Predicting economic downturns through a financial qualitative hidden Markov model

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Abstract

This paper provides both leading and coincident indicators of the US business and growth cycles through a multivariate qualitative hidden Markov model introduced by Grégoir and Lenglart (2000). The leading model applied to a set of four financial series supplies an unrevised and reliable advanced qualitative probabilistic indicator. Over the last forty years, it allows to conclude that financial markets have rarely failed to detect economic turning points. In fact, they have foreseen all the American economic slowdowns and especially the seven major recessions dated by the NBER committee. This modelling allows, through the interpretation of market moves, to forewarn economic downturns, with a significant lead varying between 3 to 6 months on a foolproof coincident indicator.

Keywords: Business Cycle, Multivariate qualitative modelling, Hidden Markov Model, Turning points, Asset prices and leading indicators.
JEL Classification : C32, E32, E44

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1 Introduction: US leading indicators and financial markets.

From the early works of Burns and Mitchell (1946), the development of leading indicators has stimulated the applied economic research. The well-known composite index of the American leading indicators presented in detail by McGuckin *et alii* (2003) has been tracking US growth and business cycles quite faithfully with a leading horizon of three to six months according to the literature. However, based upon incomplete data, its sequential computation process may lead to significant revisions and an altered real time performance to detect occurences of turning points. Besides, a first look at the index components brings the following remark: more than 60% of the weights are associated to financial variables such as the yield curve, the monetary aggregate M2 or the Standard and Poor's 500 index[3]. Likewise, Bellone and Saint-Martin (2003) and Bellone (2004a), conducting a comprehensive statistical analysis and a review of the literature on the forecast horizon of US economic indicators conclude that except for financial series, business surveys or macroeconomic statistics provide rather coincident or merely advanced information. In the same way, according to Chauvet (1999) or Chauvet and Potter (2000), the most advanced indicators are apparently to be identified among the financial variables. This can make sense since every news release is interpreted on those markets, analyzed to change expectations which are theoretically reflected by the dynamics of asset prices. Besides, those information are, by nature, never revised. Therefore, these series might provide leading indicators of the economic activity.

A vast literature concludes on the significant predictive power of asset prices concerning the future activity. Yet, as Stock and Watson (2003b) or Chauvet and Potter (2002) have noticed, those relations are characterized by a very strong instability if estimated within a linear modelling framework, which limits their possible use. Introduced by Chauvet (1999), models based on a probabilistic detection of downturns may represent a new approach to explore.

First, this paper aims at determining whether financial markets often got it wrong about the business cycle: did market expectations always forewarn the economic overturns in front of the diversity of diagnosis instruments? Should they be considered as reliable leading indicators in a short term forecast process? Second, this research discusses the extending of the multivariate qualitative hidden Markov model of Grégoir and Lenglart (2000) to mixed heterogenous data (from financial variables to coincident economic series) as a relevant framework to track turning points. Might those new stochastic tools improve the short-term economic diagnosis? The multivariate "qualitative" hidden Markov model, initially designed to extract expectations of French firm's managers through business surveys, is adapted to build both leading and coincident indicator of the US economy. It is qualitative, for by construction it does not aim at forecasting any growth rate, but can only determine whether growth is recovering or slowing. We apply this model

[3] See www.globalindicators.org/methodology

on economic and precisely on financial data in order to judge the leading power of market expectations, that are revealed by asset prices moves.

The paper is organized as follows. In the first section, we present the data. Then we show that most of the financial variables are leading indicators of the economic downturns and we remind the properties of the qualitative hidden Markov model of Grégoir et Lenglart (2000). In the second section, we analyze whether the signals supplied by the economic and financial innovations in this extended framework are reliable. In fact, an economic indicator based upon four quantitative series provides a good coincident indicator of the American growth cycle. Following Chauvet (1999), we also derive a financial indicator as a robust and reliable tool to forecast the American economic slowdowns. In the third section, we discuss the validation of these models facing short-term economic forecasts and have especially a look on their performance at the end of the "roaring 90's".

2 Detecting the US business cycle turning points.

Most economists use the NBER (National Bureau of Economic Research) recession datations as a reference. However precious, they may appear partial and incomplete: the American economy has already entered periods of growth downturns which did not turn into recession. For instance, in 1985, 1989, 1992 or 1995, temporary slowdowns have occured and have impacted the economic dynamics and monetary policy decisions. This article aims at supplying a leading indicator which could be available easily, unrevised and detect both recessions and growth slowdowns[4].

2.1 Selecting foolproof economic and financial series.

The data selection is based upon both prior works of Bellone and Saint-Martin (2003) and on a comprehensive study of thirty economic and financial American variables from the data base used by Bellone (2004b)[5]. Finally, two groups of series are considered.

