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Abstract

Are MCIs good indicators of economic activity?
Evidence from the G7 countries

Christophe BLOT * and Grégory LEVIEUGE **

The aim of this article is to determine whether Monetary Condition Indices are useful indicators for future economic activity. First, two versions of MCI are successively studied (*Long-term* MCIs defined with long-term weights and standard MCIs like those built by the IMF). In-sample regressions, out-of-sample simulations and probit analysis (intended to determine the capacity of MCIs to announce downturns) indicate that the informational content of MCIs is very sporadic. We then try to identify the reasons for these poor results, focusing on the fact that MCIs do not take into account the dynamic characteristics of its components. So, as exhange rate, interest rates and asset prices affect the economic activity with different forces and with delayed responses, it seemed important to consider past evolutions of these variables, with relative weights varying for each lag considered. Proof of the importance of past shocks that are still "in the pipeline", we demonstrate that such a *Dynamic-Weight* MCI constitutes a better indicator than standard MCIs usually used by international institutions and central banks.

Keywords: Financial and monetary conditions, MCI, forecasts, asset prices

JEL Classification: E3, E5

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Introduction

The exchange rate is generally not an objective of monetary policy in advanced economies, but it does not mean that it should be overlooked since its movements influence inflation -through import prices- and economic activity -through competitivity. The question of the integration of the exchange rate in monetary policy rules naturally arises in open economies. Besides, Ball (1999), Dennis (2000) and Gerlach & Smets (2000) show that it may be optimal. Nevertheless, such monetary policy rules encounter difficulties. Adding exchange rate to inflation and output gap targets makes the monetary policy rules more complex with a relative small gain[1]. Another major difficulty comes from the fact that the response to exchange rate is conditional to the nature of the shocks (Freedman, 2000). It is harder to deliver a clear communication when monetary policy decisions are based on such conditionality. Finally, central banks face uncertainty concerning for instance the nature of the shocks or the equilibrium value of the exchange rate. Targeting the exchange rate may be counterproductive in this context (Leitemo & Soderstrom, 2005). Consequently, it is more likely to find optimal a simple Taylor rule without the exchange rate.

On this basis, it has now been admitted that central banks should not consider the exchange rate as an objective of monetary policy. Even the Bank of Canada and the Reserve Bank of New Zealand renounced to their strategy based on the interest rate and the exchange rate and adopted a direct inflation targeting strategy. But it does not mean that the exchange rate may not play a role in the conduct of monetary policy. Benign neglect is not desirable since its movement may magnify or counteract the decisions of policy makers. In open economies, the exchange rate is part of the monetary policy transmission. Then, appreciating the monetary policy stance in open economies requires the consideration of both the exchange rate and the interest rate. This is the logic that led to the definition of a Monetary Condition Index (MCI), initially built as a weighted average of these two variables. In practice, central banks[2] but also international organizations (IMF) or financial institutions (Deutsche Bank, Goldman Sachs, J.P. Morgan, Merril Lynch, Tokai Bank) resort to MCI as a simple indicator. It may be used to explain departures from the policy rule, to evaluate the stance of monetary policy[3] or to support economic analysis. However the exchange rate is not the only transmission channel that is worth considering. Long term interest rates and asset prices may also play a role and may also be used for assessing monetary conditions. It was consequently direct to extend the definition of MCIs in such a way.

But to be a reliable indicator of monetary policy, MCI must be related to the final objectives of monetary policy. In other words, it must have some predictive power. Nevertheless, with few exceptions, no empirical analysis really focused on the information delivered by MCIs. This paper tries to fill this gap since its main motivation is to assess the usefulness of MCIs for monetary policy. It differs from Goodhart & Hofmann (2001), Batini & Turnbull (2002) and Gauthier & Al. (2004) by studying several definitions of MCIs and by using various criteria.

Monetary policy is geared to the stabilization of inflation and output. But a good indicator of monetary policy would not content to have well behaved in-sample properties since it takes time –roughly between 12 and 24 months- before policy decisions translate to the final

[1] See Svensson (2000), Batini & al. (2001) and Leitemo (1999).
[2] In Sweden, Norway or Iceland for instance.
[3] From this point of view, a parallel may be done with other indicators of monetary policy stance such as Taylor rates or natural interest rates (see Giammarioli & Valla, 2004, for a survey of the relevance of this concept).

objectives. The usefulness of this kind of indicator has to be appreciated regarding its predictive power, its out-of-sample properties. It is only if MCIs are leading indicators that we may measure in real time the expected impact of impulsions that are still 'in the pipeline'. This study lies in the strand of literature that deals with the predictive content of simple economical variables such as interest rate spreads, monetary aggregates, or asset prices in general[4]. We do not pretend that forecasting boils down to the observation of MCIs or even of the spread. But as far as they are simply computed, we wonder whether they provide a first reliable insight for future activity?

The rest of the paper is organized as follows. We first survey the different definitions and approaches used for estimating MCIs. The econometric method implemented for revealing the informational content of MCIs is exposed in section 2: it consists in evaluating in-sample explanatory power, out-of-sample predictive power and the ability of MCIs to announce downturns (measured with probit models). Forecasts are compared with those generated by a simple auto-regressive model and by the interest rate spread. The approach is applied to various definitions of MCI that differ according to the variables they include or the method used to compute their weights (section 3). The results suggest poor out-of-sample performances. We claim that "traditional" MCIs do not provide a satisfactory information because they do not thoroughly take into account the fact that the impact of exchange and interest rates on output is not constant in time and distinct (due respectively to the price rigidity of tradable goods, or because of fixed lending rate, or delay of transmission along the maturity curve). So, as the movements of these variables echo gradually and distinctly on economic activity, MCIs defined by the only current interest and exchange rates overlook this crucial feature. To fill this gap, we propose a more explicit dynamic indicator, called *Dynamic-Weight* MCI (DW-MCI), for which the relative weights of each MCI components vary over time[5].

1. Definition and construction of MCIs

Academics and institutions have developed several kinds of MCIs, which can be summarized by the general formula:

$$(1)\quad MCI_t = \beta_r(r-\bar{r})_t + \beta_q(q-\bar{q})_t + \beta_\rho(\rho-\bar{\rho})_t + \beta_z(z-\bar{z})_t$$

In its initial version, the MCI is a synthetic indicator combining the short term interest rate (r) and the effective real exchange rate (q) with regard to their respective long term value ($\bar{r}$) and ($\bar{q}$). But thereafter, long term interest rate or asset prices could no longer be ignored as long as the aim of MCI was to capture the different channels of monetary policy transmission. The concept was then extended first with ρ, the long term interest rate and finally with z, the stock market price, to define a Financial and Monetary Condition Index (*FMCI*).

