 8: 1-y-ahead weights on variables: $\alpha = 0.9$, $\lambda = 0.95$

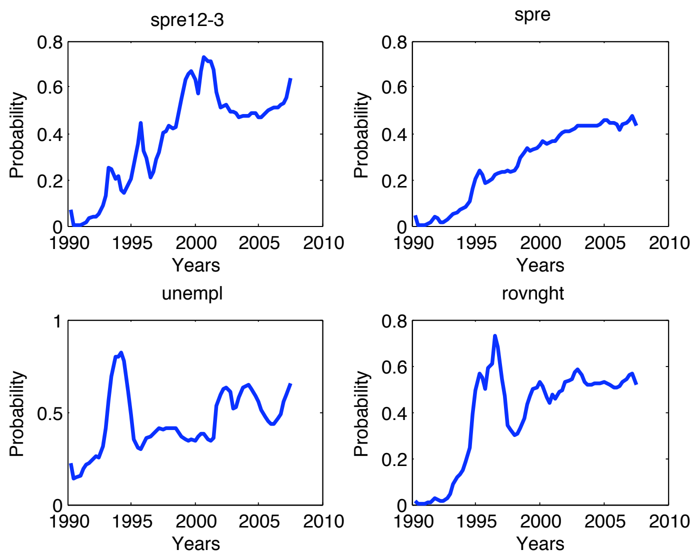

Figure 9: 1-y-ahead weights on variables: $\alpha = 0.9$, $\lambda = 0.95$

5 Robustness checks

5.1 Controlling for the European and Global cycle

Since our baseline DMA includes credit spread data from outside Italy (the Merril Lynch credit spread and the KFC), we want to check previous results by including in the set of regressors some explicit indicators for the european and global cycle, respectively the Eurocoin indicator and the Baltic Dry Index (see Kilian (2009)). As our main results are roughly unchanged with respect to previous exposition, we only comment nowcasting, for which we observe the largest change in weights, albeit mainly not for the interest rate spreads.[25]

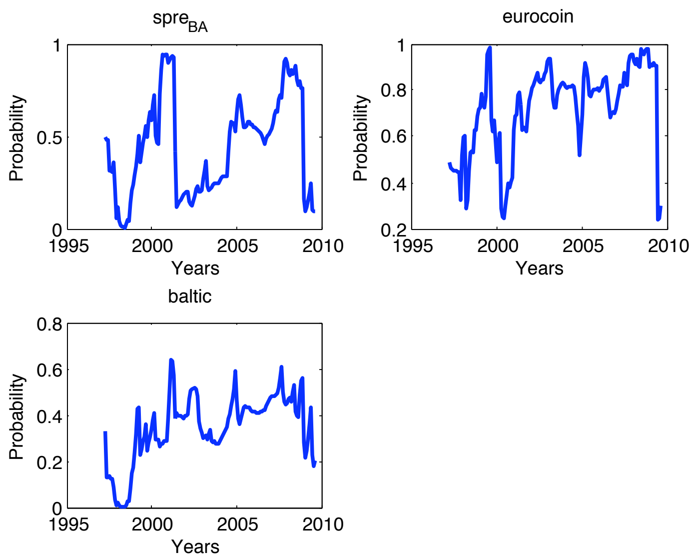

Figure 10: Nowcasting weights on variables: $\alpha = 0.9$, $\lambda = 0.95$

Figure 10 describes the weights on –from above-left– the Merril Lynch indicator, Eurocoin and the baltic dry index. As in our previous results the spread peaks during the 2001 recession and again peaks at the onset of the Great Recession; compared to Eurocoin it seems to provide a complementary rather than substitute information. Over the Euro period eurocoin, tracks well the Italian GDP growth, its forecasting contribution remaining high and rather constant. The Baltic Dry

[25]It is also fair to notice that both Eurocoin and the Baltic Dry index are better suited for nowcasting purposes, here we do not dwell further in this line of research.

Index does not seem to add much value also accross the different calibration of the λ.