Four "macroeconomic" time series have been selected: the industrial production index, the unemployment rate, the help wanted advertising index and the residential and non residential construction spending index[6]. These four series, used by Bellone (2004a) in order to develop coincident probabilistic indicators of recession, may allow to constitute a good benchmark of the NBER datations. Following the initial selection from Chauvet (1999), four financial variables have been considered. Three of them are daily available: the Standard and Poor's 500 index which reproduces the evolution at the New York Stock Exchange of 500 stocks,

[4]See Baron and Baron (2002) for a description and theoretical underpinnings of the growth cycle.

[5]The data set is available on the MSVARlib package at http://bellone.ensae.net

[6]The first three series have been available since January 1960, the last one since January 1964. All these series are published with a delay of one month.

the spread between the 3-month Fed Funds interest rate and the 10-Year Treasury Bond rate and the spread between corporate bond Moody's "BAA" and "AAA"[7]. Then, the money supply (M2) has also been selected, as a major component of the conference board leading indicator.

Once made stationary, aside from a basic study of statistical properties of those series[8], empirical densities have been estimated by using a non parametric kernel density method. Those densities seem, in most cases, to be strongly asymmetric around their mean value, their distribution tails are fat[9] and two or three "peaks" can be pointed out. Starting from these observations, we can assume that their dynamics may follow a mix of distributions. At least, two main states could be determined: a regime of expansion and one of recession. As mentioned by Baron and Baron (2002), hidden Markov models might therefore provide a suitable framework to reproduce those features.

Table 1: QPS on advanced, coincident, and lagged NBER datations.

	Time-lag with the NBER datation lag (+) advance (-) in months				
	+ 3	0	- 3	- 6	- 9
Economic variables					
Industrial production	**0,06**	**0,06**	0,13	0,19	0,22
Unemployment rate	**0,03**	0,06	0,13	0,20	0,24
Help wanted advertising	0,08	**0,06**	0,12	0,18	0,24
Construction index	0,11	**0,09**	0,12	0,16	0,18
Financial variables					
Spread 3 m. - 10 y.	0,26	0,21	0,15	0,12	**0,11**
M2	0,36	0,31	0,29	**0,27**	0,29
SP 500	0,21	0,16	**0,15**	0,16	0,19
Spread corporate	**0,14**	0,15	0,17	0,18	0,18

First, basic univariate two-regime Markov switching models (Hamilton (1989)) have been applied. Thanks to these simple and parcimonious specifications, filtered probabilities of each regime has been extracted to judge if the financial variables could be leading indicators of the economic downturns. We confirm ini-

[7]A rise in this spread should be interpreted as an expectation of a slowdown because agents assume that for a weak quality of loans, the risks associated to the more vulnerable firms are growing. We could not take include High yield spreads, which should also be good leading indicators, because of too short historical time series.

[8]The four real economic variables are non-stationary in level. A 3-month growth rate, computed as $log(X_t) - log(X_{t-3})$, has been used rather than a monthly variation because this latter remained very noisy. As the unemployment rate runs against the cycle, we used its opposite coded series. Among the financial variables, the "3 months - 10 years" spread is stationary in level and for the three other variables a 3 month growth rate is considered.

[9]For most of the series, the tails are fatter for values inferior to the mean.

tial findings of the literature : financial variables are found to anticipate most of the economic turning points whereas the economic variables are more coincident with the business cycle. Quadratic Probability Scores[10], introduced by Brier (1950) are reported in table 1. Those associated to economic series are lower (all less than 0,1) than those for the financial variables (from 0,2 to 0,3). For instance, the QPS criterion is minimized with a 9-month anticipation for the "3 months - 10 years" spread, a 6-month one for M2, and 3-month for the stock index. The indicator built on the spread corporate may seem more coincident[11].

Each financial variable happens to be a reliable advanced indicator of the activity downturns. To take into account the well-known feature of comovement, a multivariate framework should then be introduced. Chauvet and Potter (2000) represent a financial cycle and assume that the comovement could be specified with a dynamic factor model. Nevertheless, associated with Hamilton's model, the dynamic factor approach faces several drawbacks. This model is estimated with a Kim's filter which is an approximation of the Kalman filter to take into account non-linearity effects. However, consequences on the results of those approximations can not be fully estimated. To face these drawbacks, we thus propose to follow a competing approach, aiming at measuring a kind of "surprise index" including a markovian framework, gauging whether the economic activity is to be on the upside or the downside.

2.2 A two-step multivariate qualitative hidden Markov model.

Financial markets provide daily analysis and interpret a large set of new micro and macroeconomic information leading them to update their expectations on the future growth path. Theoretically, these alterations must be mirrored in the dynamics of asset prices or monetary aggregates. How could these economic "innovations", which measure the gap between expected and unexpected real information, be modelled and represented? What kind of global economic movement could then be inferred from?