The construction of MCIs requires on the one hand the estimation of the weights β_x and on the other hand the determination of the equilibrium values $\bar{x}$ (with $x = \{r,q,\rho,z\}$), i.e. the determination of $(x-\bar{x})$. The β_x coefficients translate the sensitivity of output to the movements of interest rates, exchange rate and stock market prices. A reliable and often-used way to determine these weights consists in estimating elasticities from VAR models.

[4] See for instance Stock & Watson (2001), Mauro (2000), Campbell (1999).

[5] This so-called DW-MCI is an extended version of the dynamic MCI proposed by Batini & Turnbull (2002).

Then, $\left(x-\bar{x}\right)$ is treated as the difference between actual and long-term values of x. That way, the MCI is an indicator of monetary and financial conditions in respect to a "neutral" situation. In practice, it is defined as the gap between x and its HP filter trend.

Investigating the informational content of MCIs requires the examination of the way MCIs are constructed. Which variables should integrate the MCI? Shall we pay attention to a broad set of transmission channels or only to the short-term interest rate and the exchange rate? Does the method used to compute the weights matter? In particular, how should we consider the dynamics of the transmission of the shocks to variables of interest? On this grounds, following Goodhart & Hofmann (2001), we will first examine the informational content of various MCIs, whose definition are resulting from VAR models, which are called *long-term* MCIs (LT-MCI). They will be compared to MCIs calculated by the IMF. Finally we propose a modified MCI with *dynamic*-weights (*DW-MCI*). Each of them will successively include:

- the short term interest rate and the exchange rate (hereafter *MCI1*, with $\beta_r \neq 0$, $\beta_q \neq 0$, and $\beta_\rho = \beta_z = 0$)
- the short term interest rate, the exchange rate and the long term interest rate (hereafter *MCI2,* with $\beta_r \neq 0$, $\beta_q \neq 0$, $\beta_\rho \neq 0$ and $\beta_z = 0$)
- the short term interest rate, the exchange rate, the long term interest rate and the stock prices (hereafter *FMCI,* with $\beta_r \neq 0$, $\beta_q \neq 0$, $\beta_\rho \neq 0$ and $\beta_z \neq 0$.).

Data (including effective real exchange rates) are stemming from the IMF database. MCIs are expressed in real terms. To this end, the ex post real short and long term interest rates are calculated with the next period inflation rate. Stock market prices are deflated by the consumer price index. As a monthly frequency allows a sharper analysis of the predictive content of MCIs, industrial production is used instead of GDP to represent economic activity.

2. Analysing the informational content of MCIs: Method and evaluation criteria

Before describing the econometric procedure, the argument developed by Woodford (1994) may be reminded. He states that a weak predictive content does not necessarily imply that an indicator is not relevant. Suppose indeed that a given variable *X* is *ex-ante* perfectly correlated to *Y*. If the central bank decides to target *X* in order to stabilize *Y,* and if it perfectly controls the former, the relation between *X* and *Y* breaks down. Consider the following example: if the value of X announces a recession, then the central bank will react to reach its final goal (stabilization of *Y*). Finally, *Y* has been stabilised and the variation of *X* is not followed by a recession. An *ex-post* analysis would lead to the conclusion that X does not contain any information on *Y*. That is why Woodford (1994) claims that "*one might argue that in any event a finding of insignificant forecasting power for a given indicator allows me to make the recommendation that policy should respond to that variable exactly to the extent that it already does, neither more nor less*".

Following this line of argument, when we test the predictive power of MCI on *Y*, we implicitly proceed with a joint hypothesis test: *X contains information about Y, the central bank does not target X and the central bank does not control X perfectly*. Consequently, the reasons why H_0 is rejected might be unclear. Yet we have all the reasons to believe that, in practice, central banks do not target *X* (MCI). Furthermore, central banks cannot perfectly control *X*, since long term interest rates, exchange rates or stock market prices are mainly determined by financial markets. So, in the following analysis, it can reasonably be considered that any rejection of H_0 stems only from the lack of informational content of *X* on *Y*.

2.1 The explanatory power of MCIs: a prerequisite

As it is generally done with other similar indicators such as the spread term, we first gauge the in-sample econometric fit of the different versions of MCIs on the growth of industrial production. The following regression is run:

$$(2)\ \left(\frac{1200}{k}\right)\log\left(\frac{y_{t+k}}{y_t}\right) = \alpha + \lambda\left(\frac{1200}{k}\right)\log\left(\frac{y_t}{y_{t-k}}\right) + \beta W_t + \varepsilon_t$$

where the left-hand side stands for the industrial production growth (in %) at the different forecast horizons (k=3, 6, 12 months) and W_t is the exogeneous variable : MCIs, FMCIs and the yield curve spread. Indeed, the latter, defined as the difference between a 10-year Treasury Bond rate and a 3-month rate, is widely acknowledged as one of the best simple leading indicator[6]. These relations are estimated over the period 1980 :01 - 2003 :01 for the G7 countries. To handle with the residuals autocorrelation (due to overlapping), the variance-covariance matrix is corrected using the Newey and West (1994) estimator.

2.2 Out-of-sample forecasts

The predictive power of MCIs is then investigated through an out-of-sample analysis. The model (2), with alternative indicators X (=MCI1, MCI2 and FMCI), a complete model and a purely first order autoregressive model[7] for y, are successively used to forecast the growth rate of industrial production k-month ahead (k = 3,6,12). Projections are determined from a forecaster's point of view. Model (2) is estimated recursively over the period 1980:01-t adding a new period at each step with t=1997:12 - 2002:11. In short, the forecaster makes use of all available information at each date when he sets its forecast. That is, the monetary and financial indicators, as well as the yield curve spread are updated, and the model is re-estimated before determining the next period forecast[8]. The expected economic activity growth, noted g, is then determined in the following way:

(3) Autoregressive Model: $E_t(g_{t+1+k}) = \hat{\alpha}_t + \hat{\lambda}_t(g_{t+1})$

(4) MCI Model: $E_t(g_{t+1+k}) = \hat{\alpha}_t + \hat{\lambda}_t(g_{t+1}) + \hat{\beta}_t X_{t+1}$

(5) Spread Model: $E_t(g_{t+1+k}) = \hat{\alpha}_t + \hat{\lambda}_t(g_{t+1}) + \hat{\theta}_t spread_{t+1}$

Once forecasts are made, the root mean square error (henceforth RMSE) is calculated for each model and each forecast horizon (k). We then compute the ratio of RMSE obtained with models including (F)MCIs over the RMSE of the purely autoregressive model. A ratio below unity indicates that the MCIs or the FMCI outperform the purely autoregressive model and conversely when it is above unity. Following the same methodology, we compare the (F)MCIs models with the model integrating the term structure spread. The equality to one of

[6] For empirical examinations, see for example Estrella & Mishkin (1998), Dotsey (1998) and Stock and Watson (2001).

