Value-at-Risk across horizons and financial cycle: Are solvency capital requirement rules pro-cyclical?

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(Very preliminary version)
Paris, 30 December 2008

Abstract: This paper explores empirically the link between French equities returns Value-at-Risk (VaR) and the state of financial markets cycle. The econometric analysis is based on a simple vector autoregression setup. Using quarterly data from 1970Q4 to 2008Q3, it turns out that the k-year VaR of French equities is strongly dependent on the cycle phase: the expected losses as measured by the VaR are twice smaller in recession times than expansion periods. These results strongly suggest that the European rules regarding the solvency capital requirements for insurance companies should adapt to the state of the financial market's cycle. To this end, we propose a cycle-dependent measure of the Solvency Capital Requirement.

Keywords: Expected equities returns, Value at Risk, Investment horizon, Vector Auto-regression.
JEL classification: G11.

Acknowledgments: This version of the paper has benefited from numerous discussions with Severine Marion. All remaining errors are ours. The authors gratefully acknowledge financial support by the Fédération Française des Sociétés d'Assurance.

Introduction

A growing empirical literature points to predictability in equities returns, at least to some extent (see e.g. Campbell [1991], Campbell [1996], Barberis [2000], or Campbell and Viceira [2002] for U.S. data and Bec and Gollier [2007] for french data). This in turn implies the existence of an horizon effect in the risk of equities returns. More precisely, U.S. and French equities risk are found to be mean reverting, in the sense that the risk associated with long holding periods is lesser than the one associated with short holding horizons as e.g. the widely scrutinized one-year horizon.

Our claim, in this paper, is that the equities returns dynamics, and hence their Value-at-Risk (VaR hereafter) may be influenced by the state of the financial market cycle. The idea is that the expected $k-$period returns should not be the same depending on whether the financial market is near a peak or near a trough. This potential influence is explored empirically by modelling the joint dynamics of excess return of equities and an indicator of the financial market cycle from a vector autoregression model. Actually, in the recent empirical literature devoted to asset returns predictability, the vector autoregressive dynamics is often retained. The choice of this representation is basically motivated by two reasons. The first one is that this framework allows for straightforward computation of the conditional first and second-order moments matrices, namely the conditional mean and variance-covariance matrices. Hence, two crucial variables for dynamic portfolio allocation optimization obtain easily — the time-t conditional expectation (forecast) and conditional variance (risk measure) for asset returns at horizon $t + h$. The second reason is that under the assumption that asset returns are well described by such a vector autoregression model, it is possible to obtain approximate solutions to some multiperiod portfolio choice model as e.g. the one developed in Campbell, Chan and Viceira [2003].[1]

Some recent papers (Adrian and Shin (2007, 2008), Plantin, Sapra and Shin [2008], Rochet [2008]) suggest that Basel II and the International Accounting Standards norm

[1] In their model, the investor is infinitely-lived with Epstein-Zin utility and there are no borrowing or short-sales constraints on asset allocation.

39 will exacerbate financial cyclical fluctuations. Adrian and Shin [2007] in particular claim that fixed solvency capital requirements may have devastating procyclical consequences on the dynamic investment strategies of the financial intermediaries. Changes in assets valuations show up immediately on balance sheets that force banks and insurance companies to sell more assets during downturns in order to restore their solvency ratios. Our suggestion is to recognize the existence of mean reversion in equity returns in the way we determine the SCR. This modification of the methodology is countercyclical. It should induce intermediaries to be more conservative in long expansionary phases, and to be more risk-taking in downturns.

So, this paper proposes a measure of the Value-at-Risk based on the vector autoregression estimates. It is in line with existing measures in that it derives from the empirical distribution of the expected $k-$period returns. Nevertheless, it has the advantage of not imposing any assumption regarding the law of distribution of the sample but relies on bootstrapped quantiles instead. Our contribution to this topic is twofold. First, we exploit the joint autoregressive dynamics of equities returns and financial market cycle so as to take into account the influence of the recent cycle conditions on the VaR measure. Second, we propose a cycle-dependent measure of the Solvency Capital Requirement (SCR hereafter) which accounts for the illiquidity risk.