Grégoir and Lenglart (2000) propose a complete framework for a non linear factorial analysis. They consider that a phase of high (resp. low) activity should begin with the occurrence of unpredictable shocks driving the activity in positive (resp. negative) direction. Consequently, they suggest to isolate in real-time new information included in each time series, and then to determine the related direction: upside or downside? Practically, these news releases consist in weak innovations extracted from an univariate auto-regressive model. In this framework,

[10] The QPS estimates the advance or the delay of a variable on the business cycle. The next formula defines it: $QPS = \frac{1}{T}\sum_{t=1}^{T}(R_t - P_t)^2$ where for $t = 1, \ldots, T, (P_t)_t$ are the filtered probabilities to be in recession and $(R_t)_t$ are the NBER datations, 1 for recession and 0 for expansion.

[11] Note that for this variable, the estimates may suffer from a weaker quality.

n series y_t^i $(i = 1, \ldots, n)$ follow each an autoregressive process:

$$y_t^i = \sum_{k=1}^{p^i} \phi_k y_{t-k}^i + \epsilon_t^i$$

where $\epsilon_t^i \sim N(0, \sigma_\epsilon^2)$ is a white noise. These innovations are then coded $+1$ (as upside or positive innovations) or -1 (as downside or negative innovations) to produce a new qualitative variable x_t^i (x_t is the vector of all x_t^i, $i = 1, \ldots, n$). An unobservable common factor Z_t which is assumed to follow a two-states first order Markov chain, can then be inferred. It describes the state of the economy ($Z_t = -1$ or $Z_t = +1$) and is such that $P(Z_{t+1} = j | Z_t = l) \equiv \eta_{j|l}$. Moreover:

$$P(x_t | Z_t) = \prod_{i=1}^{p} P(x_t^i | Z_t) \tag{1}$$

The likelihood can be written as :

$$P(x_T, \ldots, x_1) = \prod_{t=2}^{T} P(x_t | I_{t-1}) P(x_1) \tag{2}$$

Then, $\pi_j^i(s)$ is the probability that the variable i takes the modality s if Z took the modality j :

$$\pi_j^i(s) = P(x_t^i = s | Z_t = j) \tag{3}$$

Like in the model of Hamilton (1989), we solve the model with a recursive filter. Suppose that $P(x_2|I_1), \ldots, P(x_t|I_{t-1})$ and $P(Z_2|I_1), \ldots, P(Z_t|I_{t-1})$ are known, we obtain:

$$P(Z_t | I_t) = \frac{P(Z_t | I_{t-1}) \prod_{i=1}^{p} \prod_{s \in \{-1,+1\}} \{\pi_{Z_t}^i(s)\}^{1_{|x_t^i = s}}}{P_{x_t | I_{t-1}}} \tag{4}$$

$$P(Z_{t+1} | I_t) = \sum_{Z_t = 1}^{K} P(Z_t | I_t) \cdot \eta_{Z_{t+1} | Z_t} \tag{5}$$

$$P(x_{t+1} | I_t) = \sum_{Z_{t+1}=1}^{K} P(Z_{t+1} | I_t) \prod_{i=1}^{p} \prod_{s \in \{-1,+1\}} \{\pi_{Z_{t+1}}^i(s)\}^{1_{|x_{t+1}^i = s}} \tag{6}$$

The filter is initialized with the ergodic probabilities, such that:

$$P(Z_1 | I_0) = P^* = \eta \cdot P^*$$

Grégoir and Lenglart (2000) do not consider the relation between the observable variable of coded innovations and this unobservable variable as deterministic but rather stochastic. For this purpose, a second independent hidden markovian process, W_t, is introduced to determine whether the information brought by innovations are significant or not (such as $W_t = yes$ or $W_t = no$). Indeed, it is difficult to interpret the filtered probabilities directly computed from the innovation process because of an absence of persistence in the movement of the state variable. In fact, considering uncertainty about the coding process corrects these flaws and creates an implicit third state of indeterminacy. A new process $\tilde{Z}_t = (Z_t, W_t)$, following a Markov chain and taking four modalities: $(-1, yes)$, $(-1, no)$, $(+1, yes)$ and $(+1, no)$, is then introduced. The related probability transition matrix is noted $\tilde{\eta}$. As Z_t (whose transition matrix η) and W_t (whose transition matrix ξ) are two independent processes, we find out the transition probabilities of the process $\tilde{Z}_t$: $\tilde{\eta} = \eta \otimes \xi$. In the same way, we define $\tilde{\pi}$ the conditional probability matrix associated to the $\tilde{Z}_t$ process such as $\tilde{\pi}^i_j(s)$ is the probability that the variable i takes the modality s if $\tilde{Z}$ took the modality[12] j:

$$\tilde{\pi}^i_j(s) = P(x^i_t = s | \tilde{Z}_t = j) \tag{7}$$

Finally, the filtered probability is derived from:

$$P(Z_t = s | I_t) = P(\tilde{Z}_t = (s, yes) | I_t) + P(\tilde{Z}_t = (s, no) | I_t) \tag{8}$$

for $s = -1, +1$.