[7] The first-oder autoregressive model is defined as (2) with β = 0. The complete model includes simultaneously the autoregressive part of y, the spread and W. This model was estimated in order to examine the robustness and the originality of the information delivered by (F)MCIs.

[8] We always use observed values for the variables of the MCI. We therefore avoid correlations between forecasts errors of the MCI variables and the economic activity (see Gamber and Hakes, 2005, on this specific issue)

the ratio is tested following Diebold and Mariano (1995). The alternative hypothesis is: the ratio is below or above unity.

2.3 Testing the ability to forecast downturns

Focusing on the ability to predict future downturns is another way through which MCIs can be analysed. To this end, we estimate the probability of the economy being in recession *k* months ahead with probit models. We follow the same two-stage approach. We first look at the in-sample performances and then generate forecasts that are compared with the realisation of the dependent variable (Recession).

Starting from the data on industrial production growth, a dummy variable is defined, that takes the value 1 when the economy is in recession *k* months ahead. The occurrence of the recession is noted $RE_t=1$. Otherwise $RE_t=0$. The forecasts are generated by the following relations, which have first been estimated in-sample:

(6) MCI Model: $E_t\left[P\left(RE_{t+k+1}=1\right)\right]=\Phi\left[\hat{\alpha}_t+\hat{\lambda}_t P\left(RE_{t+1}=1\right)+\hat{\beta}_t X_{t+1}\right]$

(7) Spread Model: $E_t\left(RE_{t+k+1}=1\right)=\Phi\left[\hat{\alpha}_t+\hat{\lambda}_t P\left(RE_{t+1}=1\right)+\hat{\theta}_t spread_{t+1}\right]$

where Φ is the standard Normal cumulative distribution function and X represents one of the different MCI (MCI1, MCI2, FMCI).

The equations are estimated for the G7 countries, at different forecasting horizons. Residual autocorrelation is corrected and the pseudo adjusted R^2 proposed by Estrella (1998) is used as a fitting criteria. Using actual data for the various indicators, we directly determine the probability of a downturn *k* months ahead. As for the industrial production growth forecasts, we estimate rolling regressions over the period 1980 : 01 to (*t-k*) with *t*=1997:12 - 2002:11. Once we get the forecasts for the different models, we compute the forecast errors and then the RMSE. Forecast errors are calculated as the difference between the estimated probability and the dummy variable RE_t. Finally, the Diebold and Mariano test is implemented in order to compare the forecasting ability of the different models. The results are exposed in the next section.

3. The informational content of (F)MCIs

The motivation is not only to assess the usefulness of MCIs for monetary policy but it also aims at identifying the most powerful indicator among the different definition that have been proposed in the literature. The differences come either from the variables included in the indicator or from the method used to calculate the weights. After explaining their construction, we first analyse MCIs whose weights are derived from VAR models. These results are then compared with MCIs derived from the weights calculated by the IMF.

3.1 Definition and construction of Long-term MCIs

Following Goodhart and Hofmann (2001), we estimate VAR models for each country. We always consider the same set of variables, which are introduced in the following order[9]:

[9] As impulse response functions will be based on a Cholesky decomposition, this order is not neutral. It relies on implicit restrictions that are theoretically relevant. See notably Christiano and al. (1999) for the place of the

growth rate of economic activity (y), (annual) inflation (π), long (ρ) and short (r) term interest rates, effective exchange rate (q) and stock market prices (z).

$$(8)\quad Y_t = \sum_{n=1}^{p} Y_{t-n} + \varepsilon_t \quad \text{with} \quad Y = [y,\ \pi,\ r,\ \rho,\ q,\ z]'$$

The number of lags (p) applied to each model is determined by a likelihood ratio chi-squared test. Tests of residuals autocorrelation are examined to increase the number of lags if necessary[10]. The VAR models are used to derive the elasticities which serve to build MCIs. Precisely, the weights β_x are based on the impulse response functions (IRF) of the VAR models. Defining $\phi_{ij,m}$ the dynamic multipliers stemming from the VMA representation of the VAR as:

$$(9)\quad \phi_{ij,m} = \frac{\partial Y_{i,t+m}}{\partial \varepsilon_{j,t}}$$

i.e. as the response of the i^{th} variable at time $t+m$ ($Y_{i,t+m}$) for a one-unit increase in the j^{th} variable's innovation at date t ($\varepsilon_{j,t}$). It stands out the response of the economic activity following non-anticipated shocks to the various components of the (F)MCIs. Thus, for every source of shock, we calculate the medium-term elasticity of the economic activity relative to the variable x, that is the absolute value of the sum of responses for a given horizon. Noting $\phi_{1x,t}$ the response at the date t of the economic activity to a shock on the variable x, the weights β_X are determined according to the following relation:

$$(10)\quad \beta_x = \frac{\left|\sum_{t=1}^{t=n} \phi_{1x,t}\right|}{\sum_x \left|\sum_{t=1}^{t=n} \phi_{1x,t}\right|}$$

Note that as the growth rate of industrial production is the only endogenous variable considered here, i=1 and $Y_{1,t} = y_t$. Moreover, the useful variables for the determination of the weights are $x = \{i, \rho, q, z\}$. In short, this method implies that every component is weighted according to its relative influence on the activity at a medium-long term.

Considering that a one-year horizon is enough to capture the entire response of economic activity in particular to the various shocks, n is fixed to 12. That is why MCIs obtained with this method can be named *long-term* MCIs.

Table 1 reports the weights obtained with this method. As expected, the weight of short term interest rate always exceeds that of the exchange rate. This latter (β_q / (β_r + β_q)) is between 40% for Italy and 11% for Japan. It is close to 24% in France and in Canada, amounts to 33% in United Kingdom and does not exceed 21% in the United States. The table also reports weights calculated by the IMF (S-MCI). There are a few differences between S-MCI and LT-

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exchange rates in this type of model, or Goodhart Hofmann (2001) for a VAR model integrating both exchange rate and equity prices.

[10] Moreover, dummies are inserted to neutralize the effects of the 1992-1993 exchange rate crises in United Kingdom and in Italy. For the former, a dummy is introduced over the period 1990:10 - 1992:09. For the latter, the dummy variable covers the periods 1992:06 - 1993:06 and 1995:02 - 1995:06.