Our application to French data points to a significant influence of the financial market cycle in explaining stock returns: the financial market cycle indicator Granger-causes returns on equities. Consequently, the VaR is also affected by the financial cycle. This finding is of particular interest in the current European context. Nowadays, one of the most important questions debated within the so-called Solvency II project is the definition of the rules determining the SCR. So far, the main propositions put forward to calibrate this SCR in Europe rely on the VaR at the one-year horizon and do not take into account neither the state of the financial cycle nor the investors horizon.

The paper is organized as follows. Section 1 presents the econometric methodology. Section 2 describes the data used for the vector autoregressive model estimation presented in Section 3. In Section 4, French equities VaR are compared across investment horizons and phases of financial cycle. Section 6 concludes.

1 Vector autoregression modelling of VaR

1.1 The vector autoregressive model

So as to simplify the presentation, and without loss of generality, let us consider the following vector autoregression of order one[2] :

$$\mathsf{z}_t = \Phi_0 + \Phi_1 \mathsf{z}_{t-1} + \mathsf{v}_t, \tag{1}$$

where

$$\mathsf{z}_t = \begin{bmatrix} \mathsf{x}_t \\ \mathsf{s}_t \end{bmatrix}$$

is a $m \times 1$ vector with x_t, the $n \times 1$ vector of log excess returns and s_t the $m - n - 1 \times 1$ vector of variables which have been identified as financial markets cycle indicators. In equation (1), Φ_0 is the $m \times 1$ vector of intercepts and Φ_1 is the $m \times m$ matrix of slope coefficients. It is assumed that the roots of the characteristic polynomial $\Phi(z) = I_m - \Phi_1 z$ lie strictly outside the unit circle in absolute value, a condition which rules out nonstationary or explosive behavior in z_t. Finally, v_t is the $m \times 1$ vector of innovations which is assumed to be *i.i.d.* distributed with mean zero and covariance matrix Σ_v.

A very parsimonious version of this autoregressive model will be retained for the evaluation of VaR from French data. Let R_{0t} denote the nominal short rate and $r_{0t} = \log(1 + R_{0t})$ the log (or continuously compounded) return on this asset that is used as a benchmark to compute excess returns on equities. Then, with r_{et} the log stock return, let $x_{et} = r_{et} - r_{0t}$ denote the corresponding log excess returns. Finally, let m_{ct} denote the cyclical component of the log price index, to be defined later in the paper. In our empirical work, we will estimate a vector autoregression in which $\mathsf{z}_t = (x_{et}, m_{ct})'$.

[2]The analysis can be easily extended to more than one lag.

1.2 From vector autoregression to Value-at-Risk

Following Campbell and Viceira [2004], the one-period log returns are added over k successive periods in order to get the cumulative $k-$period log returns. The one corresponding to the log excess return on equities is denoted $x_{et}^k \equiv \mathsf{x}_{e,t+1} + \cdots + \mathsf{x}_{e,t+k}$. The vector autoregression is particularly well suited for forecasting purposes. By forward recursion of equation (1), it is possible to derive the expression of $(\mathsf{z}_{t+1} + \cdots + \mathsf{z}_{t+k})$:

$$\begin{aligned}
\mathsf{z}_{t+1} + \cdots + \mathsf{z}_{t+k} &= [k + (k-1)\Phi_1 + (k-2)\Phi_1^2 + \cdots + \Phi_1^{k-1}]\Phi_0 + (\Phi_1^k + \Phi_1^{k-1} + \cdots + \Phi_1)\mathsf{z}_t \\
&\quad + (1 + \Phi_1 + \cdots + \Phi_1^{k-1})\mathsf{v}_{t+1} + (1 + \Phi_1 + \cdots + \Phi_1^{k-2})\mathsf{v}_{t+2} + \cdots \\
&\quad + (1 + \Phi_1)\mathsf{v}_{t+k-1} + \mathsf{v}_{t+k},
\end{aligned}$$

or equivalently:

$$\mathsf{z}_{t+1} + \cdots + \mathsf{z}_{t+k} = \left[\sum_{i=0}^{k-1} (k-i)\Phi_1^i\right]\Phi_0 + \left[\sum_{j=1}^{k} \Phi_1^j\right]\mathsf{z}_t + \sum_{q=1}^{k}\left[\sum_{p=0}^{k-q} \Phi_1^p \mathsf{v}_{t+q}\right], \qquad (2)$$

where the first two terms on the RHS correspond to the $k-$period conditional mean, $E_t(\mathsf{z}_{t+1} + \cdots + \mathsf{z}_{t+k})$. Finally, the cumulative $k-$period log excess return on equities derives from equation (2) as follows:

$$x_{et}^k = M_r(\mathsf{z}_{t+1} + \cdots + \mathsf{z}_{t+k}), \qquad (3)$$

where the selection matrix is defined by $M_r = [\mathbf{I}_{n \times n}\ \mathbf{0}_{n \times (m-n-1)}]$. Dividing both sides of equation (3) by k gives the annualized log excess return.

The value-at-risk obtains straightforwardly from equation (2). The VaR is basically defined as a number such that there is a probability p that a worse excess (log-)return occurs over the next k periods. As such, the VaR is a quantile of this return distribution. The VaR of a long position (left tail of the distribution function) over the time horizon k with probability p may hence be defined from:

$$p = Pr\left[x_{et}^k \leq VaR\right] = F_k(VaR), \qquad (4)$$

where $F(\cdot)$ denotes the cumulative distribution function of x_{et}^k. The quantile function is the inverse of the cumulative distribution function from which the VaR obtains:

$$VaR_k(p) = F_k^{-1}(p). \tag{5}$$

Since x_{et}^k is the sum of log excess returns over k periods, it is also the log of the product of the excess returns (not taken in log) over k periods. Hence, the VaR of the corresponding capital requirement simply obtains as:

$$VaR_k^{cr}(p) = \exp(VaR_k(p)) - 1$$

Since we are interested in the value-at-risk for various time horizons, it is desirable to keep an equivalent risk level over all the horizons, which means adjusting p with k. For instance, the standard $1 - p = 99.5\%$ level retained in VaR analysis translates into one chance out of 200 for an event to occur on a yearly basis. In order to maintain the same yearly probability, the corresponding probability for horizon k must be adjusted accordingly, that is $1 - p = (99.5\%)^k$. All the computations below will retain this horizon-adjusted probability.

As can be seen from equation (5), such a VaR measure is directly affected by the distribution chosen for $F(\cdot)$. It is now well-known that the normal distribution is not suitable for most speculative assets, even at the quarterly or yearly frequency. Since there is no consensus regarding which alternative distribution to choose, we propose to retain a bootstrap approach relying on the empirical distribution. Basically, this approach consists in resampling S times the residuals estimated from model (1) so as to re-built S simulated sequences of $\frac{1}{k}(\mathsf{z}_{t+1} + \cdots + \mathsf{z}_{t+k})$ using equation (2). The method will be discussed to greater extend below and will be applied to the French data described in the next section.

2 The French assets return data

The short term rate is the 3-month PIBOR rate, obtained from Datastream from 1970Q1 to 1998Q4. It is then continued using the 3-month EURIBOR rate from 1999Q1 to

2008Q3. The end-of-quarter values from this monthly series are retained to get quarterly observations, and r_{0t} denotes the log return on this 3-month rate.

French data for equities prices and returns come from Morgan Stanley Capital International (MSCI) database and are available since December 1969. More precisely, quarterly stock market data are based on the monthly MSCI National Price and Gross Return Indices in local currency. From these data, a quarterly stock total return series and a quarterly dividend series are obtained following the methodology described in Campbell [1999][3]. Note that we depart from Campbell's approach by not including the tax credits on dividends which are applicable to France. Indeed, MSCI calculates returns from the perspective of US investors, so it excludes from its indices these tax credits which are available only to local investors. Campbell chooses to add back the tax credits quite roughly, by applying the 1992 rate of 33.33% to all the sample. Nevertheless, this rate hasn't remained fixed over the sample considered here (1970Q1—2008Q3). On top of this, the way dividends are taxed has also changed during that period. We couldn't find exact tax rate data for our sample, and guess that on average, the French tax credits system has increased the nominal stock returns by around 40%. Nevertheless, we choose to work with data excluding tax credits.