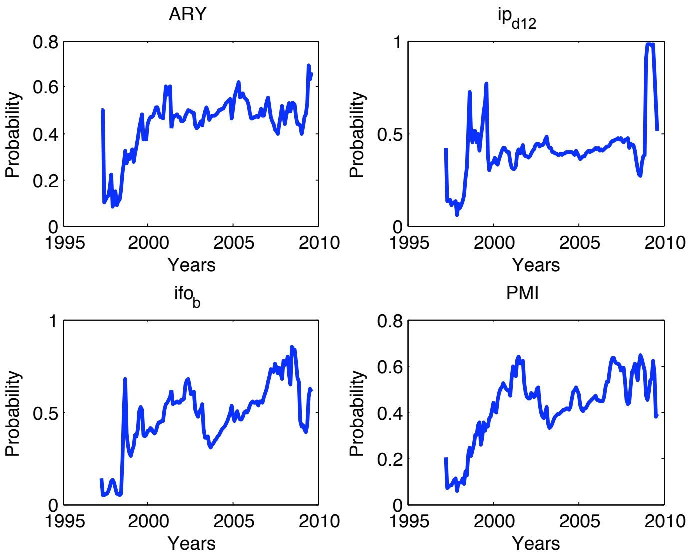

Figure 11: Nowcasting weights on variables: $\alpha = 0.9$, $\lambda = 0.95$

The introduction of Eurocoin makes both the PMIs and the ifo business indicator rather redundant. The industrial production index plays a limited role as before, but it now peaks mostly in the period when both the Merril Lynch and Eurocoin tend to display a weakness.[26]

As in the benchmark results, figure 12 confirms that banking information adds little information to nowcasts, while the KFC indicator seems to increase its role after the introduction of the Baltic Dry index, expecially at the end of the sample.

Overall, the baseline results are robust to the introduction of our controls, with the only notable difference that, differently from the baseline case, the weight on the Merril Lynch spread falls at the end of the sample while the weight on the KFC indicator picks up. In this respect there is a substitution between two related credit indicators, but this last result is the only one to be no robust to the calibration of the λ parameter. For a higher degree of parameter flexibility the weight of the KFC index first peaks in the financial crisis, but then it drops quite significantly.

[26]The spike in the IP weight might also have been generated by the way we handle its publication lag. To control for that we rerun routines assuming no publication lag for IP and we verify that this type of spike still persists.

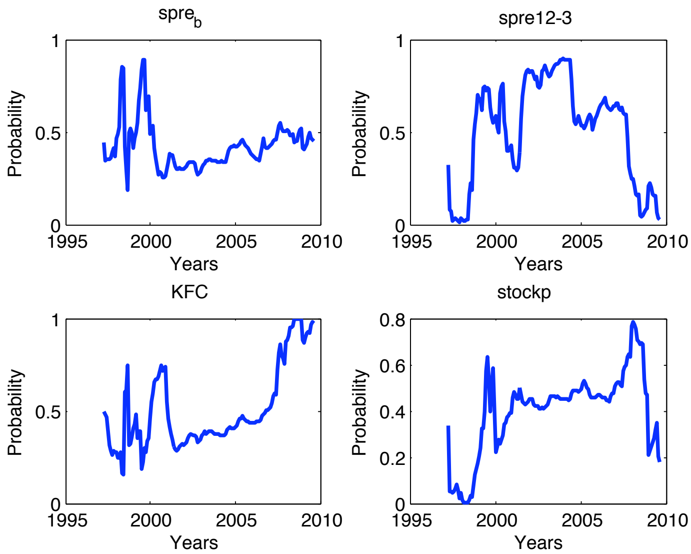

Figure 12: Nowcasting weights on variables: $\alpha = 0.9$, $\lambda = 0.95$

5.2 Others government yield spreads and US GDP

Since we selected government interest rate spreads on the grounds of LARS and this latter tends to (over) exclude from the dataset collinear variables,[27] in this section, we reintroduce the long term spread on government bonds in nowcasting to provide to check robustness of previous results; in this section we also report results using the 6-3 spread rather than the 12-3, showing that it has very similar implications.[28]

To save on space we present here the case where also the US GDP is introduced. The inclusion of the US-GDP is a further control for global business cycle, instead of the Baltic Dry index examined in the previous section. Furthermore, the US GDP might be a sensible choice for nowcasting applications as its release leads European data: in our nowcasting exercise we take into account this publication lead.[29]

As shown in figure 13, the inclusion of US GDP and the long term spread has the main effect of reducing the contribution of PMI to forecasting, at the same

[27] We thank an anonymous referee for pointing this out to us.

[28] To save on space we report only results for nowcasting.