MCI1. But, as it was stressed by Ericsson and Al. (1998) or Eika and Al. (1996), MCIs weights are subject to coefficient uncertainty resulting from the model choice and from the estimation error inherent to any statistical approach. These differences should then not be surprising. The introduction of the long term interest rate in MCI2 is rather instructive since we observe the superiority of the long rate on the short rate in most countries. It is the case for example in France, where loans are mostly contracted at fixed and long-term rates (curiously, it does not seem to be the case for Germany). On the contrary, the short rate is more important in the United Kingdom, where loans are massively granted at variable rates. Finally, without surprise, countries where stock market prices have the most important weight are the United States, the United Kingdom and Japan. These weights remain however very modest. Anyway, it would have been difficult to believe that, normally, equity prices can affect economic activity as much as interest rates or exchange rate[11].

3.2 In-sample and out-of-sample results

Concerning the in-sample regressions, two points shall be highlighted[12]. First, the statistically significant parameters have generally the expected sign, indicating that a higher LT-MCI has a negative effect on the economic activity. Consequently, tighter monetary or financial conditions (an interest rate rise, an exchange rate appreciation or a share prices decrease) are associated with an economic slowdown. This result is fairly consistent across countries. The only exception is for Japan where LT-MCI2 seems to be positive and significant, at the 5%, level for $k=3$ and, at the 10% level, for k=6. But it may result from the particular economic context in Japan during the period of estimate and not from the way indicators are built. Indeed, the estimation has been carried over a period when interest rates were generally close to zero and did not fluctuate so much, whereas economic growth remained low. Consequently, it is not surprising to find no relationship between interest rates and economic activity. This point is reinforced by the fact that the term structure spread is never statistically significant. Conversely, for the other G7 countries, as expected, a rise in the yield curve spread is associated with a higher industrial production growth.

Table 2 gives the results of the out-of-sample forecasts. As none of the LT-(F)MCIs performs good in-sample for the United-Kingdom, it is not surprising to find that the purely autoregressive model gives better forecasts compared to the models with monetary and financial variables. In the same way, the LT-(F)MCIs models do not outperform the spread model. In Germany, the results are not very different since only the MCI1 indicator fits well in-sample when explaining the industrial production growth 3 or 6 months ahead. In that case, the coefficients relative to monetary and financial indicators are still statistically significant when controlling for the information contained in the yield curve. Nevertheless, the out-of-sample forecasts are systematically less precise than those obtained with the purely autoregressive model or from the spread model. Indeed, table 2 shows that the RMSE associated with the LT-MCI models are always significantly superior to the RMSE of the spread model (figures are above unity). As it has been already suggested, none of the three indicators succeeds in explaining the Japanese economic activity. The inadequacy of interest

[11] It would have been interesting to support these results with the conclusions of papers dealing with the sensitivity of economies to monetary policy impulses. Unfortunately, it is hard to find a consensus on that point. Considering only France, Germany and Italy, conclusions already diverge completely from one study to another, whatever the method. See for example the conclusions of Dornbusch and Al. (1998), DeBondt (1997), Mihov (2001) and Mojon (2000).

[12] For parsimonious purposes, tables of in-sample results are not reproduced here, but they are available from the authors upon request.

rates to explain or to predict economic activity in this country also justifies the systematic non-significativity of the terms structure of interest rates. As a whole, the LT-MCIs-based forecasts, although they are bad, turn out to be less piteous than those based on the autoregressive or spread models. But to sum up, the LT-MCI models are not better, they are only less bad.

Results are more favourable for Canada, one of the first country where the use of LT-MCI had been promoted as a monetary policy operational target (Freedman, 1995). LT-MCI1 is in-sample significant whatever the horizon. But the addition of the yield curve spread reduces the significativity of the parameters associated with the LT-MCIs. The latter would then be redundant with the information already contained in the term structure of interest rates. Referring now to the out-of-sample forecasts exercise, it appears that only the LT-MCI1 performs well 6 and 12 months ahead. Compared to the spread model, the RMSE is significantly inferior when k=12. At other horizons, the ratios of RMSE are not statistically different from unity.

The three indicators also perform well in-sample in the United States, for all the values of k. This informational content resists to the introduction of the yield curve, which is also systematically significant. Information provided by the LT-MCI would then be original. But the forecasts provided by LT-MCI1 or LT-MCI2 models are not better than those determined by the purely autoregressive model or by the spread model. Otherwise, the RMSE associated with the LT-FMCI is significantly lower than the RMSE of the purely autoregressive or of the spread model.

LT-MCIs show up statistically significant at explaining the French industrial production growth 3, 6 and 12 months ahead. The coefficients are even still significant in the complete model in which the parameters on the yield curve also appear significant. Afterward, the LT-(F)MCIs generate better forecasts than a purely autoregressive model, but less precise than those determined by the spread model (table 2).

Finally, in Italy, LT-MCI2 and the LT-FMCI explain significantly the industrial production, for all horizons. It is also the case of LT-MCI1 but only when k=3 and k=6. These results are not modified by the introduction of the yield curve. Table 2 reveals that LT-MCI1 and LT-MCI2 models give better 3-month forecasts compared to the purely autoregressive model. They also outperform the interest rates spread on the same step-ahead forecast. Regarding the bad performances of the LT-FMCI, it comes out that the share prices would finally introduce noise on the predictive power of the LT-FMCI.

3.3 Forecasting recessions with long-term MCIs

Addressing first in-sample evidence, it seems again that the *long-term* MCIs do not explain recessions in the United-Kingdom and in Japan. Actually, *long term* MCIs are sometimes significant but with the wrong sign indicating that if monetary and financial conditions tighten, the probability of being in recessions diminishes. Concerning Germany, the in-sample informational content of long-term MCIs is very rare and only significant for LT-MCI1, except when k=12. Even if results are better for Canada, it is still the LT-MCI1 indicator that fits best. In this case, for all horizons but k=3, the relation between the monetary condition indicator breaks down when the term spread is introduced in the equation.

In fact, *long-term* MCIs perform well in-sample in Italy and France and especially in the United States. For Italy and France the significant results are respectively obtained for $k = 3$, $k = 6$ or both. The different *long-term* MCIs are significant and with the expected sign in the United States except when k=12 and when the term spread is added in the regression of LT-MCI1 and LT-MCI2 models.

Table 3 reports the results of out-of-sample probit regressions. The evidence of forecasting power is very weak. As it was already the case with the industrial production growth forecasts, Japan performs surprisingly well. But we previously stressed that these results are certainly due to the poor fit of the models for Japan in a particular context. Otherwise, the only positive and significant results are obtained for France and Germany where the three long-term indicators and the LT-MCI1 model respectively outperform the purely autoregressive model but not the spread model. Even in the United-States, the purely autoregressive model or the spread model significantly outperform the long-term monetary and financial indicators whereas they were systematically significant in-sample.