A new indicator, varying between -1 and $+1$, can then be computed as $P(Z_t = +1 | I_t) - P(Z_t = -1 | I_t)$. The closer the indicator -1 (resp. $+1$), the likelier the economy is to fall in a "low growth regime" (resp. "high growth regime").

3 Qualifying leading and coincident information by using "weak innovations".

The filtered indicators built from both sets of series[13] are quite persistent but provide an erratic signal. Smoothed stochastic release are presented here to facilitate their reading. However, as the authors remind, as filtered probabilities have a larger variance because of their conditional estimating on a narrower set of information, the end of series of smoothed probabilities might strongly vary in successive estimation. This makes their use inconsistent to a forecasting or real-time detection purpose. The filtered signals should then be the only indicator to focus on in real-time. They are both presented in Appendix A p. 16 and discussed in the next section.

3.1 A coincident stochastic indicator based upon economic series.

As presented in figure 1, the economic indicator[14], based upon the four quantitative series is more frequently positive[15], which fits with the main observations

[12] Here it is a bimodal modality lying among $(-1, yes)$, $(-1, no)$, $(+1, yes)$ et $(+1, no)$.
[13] The programs used are an adaptation from the Gauss library initially developed by S. Grégoir and F. Lenglart.
[14] See Appendix B p. 17 for estimation of the probability matrices.
[15] See Appendix B p. 17 for an estimate of the transition and conditional probability matrices.

of Hamilton (1989). According to his results, the expansions are much longer on average than the periods of slowdowns.

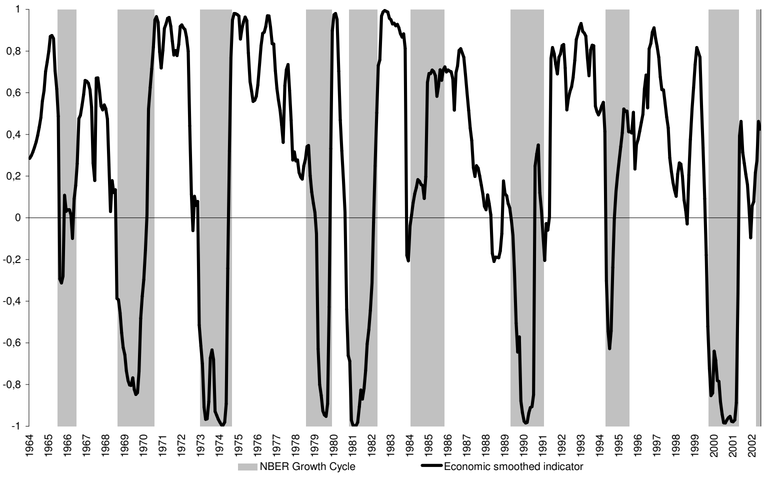

Figure 1: Smoothed indicator of Grégoir and Lenglart - Economic variables

It points out the seven NBER recessions each time it breaks down the -0,5 value during more than two months[16]. Apart from recession periods, the slowdowns at the end of 1985, of 1989, and the period of the 1992-1993 jobless recovery are highlighted by a negative value but which does not overcome the threshold of -0,5. All of these periods correspond to the ex-post NBER datations of "weak growth" phase. A last slowdown is determined by our indicator in 1995 which is a well-known consequence of the Fed Funds rising in 1994. At the end of the nineties, a mild signal is short and identified during the 1997-1998 Asian crisis, which did not lead to a pronounced slowdown of the business activity in the United States contrary to other economic zones. The model developed by Grégoir and Lenglart allows to detect in real-time not only recessions but also growth slowdowns which may be distinguished by the amplitude of the indicator: a durable slowdown under the breaking value of -0,5 forewarns an undergoing recession.

3.2 A leading stochastic indicator based upon financial series.

Financial markets daily consolidate their expectation through new information. How may the previous model catch those anticipations?

[16]Smoothed stochastic release are presented here to facilitate the reading. See Appendix A p. 16 for the graphs of filtered indicators.

We then use our real time coincident stochastic index as a benchmark to compare the leading performance of the financial indicator on growth slowdowns detection. To let the reading easier and to get a real-time datation of the American growth cycle, the economic indicator is recoded through a datation dummy: the positive (resp. negative) values are coded 0 (resp. 1). [17].