Finally, we have to find a proxy variable for the financial market cycle. From a practitioner's point of view, a variable such as a moving average of the log of the stock market price index would seem to be a good candidate because of its simplicity. Nevertheless, such kind of proxy variable has the serious drawback that a moving average is backward-looking by nature, and for this reason would always be late compared to the current cycle. For this reason, we have chosen to extract the trend component of the log stock market price index using the filter proposed in Hodrick and Prescott [1997]. This filter is the most used one in the business cycles literature since more than three decades. Of course, this filter is not perfect (see e.g. King and Rebelo [1993], Cogley and Nason [1995] or Pederson [2001] on this point) but it has the desirable property

[3]See also Campbell's "Data Appendix for *Asset Prices, Consumption and the Business Cycle*", March 1998, downloadable from Campbell's homepage.

to eliminate unit roots up to order four: the Hodrick-Prescott (HP hereafter) filtered cyclical component of a non stationary series is stationary. Furthermore, because the HP filter uses all the sample to extract the cyclical component, it is well in line with the current cycle contrary to such backward-oriented filtering methods as the moving average class of filters for instance. The last, but not least, reason which motivated our choice is that it is available in most, if not all econometrics softwares. Finally, m_{ct} denotes the HP filtered cyclical component of the quarterly log stock market price index data described in the previous paragraph. Figure 3 in Appendix reports the log returns and stock market cycle data.

Table 1 reports sample means, standard deviations and Dickey-Fuller unit root tests of our data computed for the whole sample, i.e. 1970Q4-2008Q3. To annualize the raw quarterly data of log returns, means are multiplied by 400 while standard deviations are multiplied by 200 since the latter increase with the square root of the time interval in serially uncorrelated data. Moreover, the means of log returns are adjusted by adding one-half their variance so that they reflect mean gross return.

Table 1: Sample statistics

	mean	standard deviation	ADF stat (lags)	p-value
r_0	7.18	1.73	-2.06 (1)	0.261
x_e	5.72	22.88	-11.61 (0)	0.000
m_c	0.00	0.16	-4.36 (0)	0.000

Remind that the stock return here does not include tax credits. When adding back, say, a 40% tax credit rate, the stock excess return would reach more than 8% per year. Volatility is much higher for stocks returns than for the PIBOR rate (22.88% and 1.73% resp.). Regarding the ADF unit root tests, the deterministic component includes at most a constant under the stationary alternative. The lag order of the ADF regression was selected as the smallest one succeeding in eliminating residuals autocorrelation up to order 8. Unsurprisingly, the unit root null is strongly rejected for the excess log returns on equities and the financial market cycle series. By contrast, a unit root is found in the nominal 3-month log return process, but this series will not be included in the vector autoregression.

3 Empirical assessment of the influence of the financial market cycle on excess equities log returns

In the sequel, we will consider an autoregressive model for $\mathsf{z}_t = (x_{et}, m_{ct})$ in equation (1). The lag order of is set to three, so as to eliminate residuals serial correlation: the null of no residuals autocorrelation up to order 8 is not rejected at the 38% level according to Box-Pierce statistics. The estimated model writes as follows:

$$\mathsf{z}_t = \Phi_0 + \Phi_1 \mathsf{z}_{t-1} + \Phi_2 \mathsf{z}_{t-2} + \Phi_3 \mathsf{z}_{t-3} + \mathsf{v}_t. \tag{6}$$

Due to the stock market data and the lag order, our estimation sample is 1971Q3–2008Q3, i.e. 149 observations. The results are reported in Table 3, see Appendix.