At this stage, we do not find any clear superiority of the predictive power of LT-(F)MCIs. It also seems that adding variables does not improve the forecasts. There is indeed no advantage to insert the long term interest rates and there are no cases where FMCIs performed better than the autoregressive or spread models. But adding variables is not the only way to get different MCIs. The method that is used to derive weights is another point that matters.

3.4 Comparison with standard MCIs

As it has been stated, the weights of MCIs are model-specific. That is why it is informative to compare the results obtained with MCIs that have not been derived from VAR models. We consider here the weights calculated by the IMF (*standard* MCI) with only the short term interest rate and the exchange rate. Following the same approach, we first assess the in-sample information given by MCIs and then compute the forecasts issued from rolling regressions[13]. Considering first industrial production growth (cf. last columns of table 2), we find that LT-MCI1 outperforms S-MCI in the United-Kingdom (k=3 and k=6) and in France (k=6 and k=12). LT-MCI2 seems to beat the S-MCI model in Japan (k=6 and k=12) but LT-FMCIs never outperform the *standard* MCI model. Another striking result is that S-MCI models generally outperform the *long-term* MCIs in Canada, Italy and in the United-States for most horizons. If we now turn to the future downturns, we can draw similar conclusions (cf. last column of table 3). LT-MCI1 generate more precise predictions only when k=6 for Germany and France. LT-MCI2 and LT-FMCI respectively perform better in Japan and in the United-Kingdom. Otherwise, the S-MCI model gives better results especially for Germany (except for k=6 and LT-MCI1), for Canada, for the United-States and to a lesser extent for Italy. Consequently, the efforts made to improve MCI and to determine long-term weights do not provide a more performing indicator than those used by international institutions and central banks.

To sum up: the predictive content of all the different MCIs is disappointing. How can it be explained? May it be improved? We consider that *standard* and long-term MCIs suffer from an important shortcoming: they do not capture the dynamic impacts of its components. Indeed, the effect of interest rate fluctuations can be more or less rapid than the influence of the exchange rate variations depending on the complex dynamic of the transmission channels

[13] Due to space consideration, we only reproduce the ratios of the LT-MCI-model RMSE over the *standard* MCI model RMSE

in each country. Past evolutions of the components should then be explicitly taken into account in a MCI. So that, β_r / β_q could be higher (or weaker) for the near-past information than for a more distant past information. We focus on this issue in the next section where we demonstrate the advantages of such a *Dynamic-Weights* MCI.

4. The informational content of *Dynamic weights* MCIs (DW-MCI)

4.1 Definition and construction

Considering the fact that components of the MCIs affect economic activity with different lags, we propose the following definition[14] of a *Dynamic-weights* Monetary Condition Index (DW-MCI):

(11)

$$DW\text{-}MCI_t = \sum_{m=0}^{p} \alpha_{r,m} \left(r - \overline{r} \right)_{t-m} + \sum_{m=0}^{p} \alpha_{q,m} \left(q - \overline{q} \right)_{t-m} + \sum_{m=0}^{p} \alpha_{\rho,m} \left(\rho - \overline{\rho} \right)_{t-m} + \sum_{m=0}^{p} \alpha_{z,m} \left(z - \overline{z} \right)_{t-m}$$

In reference to the VAR model (8), the definition of the *DW-MCI* can be generalized as:

(12) $$DW\text{-}MCI_t = \sum_{x} \sum_{m=0}^{p} \alpha_{x,m} \left(x - \overline{x} \right)_{t-m}$$

As for the other MCIs, DW-MCI can be defined under three versions:

- *DW-MCI1* : with $x = \{r,q\}$ and $\alpha_{\rho,m} = \alpha_{z,m} = 0 \ \forall \ m$.
- *DW-MCI2* : with $x = \{r,q,\rho\}$ and $\alpha_{z,m} = 0 \ \forall \ m$.
- *DW-FMCI* : with $x = \{r,q,\rho,z\}$.

To determine the weights $\alpha_{x,m}$ we consider the impulse response functions of Y_1 (for each component shock) as in (9), but this time 1) considering impulse-responses at each period (and not the aggregated-relative response of medium term) and 2) considering only significant responses. In other words, subject to its significance, the weight $\alpha_{x,m}$ corresponds exactly to the dynamic multiplier $\phi_{ix,m}$, such that, for instance[15] :

(13) $$\alpha_{r,m} = \frac{\partial Y_{1,t+m}}{\partial \varepsilon_{r,t}} = \frac{\partial y_{t+m}}{\partial \varepsilon_{r,t}} \equiv \phi_{1r,m}$$

which represents the effect of an interest rate shock (ε_r) occurred in *t* on industrial production (Y_1 or *y*), *m* periods (months) after the initial shock. In a general way, it follows:

(14) $$\alpha_{x,m} = \frac{\partial Y_{1,t+m}}{\partial \varepsilon_{x,t}} = \frac{\partial y_{t+m}}{\partial \varepsilon_{x,t}} \equiv \phi_{1x,m} \text{ with } m = 0 \text{ to } 23$$

Doing this way, we are able to consider duly past evolutions of MCIs components. To take this past information into account, we consider the influence of the variable Y_j on Y_1 over two

[14] This is an extended version of the DMCI proposed by Batini and Turnbull (2002) p.268. It is modified in order to make it really 'coincident', as its use for predictive purposes is somewhat different than in Batini & Turnbull. See hereafter equations (15) and (16).

[15] Contrary to the previous MCIs (cf. eq. (10)), we do not sum the IRF.

years (p=23). But still it is necessary that the dynamic multipliers are significantly different from 0.
Following Sims and Zha (1999), we use Monte Carlo simulations and consider fractiles – precisely the 16% and 84% fractiles –, applied to 2500 replications in order to enclose multipliers in an error band. Non significant weights $\alpha_{j,m}$ are deliberately fixed at zero. Without surprise, knowing the cyclical dynamic of these models, some parameters are positive or negative[16] contributing to the richness of the indicators built in this way.

Once DW-MCIs are defined, we can proceed to the examination of their informative content. The key question is now: are *DW-MCIs* better leading indicators of economic activity than an autoregressive structure on Y_1 (AR-model), than the term spread and especially than the *standard* and long-term MCIs studied in the previous section? Of course, the ideal solution would be to succeed in defining indicators superior to the spread. But if at least *DW-MCIs* outperform MCIs, it could be asserted that considering explicitly the dynamics of the MCIs components is a conclusive issue.