[29] Consistently with previous analysis we use the US GDP series as available in 2010Q4, we check that no significant difference emerges if using a series of Advance estimates, available from the US real time dataset of the Philadelphia FED.

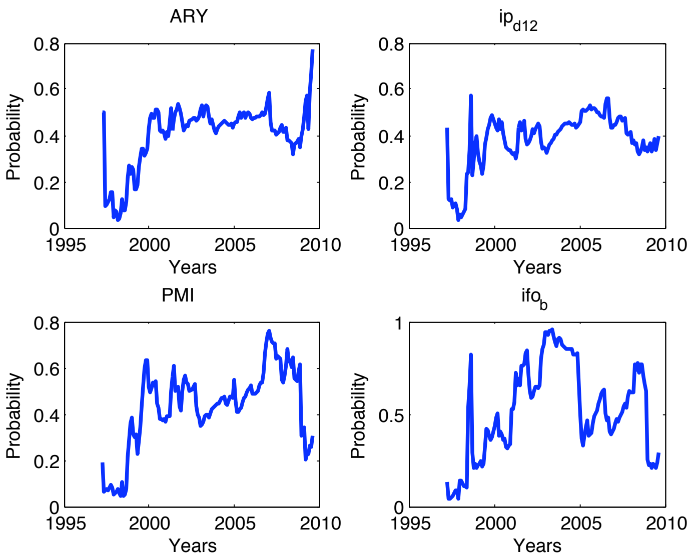

Figure 13: Nowcasting weights on variables: $\alpha = 0.9$, $\lambda = 0.95$

time both the financial indicator KFC, the banking spread and the stock returns display a higher contribution in the period close to the Great Recession. While for this dataset the banking spread has a higher contribution during the Great Recession, this is limited to a small and transitory peak of roughly two quarters. Figure 14 also shows that using the 6-3 month spread, rather than the 12-3 does not change the main message on short term bond yields: they tend to display a rather stable contribution during the Euro period, but a limited effect in the period approaching the Great Recession.

As chart 15 shows, the role of the US GDP is overall more relevant than the Baltic Dry index as global indicator for Italy, but is limited to some specific events. In particular, it peaks right after the 2001 recession. In spite of all the introduced controls, the Merril Lynch spread (upper left panel) confirms its role as predictor, both in the 2001 recession and during the most recent period. Finally the role of the long term government spread is limited to the late 2008 and it drops afterwards.