So as to check for the dynamic relationship between the market cycle and the excess equities returns, we performed Granger-causality tests using the Likelihood Ratio statistic. Table 2 reports the LR statistics and the corresponding p-values for the test that the three lags of the variables in columns are jointly zero in the equation of the variables in raw. This statistics is distributed as a Chi-squared with three degrees of freedom. As can be seen from this table, the nullity of m_c's coefficients in the equation of x_e is strongly rejected with a LR statistics of 40.37 to compare to a $\chi^2(3)$. Accordingly, we conclude that our proxy variable of the financial market cycle Granger-causes the log excess returns on equities. This confirms the relevance of the joint modelling of these two variables.

This causal link is further confirmed by the impulse response function of the log excess return on equities to an innovation in the market cycle. In order to identify this innovation, we performed a Choleski decomposition of Σ_v — the variance-covariance

Table 2: Granger (non-)causality tests

	Explanatory variables	
	$m_{c,t-i}$	$x_{e,t-i}$
Equation		
$x_{e,t}$	40.37	18.62
p-value	(0.00)	(0.00)
$m_{c,t}$	90.69	7.37
p-value	(0.00)	(0.06)

matrix of the vector autoregression estimated residuals — retaining the following ordering of the variables in the model: (m_{ct}, x_{et}). Denoting $\mathsf{v}_t = (v_t^m, v_t^x)'$ the residuals of model (1) for such an ordering of the variables, we define the structural innovations in the market cycle and the returns $\varepsilon_t = (\varepsilon_t^m, \varepsilon_t^x)'$, with $E(\varepsilon\varepsilon') = I$, by:

$$\mathsf{v}_t = G\varepsilon_t,$$

where G is the lower-triangular 2×2 matrix such that $GG' = \Sigma_v$. This choice allows the market's cycle innovations to affect instantaneously the excess return, while the return innovations influence the market cycle after one period only.[4] Figure 1 below reports this impulse response function of x_e to a favorable unit shock in the market cycle innovation, together with two-standard deviation confidence interval computed from 10,000 drawings of the estimated residuals. As can be seen from Figure 1, the instantaneous response of the excess return is positive, but then becomes significantly negative for two years before progressively going back to zero. Of course, an adverse shock would generate the reverse effect: the log returns would drop the first quarter but then would become positive the next two years before the shock's effect completely vanishes. This figure also reveals that after eight quarters, the impact of the financial cycle innovation on the excess return is not significantly different from zero.

[4] The results obtained from the alternative identification scheme are qualitatively similar.

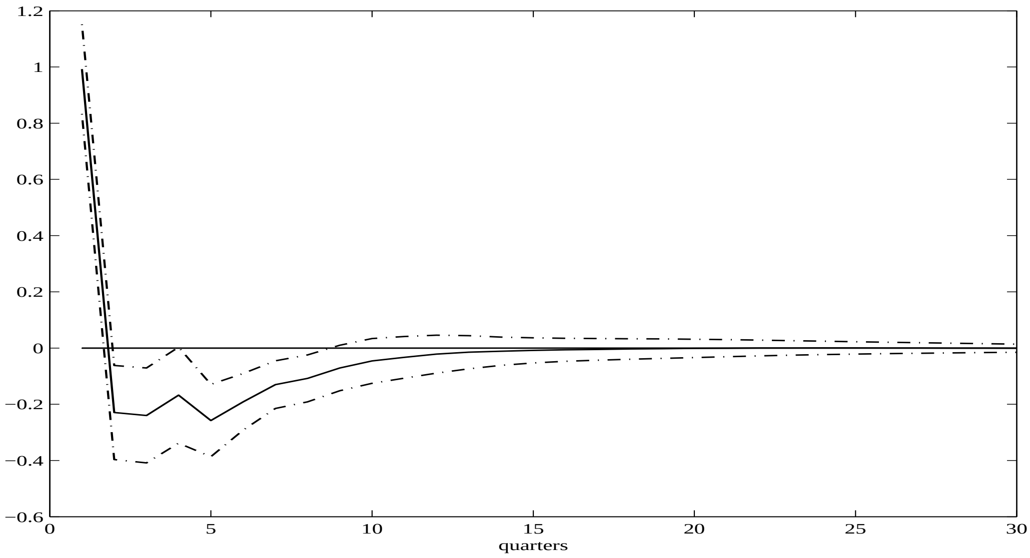

Figure 1: Response of x_e to a unit shock in ε^m

If the dynamics of the log returns is affected by innovations in market cycle, so should be the dynamics of the Value-at-Risk.