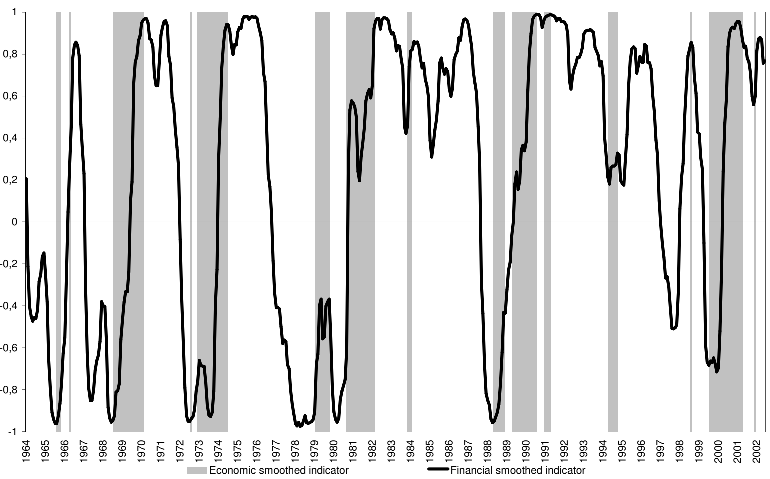

Figure 2: Smoothed indicator of Grégoir and Lenglart - Financial variables and implicit datation with the economic model

The figure 2 gives evidence that each period of low level of the coincident indicator is preceded by a phase of depressed financial indicator. Note that the filtered combined probabilities, which are the only one to trust in real time, (See in Appendix B figure 5 p. 16 the two month averaged filtered indices and Appendix B p. 17 for estimations of the probability matrices.), even if more erratic, exhibits the same signal as the smoothed one.

At the end of 1985 and in the early 90's the slowdowns might not have been clearly detected. However, the 1985 downturn remained mild and short. On the contrary, the long period of low growth, from the beginning of 1990 to mid-1992, was clearly preceded by a negative financial warning. Two other false signals can be pointed out: in 1965 and in 1998. First, several analysts considered the 1965 episode was a quasi-recession. In 1998, the world economy faced a deep manufacturing slowdown and currency crisis in emerging countries stressed bond and stock markets. However, contrary to market expectations, this shock was easily absorbed by the US economy, facing a momentary slowing real income thanks to a very aggressive monetary policy, robust job creations and dynamic

[17]Note that this implicit datation is really close to the NBER Growth cycle datation

consumer spending.

Stock and Watson (2003a), following the conclusion of a vast literature focusing on the American business cycle, identify a structural break in 1984 as the cycle seemed to be far less volatile from this year on.

Studying the business cycle, Stock and Watson (2003a) identify a structural volatility break in 1984. Many models fail to take into account this feature and either have to be estimated from 1984 as in Ferrara (2003) or to take into account endogenous breaks such as in Chauvet and Potter (2002). Indicators obtained from the model of Gregoir and Lenglart (2000) do not reveal this problem. Thanks to the recoding operation, this modeling only focuses on upside or downside directions of signals and avoid quantitative disruptions related to time varying statistical moments.
The performances of our indicators give evidence of remarkable detection scores. Nevertheless, the financial indicator provide varying leading power: whereas it used to lead by 6 to 9 months the economic turning points during the 60's and the 70's, its leading power has a bit weakened over the past 15 years to 3 to 6 months. Some questions remain: could this feature be linked with the decreasing volatility of the cycle and to a precise change in regime starting from 1984?

4 Validating qualitative indicators facing short term economic forecasts.

In the previous section, two multivariate qualitative hidden Markov indicators have been introduced, leading by 4 months on average the economic slowdowns. Nevertheless, how might they provide a guideline to short term forecasting exercises?

4.1 A look back on the end of the roaring 90's.

First, these indicators provide some qualitative reliable information on the chronology of the American business cycle. In this section, we look back on the eve of the last recession when economists could have found some help for forecasting the business cycle overturn.

In June 1999, the experts [18] forecast a brisk recovery of the American economy during the last semester of 1999. On one hand, the economic indicator, still negative, gives no sign of this recovery (See figure 3.). On the other hand, the financial indicator oscillates between $+0,6$ and $+0,8$ during all the year 1999 and would have also provided some reliable and predictive information to confirm this fast and strong recovery.

[18] We focus here on the Economic Outlook forecasts released by the OECD and the international forecasts of the French Finance Ministry available at http://www.finances.gouv.fr/minefi/publique/macroeconomie/index.htm, between 1999 and 2001.

In June 2000, the diagnosis is rather optimistic for the second quarter of 2000, economists foresee a strong growth above the trend and then a "gradual slowdown". Nevertheless, the economic indicator is already sharply declining from $+0,9$ in December 1999 to 0 in June 2000. Moreover, the financial indicator is negative around $-0,5$ since February 2000. Thus, both indicators gave significant signals of a sharp - rather than a "gradual" - slowdown of the American business cycle.

The forecasts at the end of 2000 have been studied by Stock (2003) who mentions that even as late as the fourth quarter of 2000 the median Survey of Professional Forecasters(SPF) was predicting strong economic growth throughout 2001. At that time, both indicators are close from -1 and anticipate not a slowdown as forecasted by experts but a recession. Stock even adds that, whereas the US economy was getting out of recession in December 2001, the consensus probability of a negative growth was more than 80%. In the end, whereas the beginning of the last recession was dated by the NBER committee on November 2001, the financial indicator had been given signals of an expected recovery since the mid-2001, with a 6-month lead.