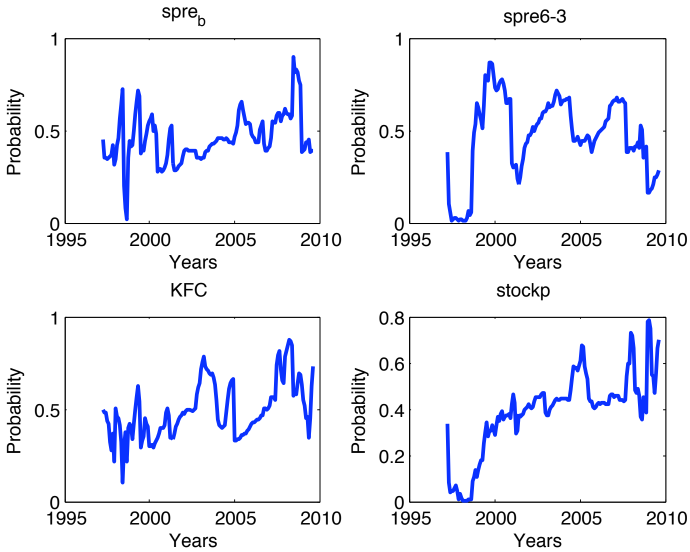

Figure 14: Nowcasting weights on variables: $\alpha = 0.9$, $\lambda = 0.95$

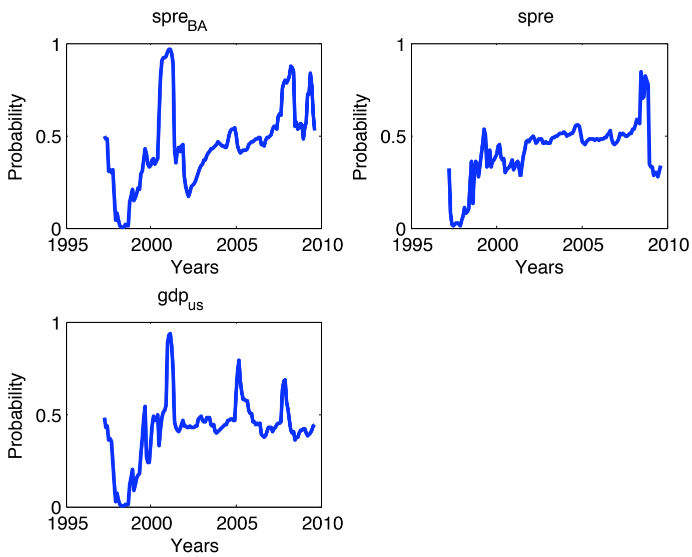

Figure 15: Nowcasting weights on variables: $\alpha = 0.9$, $\lambda = 0.95$

5.3 A comparison with BMA

While DMA allows to track the real time evolution of coefficients and model weights, one might wonder about how results would differ using Bayesian Model Averaging techniques with rolling window regressions. We conduct this last robustness check by following the MCMC procedure used by Fernandez, Ley, and Steel (2001):

1. Set up a linear regression with Zellner's g-prior, using a window of the first 35 observations.[30] The prior distribution on coefficient β_k for variable X_k is given by:
$$\beta_k \sim \mathcal{N}(0, \sigma^2(\phi X_k' X_k)^{-1}),$$
and the prior on σ is uninformative

2. Include at least one regressor randomly from the dataset and compute the marginal likelihood of model j: this is given by:
$$l_y(M_j) \propto \left(\frac{\phi}{\phi+1}\right)^{k_j/2} \left(\frac{1}{\phi+1} SSU + \frac{\phi}{\phi+1}(y-\bar{y})'(y-\bar{y})\right)^{-(n-1)/2},$$
where $\bar{y}$ is the sample mean of the dependent variable, SSU is the sum of squared residuals of the unrestricted model, including the X; k_k is the number of regressors in the X matrix, n are the observations in our sample.[31]

3. Include or exclude another regressor randomly and compute $l(M_{j'})$. Retain the new specification with a probability which is equal to the Metropolis-Hastings ratio $l_y(M_{j'})/l(M_j)$.

4. Compute the weights over model j by averaging over all models visited by the chain (K'):
$$P(M_j \mid y) = \frac{l_y(M_j)p_j}{\sum_i^{K'}(l_y(M_i))p_j},$$
where p_j is the prior probability over the model space, which we assume to be uniform.

5. Run the Markov Chain for 1,000,000 draws, drop half of them and retain one draw each 10.

6. Move the estimation window by one quarter/month and repeat from 1.

[30] Quarters, for nowcasting we take 35*3 months.

[31] It is straightforward to include a lagged dependent variable with an uniformative prior, as done by Faust, Gilchrist, Wright, and Zakrajsek (2011) with a small modification of the marginal density's formula. No differences emerge in our analysis by doing this.

In BMA, $1/\phi$ is the key hyperparameter: when this is high, it implies that model weights are formed mostly on the grounds of the sum of squared residuals of each unrestricted model, when the term is low, parameters β_k tend to be more strongly shrunk towards zero and weights will tend to similar, up to the equal weight case. In this respect the ϕ regulates the adjustment of model weights, but in a very different way than for the α in the DMA. To calibrate $1/\phi$ we follow the same criterion as in Faust, Gilchrist, Wright, and Zakrajsek (2011) and we set it equal to 3. We report here only the nowcasting case, from 1997. This is done both for comparison reasons with respect to previous robustness checks with DMA (section 5.2) and to save space.

Figure 16 reports the evolution of some of the weights for the 48 out- of-sample observations we dispose of:

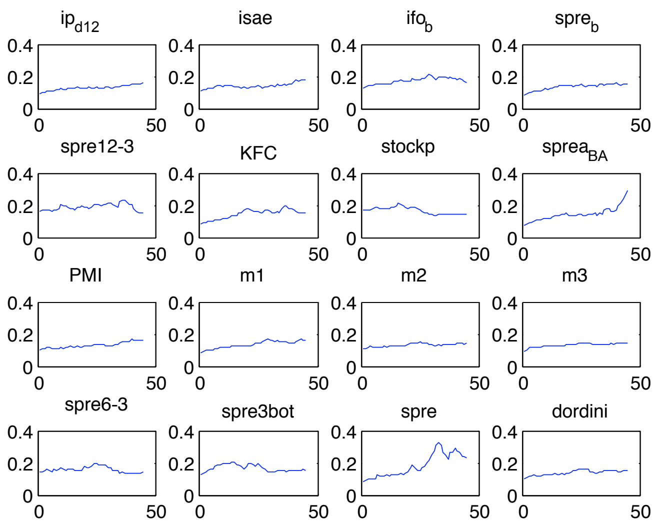

Figure 16: Nowcasting BMA weights on variables: $1/\phi = 3$, rolling windows of 35*3 observations

Given the amount of shrinkage variable weights tend to be roughly equal and they peak very rarely. Still, one can observe that the largest weight at the end of the sample is obtained by the Merril Lynch spreads (second panel from the top, right column). A larger than previously expected role is for the long term spread (second panel from the left, last row). Finally as in previous analysis the role for the other government term spreads ($spre_{6-3}$, $spre_{12-3}$) is limited and it tends to decline on the onset of the Great Recession.

6 Conclusions

We have shown that, especially in phases of financial and credit distress, information on interest rate spreads is more relevant in forecasting the Italian GDP. For what concerns credit spreads, they were relevant not only in the recent Great Recession, but also in previous crisis episodes such as in 1992 or 2001. In this respect, we can say that credit spreads help in forecasting, but sometimes they do so more. In particular, market information seems to be more useful in nowcasting, while banks information can help more in assessing future conditions.

Concerning government spreads, the slope of the term structure in Italy does not have a large forecasting ability with respect to GDP growth: better forecasting power is displayed by the spread between 12 and 3 months government bond yields, consistently with previous reseach (see Bulligan, Marcellino, and Venditti (2011)). We add to the available evidence that its forecasting contribution is higher and more stable in the period after the run-up to the Euro until the Great Recession.

As a remark for further research, our bank credit spread is only partially able to sort corporate loans by risk profile, as it is a spread between the rates paid on less risky loans (prime rate) and an average over rates for the total stock of outstanding loans. It is possible that nowcasting performance improves as risk sorting is more explicitly tackled, but we leave the construction of such data to future research.

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Appendix 1: forecasts

As we do not stress forecasting performance, we report in this appendix DMA forecasts for the period 1990-2009 and nowcasts for the period 1997-2009. Figures are consistent with the variable probability weights in the main text.

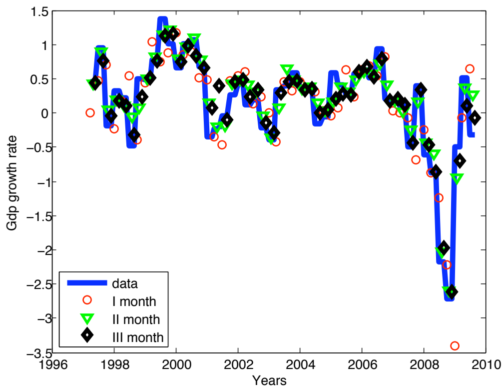

Figure 17: Nowcasting $\lambda = 0.95, \alpha = 0.9$

Figure 17 shows forecasting performance for different information sets during the quarter. Figure 18 compares the 1 quarter ahead DMA forecast against the benchmark model which includes only a (time varying) constant, under the assumption that the level of GDP follows a random walk type of process. For comparison we also show here the DMS (Dynamic Model Selection): this corresponds to the projection obtained at each point in time by the model which obtained the highest weight *after* data were released (namely, using the $\pi_{t|t}$ weights).

Figure 19 compares the 1 year ahead DMA forecast against the benchmark model. DMS is also shown for comparison as in the case of one quarter ahead forecasts. The performance of year on year forecasts is quite remarkable even as compared to institutional forecasts, though we do not insist on this aspect in the

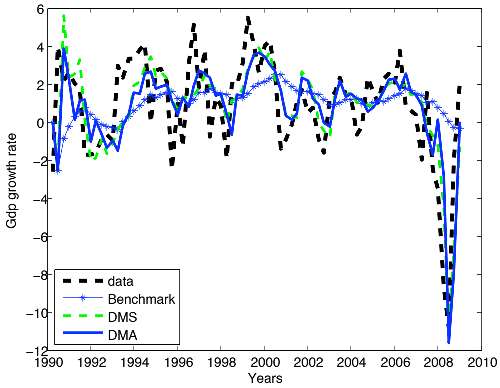

Figure 18: Forecasting 1-q-ahead: DMA against RW benchmark,$\alpha = 0.9$,$\lambda = 0.95$

paper. A reconstruction of yearly rates shows that DMA beats Consensus forecasts for Italy over the whole period $1997 - 2009$, even when Consensus forecasts are given a large informational advantage (e.g. we use April consensus forecasts for the same year). We leave an elaboration on forecasting performance to further research.