4 The dynamics of Value-at-Risk

4.1 The proposed empirical measures of the VaR$_k$

The bootstrap method we will describe below belongs to the multivariate filtered historical simulation (FHS) method presented in Chirstoffersen [2009]. This method consists in simulating future returns from a model using historical return innovations. It is qualified by "filtered" because it does not use simulations from the set of returns directly, but from the set of shocks, which are basically returns such as filtered by our vector autoregressive model.

The FHS method described in Chirstoffersen [2009] would amount in our case to the following: First, using random draws from a uniform distribution, the estimated residuals of model (6) are resampled S times. Using these S series of v^s together with the estimated parameters of model (6) and the observed values of $\{\mathsf{z}_i\}_{i=t}^{t-2}$, in equation (3),

S hypothetical sequences of x_{et}^k are obtained. The $VaR_k(p)$ then obtains by retaining — amongst these S simulated sequences — the value of return such that there is a probability p that a worse value occurs at horizon k. This method clearly accounts for the uncertainty of the shocks realization. However, by setting $\{\mathsf{z}_i^s\}_{i=t}^{t-2} = \{\mathsf{z}_i\}_{i=t}^{t-2}$, it makes the VaR measure strongly dependent on the last available observations. Since we aim at evaluating the impact of the financial cycle on the VaR for various investment horizons, we would rather control for the position in the cycle. We will do this by setting the excess return to its sample average, i.e. $\{\mathsf{x_e}_i^s\}_{i=t}^{t-2} = \bar{\mathsf{x}}_\mathsf{e}$, for $i = t-2, t-1, t$, while fixing the market cycle indicator respectively to its mean (mid-cycle measure), to its mean plus one-standard deviation (one-standard expansion case) and to its mean minus one standard deviation (one-standard recession case).

Another interesting measure of the VaR is one which would be made independent on the values retained for $\{\mathsf{z}_i^s\}_{i=t}^{t-2}$. One way to achieve this is to use the S bootstrapped series of v^s and the estimated parameters of model (6) to build S hypothetical $\{\mathsf{z}_i^s\}_{i=1}^{T}$ and then set $\{\mathsf{z}_i^s\}_{i=t}^{t-2} = \{\mathsf{z}_i^s\}_{i=T}^{T-2}$. Hence, we will use S different sets of values for $\{\mathsf{z}_i^s\}_{i=t}^{t-2}$ in order to compute the sequences of x_{et}^k. By contrast with Chirstoffersen [2009]'s approach, this measure will incorporate the uncertainty on the values conditioning the forecasts. Consequently, we expect it to be more conservative than the other ones. Let us call it the a-cyclical measure.

4.2 Empirical measures of VaR$_k$ across investment horizon and financial cycle

The results reported below were obtained for $S = 300,000$ simulations for each $k = 1, \cdots, 20$ years, from which we picked up the corresponding $(1 - 99.5^k\%)$ quantile for each VaR_k^{cr}. Figure 2 plots the four measures of VaR_k^{cr} described above, namely the mid-cycle, the $+\sigma_{mc}$, the $-\sigma_{mc}$, and the a-cyclical ones, against holding horizons up to twenty years[5]. The first important result emerging from this figure is that whatever

[5]See the corresponding figures in Table 4 reported in the appendix.