The same tests as before are implemented, with the only difference that the *DW-MCI* must be adjusted according to the forecast horizon. Indeed, as defined by equation (11), *DW-MCIs* are coincident indicators. The conditions they describe in t concern the economic activity in period t. So, $DW\text{-}MCI_{t+k}$ would theoretically be required to predict Y_{t+k}. Hereafter, $DW\text{-}MCI_{t+k}$ includes an unknown information as the analyst builds his forecast in t. Precisely, interest rates, exchange rate and equity prices between $t+1$ and $t+k$ are unknown in t. Nevertheless, it remains possible to use a *DW-MCI* to forecast in t the economic activity in $t+k$, exploiting the dynamic properties of the *DW-MCI*, namely considering all the available information between $t\text{-}p\text{+}k$ and t. We then define $DW\text{-}MCI_{t+k/t}$ the indicator built in t (with the information available in t) to forecast at the $t+k$ horizon. From (11), $DW\text{-}MCI_{t+k/t}$ has the following definition:

$$(15)\quad \begin{aligned} DW-MCI_{t+k/t} &= \sum_{m=k}^{p} \alpha_{r,m}\left(r-\overline{r}\right)_{t-m+k} + \sum_{m=k}^{p} \alpha_{q,m}\left(q-\overline{q}\right)_{t-m+k} \\ &+ \sum_{m=k}^{p} \alpha_{\rho,m}\left(\rho-\overline{\rho}\right)_{t-m+k} + \sum_{m=k}^{p} \alpha_{z,m}\left(z-\overline{z}\right)_{t-m+k} \end{aligned}$$

A priori, as the transmission delays of interest rates and exchange rate are long enough, neglecting a part of the information is not damaging for short forecasts horizon (for example for k=3 or k=6). But as the information of the DW-MCI is theoretically cut down as k increases, the predictive capacity of this dynamic indicator may be weaker for an annual forecast horizon. All in all, no simple indicator (including the interest rate spread) is able to give accurate forecasts beyond 18 months.

Finally, the following regression (*DW-MCI* model) is run, and updated each period, as would do an analyst:

$$(16)\quad \left(\frac{1200}{k}\right)\log\left(\frac{y_{t+k}}{y_t}\right) = \alpha + \lambda\left(\frac{1200}{k}\right)\log\left(\frac{y_t}{y_{t-k}}\right) + \beta\, DW{-}MCI_{t+k/t} + \varepsilon_t$$

[16] True multipliers are available from the authors

4.2 Informational content of DW-MCIs: the results

Table 4 sums up the in-sample results. They appear encouraging as in each country, there is always at least one forecast horizon for which the *DW-MCI* is significant (except in Italy). Besides, results stemming from these three indicators are relatively homogeneous. In details, *DW-MCI1* and *DW-MCI2* are particularly robust regressors in the industrial production growth equation for *k*=3 and *k*=6 in Germany, the United States, France and Italy. *DW-FMCI* seems particularly significant in Germany and Canada (for *k*=3,6), as well as in the United States (whatever *k*). As expected, results are slightly less convincing for *k*=12. Finally, note that the spread term, which is very often significant, do not deteriorate the explanatory power of *DW-MCIs*. So the information contained by *DW-MCIs* is original.

Out of sample results are summarised in table 5. We only focus on the cases that were significant in-sample. Only two countries present disappointing results: the United Kingdom and France. *DW-MCIs* are significantly less good than *LT-MCIs* in the UK and it is not possible to conclude that *DW-MCIs* outperfom *LT-MCIs* in France. Otherwise, results are very positive. Regarding Germany, significant in-sample *DW-MCIs* (except *DW-FMCI* with *k*=3) generate generally more accurate forecasts than the AR-model, the spread and the *LT-MCIs* (it is obvious for *k*=6). Considering the complete model (results are not reproduced here), the information content of *DW-MCIs* seems original. Concerning the United States, *DW-MCI1* and *DW-MCI2* outperform significantly the AR-model and *LT-MCIs*, when *k*=3 and *k*=6. *DW-FMCI* is in addition better than the yield curve. In a general way, in Italy, *DW-MCI1* and *DW-MCI2* (for *k*=3,6) turn out to be superior to the AR-Model, the spread and the *LT-MCIs* (very often at the 1% level). And this information is original. Finally, results are satisfactory for Canada. Compared with the AR-model, the spread and the previous *LT-MCIs*, the significant in-sample *DW-MCIs* generate significantly more accurate forecasts (except *DW-FMCI* for a quarterly horizon).

Finally, out-of-sample probit results are unambiguously in favour of *DW-MCIs*. Indeed, whatever the country, the horizon and the version of *DW-MCI* considered, *DW-MCIs* produce systematically better forecasts of downturns than *long-term* MCIs, at the 1% level. Moreover, *DW-MCIs* are globally[17] leading indicators of recessions at least as good as the spread term[18]. Consequently, it is possible to conclude that *DW-MCIs* are better indicators than *standard* and *long-term* MCIs and than the interest rate spread.

Conclusion

In this paper, we provide a comprehensive study of the predictive power of monetary and financial conditions indexes for the G7 countries. It is shown that that the method which consists in determining the MCIs by weighting each of its components according to their respective long-term influence on the economic activity (see Goodhart and Hofmann, 2001) does not allow to obtain reliable projections. These *long-term* MCIs are not significantly better than *standard* MCIs calculated by the IMF. The standard MCIs do not allow to generate better forecasts than a simple purely auto-regressive model or than the term spread (one of the most successful leading indicators), and they are also unable to forecast downturns.

[17] The exceptions are Canada and France for *k*=12, the United States for *TVW-MCI1* and *TVW-MCI2* ($\forall$ *k*) and Italy for *TVW-MCI2* and *TVW-FMCI* with *k*=2 in both cases.
[18] Results are available from the authors.

So, MCIs such as they are usually built offer a wrong signal of what are monetary conditions. Besides the usual problems raised by this type of exercise[19] (model-dependance, parameter inconstancy, uncertainty surrounding the models estimates, choice of components, etc...), a major issue can explain this failure. It refers to the fact that the dynamics of the components of MCIs are badly taken into account, whereas they affect the economic activity with different lags and different forces. Indeed, interest rates, exchange rate and stock market prices take different channels, and their speed of repercussion on the economy depends on the country (because of structural singularities).

This way of reasoning brought us to propose a MCI that integrates the past evolutions of all its components, with variable weights, function of their relative importance in time. We called it *Dynamic weights* MCI (*DW-MCI*). Tests show that this type of indicator is unambiguously better than *standard* and Long-Term MCIs, than a purely auto-regressive model of economic activity and than the interest rate spread. This result demonstrates the importance of considering duly the characteristic dynamics of each of the components of MCIs.