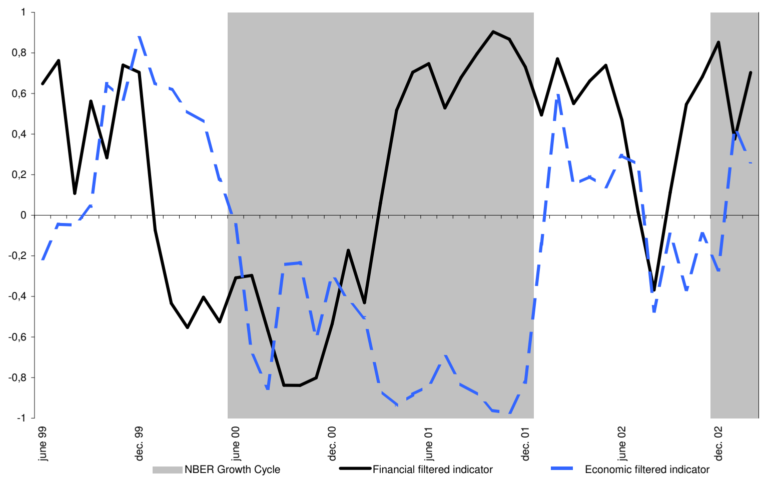

Figure 3: Qualitative forecasting exercise (1997 - 2003)

This recent episode gives evidence that the indicators built from the Grégoir and Lenglart's model should deliver a helpful qualitative signal to forecasters. However, economists would appreciate to relate these qualitative signals to quantitative projected growth rate: how can they be used for a GDP (Gross Domestic Product) forecasting exercise?

4.2 Implicit stochastic regimes and quarterly GDP growth.

Qualitative by construction, those indicators cannot be directly interpreted in term of growth rates. From a direct analysis of these results, and following the authors'opinion, one may only say that growth is recovering its medium term average when indicator is close to zero and that it becomes significantly superior (resp. inferior) to this figure when close to +1 (resp. -1).

First, we would like to check those results and second to devise a simple forecasting rule of thumb associated to the quarterly growth of GDP. Following the interpretation grid of Grégoir and Lenglart, the filtered indicators have been divided in three regimes, the "low" regime is associated to the values smaller than $-0,5$, the "mean" regime to values between $-0,5$ and $+0,5$ and the "full steam regime" to the values larger than $+0,5$. For each state, different statistics related to the GDP quarterly growth rate are computed[19] (in coincidence (T) with the indicators or in advance ($T+1$ and $T+2$)). Then, the mean or the median can be combined to the filtered index at each date to provide a quantitative forecast of the GDP.

Three regimes of GDP are clearly distinguished for a real-time projection (See Appendix C p. 19.) inspecting the economic indicator. The first state corresponds to the low and negative values of the GDP growth rate, i. e. the periods of recession. The second regime seems to be associated to a trend growth rate. The third one gathers all the values above this trend. Looking at other leading horizons, it seems more difficult to characterize the three regimes. Concerning financial variables, the three regimes are quite clearly identified for the 6-month ahead predictive horizon $T+2$. The same distinction can be made between a low regime of quasi-recession, a trend growth regime and a high regime. These relations remain quite stable over various samples, especially before and after the 1984 break, confirming the qualitative approach as quite effective and reliable.

To test its predictive performance the forecasting rule of thumb is compared to a dynamic forecast[20] dealing with the same exogenous variables on a rolling end of sample varying from 1989 to 2003. Forecasting the GDP growth rate in T with the mean-values combined to the economic indicator leads to comparable Mean Squared Errors (MSE), (cf Table 2). In real-time, our indicator seems quite reliable to produce a simple quantitative forecast. Applying the same methodology to the leading financial indicator at a 6-month horizon ($T+2$), the global path is partly reproduced except the 1990-91 recession which is the unique false signal. Apart from this episode, the MSE are quite comparable, leading to the following conclusion: at leading horizons, forecasts produced by a linear model or our rule of thumb seem quite equivalent.

[19] As our indicator is a monthly one, we have replicated quarterly GDP growth for each month of a quarter.

[20] The equation used is $\Phi(L)y_t = \Psi(L)x_t + \epsilon_t$ where y_t is GDP and x_t the exogenous variables

Table 2: Comparison of forecasting performances (MSE, 1989 - 2003).

	Dyn. forecast	"Rule" T	"Rule" T+1	"Rule" T+2
Financial variables	0,26	0,36	0,33	0,32
Economic variables	0,19	0,23	0,34	0,31

5 Conclusion.

The financial markets may be the most active and forward-looking institutions among those following news release. Not surprisingly, their expectations reveal a significant lead on the business cycle.