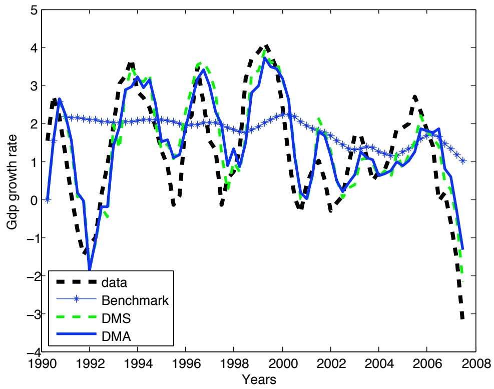

Figure 19: Forecasting 1-y-ahead: DMA against RW benchmark,$\alpha = 0.9$,$\lambda = 0.95$

Appendix 2: data description

Acronym	Description:	Source:	From:
ip_{d12}	Industrial Production Calendar but not Seasonally Adjusted	Istat: 2010m12 release	1970
IFO_b	CES IFO business confidence indicator	CES	1989
IFO_{cons}	CES IFO business confidence indicator	CES	1989
$Conf$	Business confidence	Isco/Isae/Istat	1982
$empl_{dl}$	Employment growth rate: 2010m12 release	Istat	1970
$retail$	Retail sales:: 2010m12 release	Istat	1986
$Eurocoin$	Eurocoin	CEPR-Banca d'Italia:2010m12 release	1998
Balt	Baltic Dry Index	Bloomberg	1973
baltic	Kilian's Index from Baltic Dry Index	Kilian	1973
GDP_{us}	Growth Rate US GDP:: 2010m12 release	BEA	1948
Commodity	Commodity Price Index: dollars	IMF: IFS	1980
Silver	Silver Price Index: dollars	IMF: IFS	1980
Gold	Gold Price Index: dollars	IMF: IFS	1980
CPI	Headline CPI inflation	Istat: 2010m12 release	1970
PPI	PPI overall index inflation	Istat: 2010m12 release	1970
$Brent$	Brent Crude Oil, dollars	IMF:IFS	1982
$spre_{12-3}$	Difference: 12-month T-bill and 3-months T-bill rate	Bank of Italy	1980
$spre_{6-3}$	Difference: 6-month T-bill and 3-months T-bill rate	Bank of Italy	1980
$spre$	Difference: 3-month T-bill and weighted long term rate (mat> 1 year)	Bank of Italy	1980
$Stockp$	Returns on MIB 30 Stock Exchange	Datastream	1980
PMI	PMI manufacturing index	Markit	1995
$Unempl$	Unemployment rate	Istat: 2010m12 release	1980
$R_{ovnight}$	Overnight rate on money market	Bank of Italy	1980
ip_{dl}	Industrial Production SA, growth rate	Istat: 2010m12 release	1980
$EXCH$	Nominal Effective Exchange Rate Italy	IMF: IFS (interpolated monthly)	1980
$M1$	Stock of money M1: growth rate	Bank of Italy	1980
$M2$	Stock of money M2: growth rate	Bank of Italy	1980
$M3$	Stock of money M3: growth rate	Bank of Italy	1980
$lmutui$	Mortgage loans: stock growth rate	Bank of Italy	1970
$prest$	Loans to private non firms: stock growth rate	Bank of Italy	1970
$spre_b$	Difference: Average Interest rate on short term loans and prime rate	Bank of Italy	1989
$spre_{B-A}$	Difference: yield on index BAA vs AAA	Merril Lynch	1997
KFC	Index of Financial Conditions	Hatius et al(2010)	1980
$capu$	Capacity Utilization in the manufacturing sector	Istat: 2010m12 release	1986

Table 6: Description of monthly data and related metadata