Consequently, central banks and international institutions which refer to MCIs (to justify a policy, a recommendation, or to support an argument) must be careful with such an indicator. If they really value indicators like MCIs, then they should rather consider an indicator such as *DW-MCI* than a *standard* MCI. Information delivered by the first is better and the forecast horizon can be easily controlled. Some could blame this indicator for being less clear than a *standard* MCI. But a *DW-MCI* can be expressed in base 100, as any MCI, and be presented to the public under this shape, in any simplicity and clarity.

[19] Cf. Eika and Al. (1996) and Gauthier and Al. (2004)

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Appendix

Table 1 – Long-Term and Standard MCIs Weights

Country	Indicator	Short Rate	Exchange Rate	Long Rate	Stock Prices
United-Kingdom	LT-MCI1	0,666	0,334		
	LT-MCI2	0,48	0,24	0,28	
	LT-MCI3	0,45	0,23	0,26	0,06
	S-MCI	0,75	0,25		
Germany	LT-MCI1	0,83	0,17		
	LT-MCI2	0,5	0,1	0,4	
	LT-MCI3	0,49	0,1	0,4	0,01
	S-MCI	0,8	0,2		
Canada	LT-MCI1	0,76	0,24		
	LT-MCI2	0,37	0,11	0,52	
	LT-MCI3	0,36	0,11	0,51	0,02
	S-MCI	0,75	0,25		
United-States	LT-MCI1	0,79	0,21		
	LT-MCI2	0,55	0,14	0,31	
	LT-MCI3	0,51	0,14	0,29	0,06
	S-MCI	0,91	0,09		
France	LT-MCI1	0,76	0,24		
	LT-MCI2	0,33	0,1	0,57	
	LT-MCI3	0,32	0,1	0,56	0,02
	S-MCI	0,75	0,25		
Japan	LT-MCI1	0,89	0,11		
	LT-MCI2	0,32	0,04	0,64	
	LT-MCI3	0,3	0,04	0,61	0,05
	S-MCI	0,91	0,09		
Italy	LT-MCI1	0,6	0,4		
	LT-MCI2	0,36	0,24	0,4	
	LT-MCI3	0,35	0,23	0,4	0,02
	S-MCI	0,75	0,25		

Note : *S-MCI (S for standard)* refers to MCIs calculated by the IMF.

Table 2 - Predictive Power of Long-Term MCIs According to OLS out-of-sample Estimations

Country	Model	Comparison with AR Model			Comparison with Spread Model			Comparison with S-MCI Model		
		k=3	k=6	k=12	k=3	k=6	k=12	k=3	k=6	k=12
United-Kingdom	LT-MCI1	1,002	1,019***	1,029***	0,991	1,010	1,047**	0,999*	0,997**	0,999
	LT-MCI2	1,006	1,028***	1,030***	0,995	1,019	1,049**	1,003	1,006**	1,001
	LT-FMCI	1,002	1,020***	1,025***	0,992	1,012	1,045**	0,999	0,999	0,997
Germany	LT-MCI1	0,985	0,995	0,999	1,059**	1,124***	1,321***	1,002	0,998	0,999
	LT-MCI2	1,011	1,013	1,006	1,087***	1,145***	1,329***	1,028**	1,016	1,005
	LT-FMCI	1,007	1,016	1,004	1,083***	1,148***	1,327***	1,024**	1,019*	1,003
Canada	LT-MCI1	0,969	0,951*	0,955*	0,949	0,943	0,911**	1,002**	1,004**	1,004**
	LT-MCI2	1,029*	1,052*	1,023	1,008	1,044	0,977	1,064***	1,110***	1,080***
	LT-FMCI	1,053***	1,099	1,060***	1,031	1,095	1,011	1,088***	1,160***	1,114***
United-States	LT-MCI1	1,008	0,963	0,991	1,010	1,019	1,023	1,056**	1,050***	1,036***
	LT-MCI2	1,061	1,026	1,021	1,063	1,086	1,055	1,111***	1,120***	1,068***
	LT-FMCI	1,080*	1,109***	1,097***	1,082	1,174**	1,133**	1,131***	1,210***	1,150***
France	LT-MCI1	0,989	0,989	0,960*	1,064*	1,097***	1,258***	1,000	0,999*	0,999*
	LT-MCI2	0,993	0,979	0,959**	1,069*	1,086***	1,256***	1,005	0,998	0,998
	LT-FMCI	0,994	0,998	0,977	1,069	1,107***	1,280***	1,005	1,008	1,017
Japan	LT-MCI1	0,999	0,995	0,978*	0,991	0,987**	0,947***	1,001	1,002**	1,001
	LT-MCI2	0,980*	0,970***	0,960***	0,970***	0,960***	0,930***	0,980***	0,977***	0,985***
	LT-FMCI	0,999	1,009*	1,002	0,991	0,999	0,970***	1,001	1,015*	1,026*
Italy	LT-MCI1	0,959***	0,983	0,986	0,950***	0,986	1,006	1,002	1,014*	1,013
	LT-MCI2	0,983**	1,009	1,010	0,976**	1,012	1,032	1,027***	1,041***	1,038***
	LT-FMCI	0,992	1,034*	1,044	0,985	1,037*	1,067**	1,037***	1,067***	1,074***

Note : Figures represent the ratio of the LT-MCIs models RMSE over the AR, Spread or Standard-MCIs models RMSE, with a *k* months ahead forecasts. *, **, *** indicate whether the ratio is significantly different from 1 according to the Diebold-Mariano test, at respectively 10, 5 and 1% level. Models are updated each month.