As we have applied a multivariate qualitative hidden Markov model to American mixed data, we have showed that it provides a reliable framework to track the growth cycle and that a financial related model would be helpful to predict economic downturns. For instance, the latest significant growth slowdown could have been detected in early March 2000, four months before the first signs reported from economic data and a year before the start of the recession. Nevertheless, its leading power might have eroded over the last 15 years, maybe because of the nature of the shocks (less monetary than real?), because of better policies or simply because of luck as mentioned Stock and Watson (2003b). One cannot exclude that new information technology developments have accelerated news and expectations moves. An other question remains open: is this leading power of financial markets a pure "expectation" phenomenon or rather a mix of monetary shocks and feedbacks from the economy to the financial markets?

Whatever, coding surprises or weak innovations seem an interesting ways to analyze real or financial shocks. This work could however be extended in two directions. One the one hand, because of some limitations to maximum likelihood procedures, a bayesian approach could prove promising. On the other hand, this model is a first step towards building a qualitative non linear factor analysis framework. Adapting a hierarchical markovian classification model to the interpretation of weak innovations could then be a future way of research.

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Appendix A

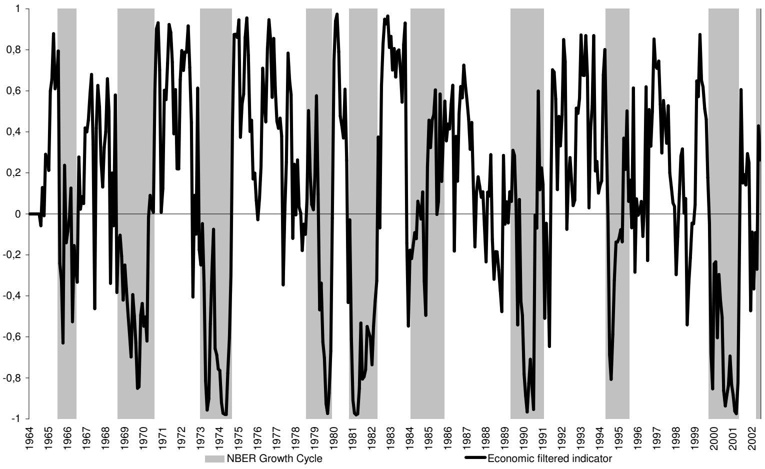

Figure 4: Filtered indicator of Grégoir and Lenglart- Economic variables

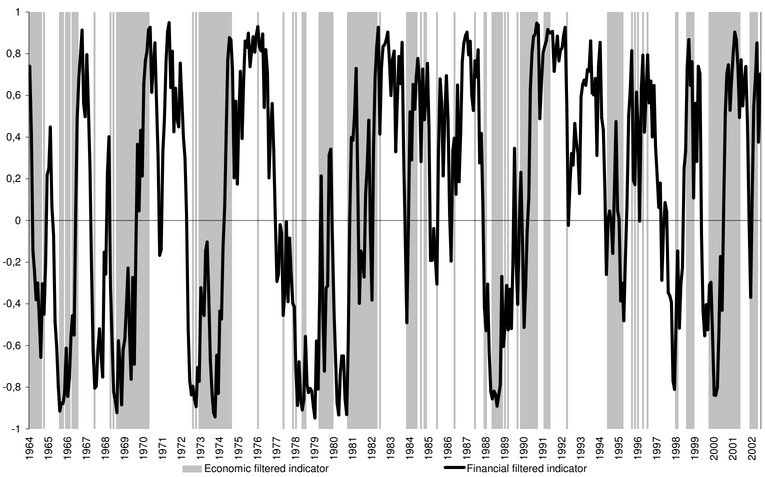

Figure 5: Filtered indicators of Grégoir and Lenglart- Economic and financial variables

Appendix B

Transition and conditional probability matrices related to the "economic" model (Standard errors are in brackets).

To test the null hypothetisis, Gregoir and Lenglart (2000) remind that the usual Student statistics cannot be used, as those statistics distributions follow a mix of laws. We followed the same methodology as the authors who recall that a 0.05 level (resp .0.10) is thus obtained by comparing the Student statistics to 1.64 (resp. 1.28). All the estimated unconstrained probabilities are then significantly different from zero to a 0.05 level.

$$\tilde{\pi} = \begin{pmatrix} 0.901 & 0.5 & 0.125 & 0.5 \\ (0.111) & & (0.104) & \\ 0.099 & 0.5 & 0.875 & 0.5 \\ (0.111) & & (0.104) & \\ 0.855 & 0.5 & 0.117 & 0.5 \\ (0.090) & & (0.104) & \\ 0.145 & 0.5 & 0.883 & 0.5 \\ (0.090) & & (0.104) & \\ 0.973 & 0.5 & 0.174 & 0.5 \\ (0.075) & & (0.093) & \\ 0.027 & 0.5 & 0.826 & 0.5 \\ (0.075) & & (0.093) & \\ 0.876 & 0.5 & 0.146 & 0.5 \\ (0.091) & & (0.088) & \\ 0.124 & 0.5 & 0.854 & 0.5 \\ (0.091) & & (0.088) & \end{pmatrix}$$

$$\tilde{\eta} = \eta \bigotimes \xi = \begin{pmatrix} 0.509 & 0.380 & 0.063 & 0.047 \\ (0.105) & (0.131) & (0.047) & (0.027) \\ 0.196 & 0.693 & 0.024 & 0.086 \\ (0.065) & (0.090) & (0.018) & (0.053) \\ & & & \\ 0.040 & 0.030 & 0.532 & 0.397 \\ (0.028) & (0.017) & (0.116) & (0.128) \\ 0.016 & 0.055 & 0.205 & 0.725 \\ (0.011) & (0.031) & (0.067) & (0.080) \end{pmatrix}$$

$$\text{with } \eta = \begin{pmatrix} 0.889 & 0.071 \\ 0.111 & 0.929 \end{pmatrix} \text{ and } \xi = \begin{pmatrix} 0.573 & 0.220 \\ 0.427 & 0.780 \end{pmatrix}$$

Transition and conditional probability matrices related to the "financial" model (Standard errors are in brackets).

$$\tilde{\pi} = \begin{pmatrix} 0.450 & 0.5 & 0.687 & 0.5 \\ (0.090) & & (0.101) & \\ 0.550 & 0.5 & 0.313 & 0.5 \\ (0.090) & & (0.101) & \\ 0.886 & 0.5 & 0.199 & 0.5 \\ (0.140) & & (0.134) & \\ 0.114 & 0.5 & 0.801 & 0.5 \\ (0.140) & & (0.134) & \\ 0.725 & 0.5 & 0.448 & 0.5 \\ (0.101) & & (0.063) & \\ 0.275 & 0.5 & 0.552 & 0.5 \\ (0.101) & & (0.063) & \\ 0.574 & 0.5 & 0.442 & 0.5 \\ (0.079) & & (0.065) & \\ 0.426 & 0.5 & 0.558 & 0.5 \\ (0.079) & & (0.065) & \end{pmatrix}$$

$$\tilde{\eta} = \eta \bigotimes \xi = \begin{pmatrix} 0.693 & 0.232 & 0.057 & 0.019 \\ (0.258) & (0.262) & (0.048) & (0.024) \\ 0.325 & 0.599 & 0.027 & 0.049 \\ (0.336) & (0.362) & (0.041) & (0.033) \\ & & & \\ 0.036 & 0.012 & 0.713 & 0.239 \\ (0.031) & (0.016) & (0.268) & (0.268) \\ 0.017 & 0.031 & 0.335 & 0.617 \\ (0.027) & (0.022) & (0.349) & (0.366) \end{pmatrix}$$

with $\eta = \begin{pmatrix} 0.924 & 0.048 \\ 0.076 & 0.952 \end{pmatrix}$ and $\xi = \begin{pmatrix} 0.749 & 0.352 \\ 0.251 & 0.648 \end{pmatrix}$

Appendix C

Table 3: Statistics relating GDP growth rates and implicit regimes related to the filtered indicators.

Regime 0[21]	**Economic Model**			**Financial Model**		
Stat.	GDP T	GDP T+1	GDP T+2	GDP T	GDP T+1	GDP T+2
Mean	**-0.29**	0.08	0.35	0.78	0.45	**0.18**
Median	**-0.17**	0.13	0.43	0.63	0.45	**0.33**
Min.	-2.04	-2.04	-1.66	-1.11	-2.04	-2.04
Max.	1.19	2.79	2.79	2.55	2.03	2.39
Std	0.80	0.97	0.98	0.84	0.76	0.77

Regime 1						
Stat.	GDP T	GDP T+1	GDP T+2	GDP T	GDP T+1	GDP T+2
Mean	**0.81**	0.76	0.82	0.74	0.77	**0.85**
Median	**0.77**	0.75	0.78	0.75	0.75	**0.83**
Min.	-1.07	-2.04	-2.04	-2.04	-2.04	-2.04
Max.	2.79	3.85	3.85	3.85	3.85	3.85
Std	0.62	0.80	0.85	0.93	0.98	0.94

Regime 2						
Stat.	GDP T	GDP T+1	GDP T+2	GDP T	GDP T+1	GDP T+2
Mean	**1.39**	1.26	0.96	0.91	1.04	**1.09**
Median	**1.40**	1.19	0.90	0.85	0.93	**0.93**
Min.	-0.70	-0.03	-2.04	-1.28	-1.66	-0.03
Max.	3.85	2.55	2.55	2.79	2.79	2.79
Std	0.80	0.69	0.82	0.82	0.71	0.63