Table 3 - Predictive Power of Long-Term MCIs According to out-of-sample Probit Estimations

Country	Model	Comparison with AR Model			Comparison with Spread Model			Comparison with S-MCI Model		
		k=3	k=6	k=12	k=3	k=6	k=12	k=3	k=6	k=12
United-Kingdom	LT-MCI1	1,002*	1,013*	1,022***	0,995	1,065	1,027	1,002	0,997	0,999
	LT-MCI2	0,998	1,023***	1,020	0,991	1,027	1,025	0,998	1,007*	0,998
	LT-FMCI	1,000	1,011**	1,009	0,992	1,015	1,014	0,999	0,996*	0,987**
Germany	LT-MCI1	0,979*	0,995	1,028**	1,013	1,085***	1,117***	1,002*	0,998*	1,002*
	LT-MCI2	0,999	1,008	1,033***	1,033**	1,100***	1,123***	1,022***	1,012*	1,006*
	LT-FMCI	0,998	1,011	1,032***	1,032**	1,103***	1,122***	1,021***	1,014*	1,006*
Canada	LT-MCI1	0,988	0,988	0,983	0,986	1,009	1,212***	1,002***	1,002**	0,999
	LT-MCI2	1,022**	1,041***	1,018	1,019	1,063	1,251***	1,036***	1,056***	1,035**
	LT-FMCI	1,027***	1,054***	1,032***	1,024	1,076	1,272***	1,041**	1,068***	1,049**
United-States	LT-MCI1	1,008	1,005	1,022*	1,041	1,087**	1,192**	1,016*	1,023**	1,017
	LT-MCI2	1,028*	1,049**	1,047***	1,061**	1,135***	1,221***	1,036***	1,068***	1,042***
	LT-FMCI	1,035*	1,098***	1,071***	1,064*	1,188***	1,248***	1,043**	1,117***	1,066***
France	LT-MCI1	0,977*	1,003	0,981	0,989	1,079***	1,181***	1,000	0,999**	0,993*
	LT-MCI2	0,982**	1,002	0,977	0,996	1,078***	1,176***	1,006	0,998	0,995
	LT-FMCI	0,985**	1,006	0,979	0,998	1,082***	1,179***	1,008	1,002	0,998
Japan	LT-MCI1	0,998	0,997	0,976**	0,991	0,987	0,951***	1,000	0,999	0,998
	LT-MCI2	0,980	0,975**	0,976**	0,973*	0,966**	0,951***	0,982*	0,978***	0,998
	LT-FMCI	1,000	1,007*	1,040***	0,993	0,997	1,013	1,002	1,009*	1,063***
Italy	LT-MCI1	0,994	1,006	0,998	1,024**	1,013*	0,999	0,999	0,999	0,997
	LT-MCI2	1,003	1,018**	1,010	1,034***	1,025***	1,011	1,009**	1,011***	1,008*
	LT-FMCI	1,008	1,023	1,023*	1,038***	1,052***	1,024**	1,013*	1,016**	1,021**

Notes : Figures represent the ratio of the LT-MCIs models RMSE over the AR, Spread or Standard-MCIs models RMSE, with a *k* months ahead forecasts. *, **, *** indicate whether the ratio is significantly different from 1 according to the Diebold-Mariano test, at respectively 10, 5 and 1% level. Models are updated each month.

Table 4 - In-sample significance of DW-MCIs

Country	DW-MCI1	DW-MCI2	DW-FMCI
United Kingdom	k = 6 (5%)	k = 6 (5%)	k=12 (10%)
Germany	k = 3, 6 (1%)	k = 3, 6 (1%)	k = 3, 6 (1%)
Canada	k = 3 (1%)	k = 3 (1%)	k = 3, 6 (1%)
United States	k = 3, 6 (5%)	k = 3, 6 (5%)	k = 3, 6, 12 (1%)
France	k = 3, 6 (1%)	k = 3, 6 (1%)	k = 3 (1%)
Japan	k = 12 (5%)	k = 12 (1%)	k = 12 (1%)
Italy	k = 3, 6 (5%)	k = 3, 6 (5%)	No -

Note : Figures represent the horizon for which the indicator is statistically significant. The level of significance is in brackets. For example, DW-MCI1 is a significant regressor of the industrial production in Italy, at a 5% level, whereas DW-FMCI is not.

Table 5 - Predictive content of DW-MCIs compared to the spread and LT-MCIs

DW-MCI *versus* ⇒		AR	Spread	LT-MCI1	LT-MCI2	LT-FMCI
			United Kingdom			
k = 3	DW-MCI1	0,997	0,996	1,084*	1,086*	1,077
	DW-MCI2	0,993	0,992	1,080	1,083*	1,073
k = 12	DW-FMCI	1,014**	1,027*	1,089***	1,084***	1,078***
			Germany			
k = 3	DW-MCI1	0,926**	0,998	0,944*	0,917**	0,923**
	DW-MCI2	0,927**	1,000	0,946*	0,919**	0,925**
	DW-FMCI	0,962	1,037	0,981	0,953	0,959
k = 6	DW-MCI1	0,785***	0,885***	0,769***	0,758***	0,766***
	DW-MCI2	0,787***	0,887***	0,771***	0,759***	0,768***
	DW-FMCI	0,777***	0,877**	0,762***	0,750***	0,759***
k = 12	DW-FMCI	0,998	1,271***	0,852***	0,852***	0,855***
			Canada			
k = 3	DW-MCI1	0,964*	0,931*	0,966	0,952**	0,954**
	DW-MCI2	0,960**	0,927*	0,963*	0,948**	0,950**
	DW-FMCI	1,125**	1,086	1,127**	1,110**	1,113**
k = 6	DW-FMCI	0,856**	0,846**	0,869*	0,854**	0,852**
			United States			
k = 3	DW-MCI1	0,967**	1,006	0,845***	0,840***	0,832***
	DW-MCI2	0,970**	1,009	0,849***	0,843***	0,835***
	DW-FMCI	0,882***	0,917***	0,771***	0,766***	0,758***
k = 6	DW-FMCI	0,700***	0,766***	0,652***	0,649***	0,636***
k = 12	DW-FMCI	1,050	1,139**	0,983	0,982	0,967
			France			
k = 3	DW-MCI1	0,996	1,061	0,989	1,016	1,013
	DW-MCI2	0,986	1,050	0,979	1,005	1,003
	DW-FMCI	0,921**	0,982	0,915	0,939	0,937
k = 6	DW-MCI1	0,930	0,999	0,919	0,950	0,952
	DW-MCI2	0,921	0,989	0,909	0,941	0,942
			Japan			
k = 12	DW-MCI1	0,922***	0,895***	1,064*	1,090**	1,073**
	DW-MCI2	0,905***	0,878***	1,045	1,071*	1,053*
	DW-FMCI	0,929**	0,902***	1,073*	1,099**	1,082**
			Italy			
k = 3	DW-MCI1	0,966**	0,962**	0,934**	0,942***	0,981
	DW-MCI2	0,962**	0,958**	0,931**	0,938***	0,977
k = 6	DW-MCI1	0,857***	0,837***	0,875**	0,826***	0,875***
	DW-MCI2	0,858***	0,838***	0,876**	0,827***	0,877***

<u>Note</u> : Figures represent the ratio of the DW-MCIs models RMSE over the AR, Spread or LT-MCIs models RMSE. *, **, *** indicates whether this ratio is significantly different from 1 according to Diebold-Mariano Test, respectively at the 10, 5 and 1% level. Models are updated each month.