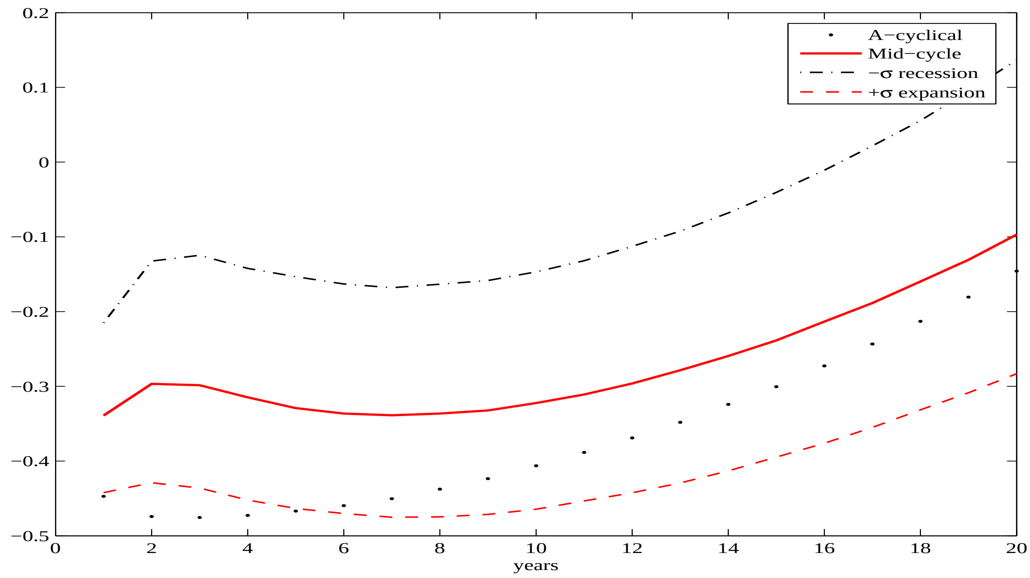

Figure 2: Value-at-Risk($99.5^k\%$) across holding horizons

the investment horizon, the VaR depends on the position in the financial cycle. When starting from a one-standard recession, the one-year VaR is around -22% while it drops to -44% when starting from a one-standard expansion. For all horizons, the VaR is stronger in expansion than in recession. This suggests that a rule imposing the same solvency capital requirement whatever the state of the financial market cycle could actually be pro-cyclical. It is worth noticing that our empirical measure of the VaR^{cr} at the one-year horizon starting from a mid-cycle position (-34%) is very close to the ones reported in the 2007 Quantitative Impact Studies QIS3 of the Committee of European Insurance and Occupational Pensions Supervisors. Assuming a Gumbel distribution of returns, this study reports a $VaR^{cr}(99.5\%)$ of -36% using quarterly data of a European aggregate index from 1970 to 2006.[6]

The second important result concerns the dynamics of the VaR across investment horizons. In a previous study (see Bec and Gollier [2007]), we have found mean-reversion

[6]See the report "QIS3, Calibration of the underwriting risk, market risk and MCR", Committee of European Insurance and Occupational Pensions Supervisors, April 2007, p.36.

in log returns on equities relatively to other assets returns: their relative risk was found decreasing with the holding period. This is confirmed by the results in Figure 2. Indeed, the worst expected loss in terms of capital requirement, at the $(1-0.995^k)-$percent level, decreases with the investment horizon. Starting from a standard recession, it could even become a gain after 17 years according to our estimates. These results are quite robust to the estimation period. The same exercise performed for the periods 1971Q3-2000Q4 and 1971Q3-2003Q4 yields very close VaRs[7].

Finally, due to the additional uncertainty it includes, the a-cyclical measure is always more conservative than the mid-cycle or the standard recession measures.

5 Concluding remarks

The vector autoregressive joint modelling of French equities excess returns and financial market cycle indicator reveals that the latter helps predicting the former. Put in other words, the financial market cycle variable Granger-causes the excess returns on equities. Since the Value-at-Risk is evaluated from the expected excess returns, it is also influenced by the state of the financial cycle. If, starting from a mid-cycle position, the VaR at the one year horizon is found to be close to other existing measures (34%), it can fall to -44% when calculated from a one-standard expansion and even become a gain instead of a loss when calculated from a one-standard recession. Our results provide support to the claim that fixed solvency capital requirements may have important procyclical consequences on the dynamic investment strategies of the financial intermediaries. Finally, this paper confirms the French equities returns predictability already found in an earlier work (Bec and Gollier [2007]). Our results indeed point to a decrease in the VaR as the holding period increases.

[7]In order to save space, these results are not reported but they are available upon request from the authors.

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Appendix

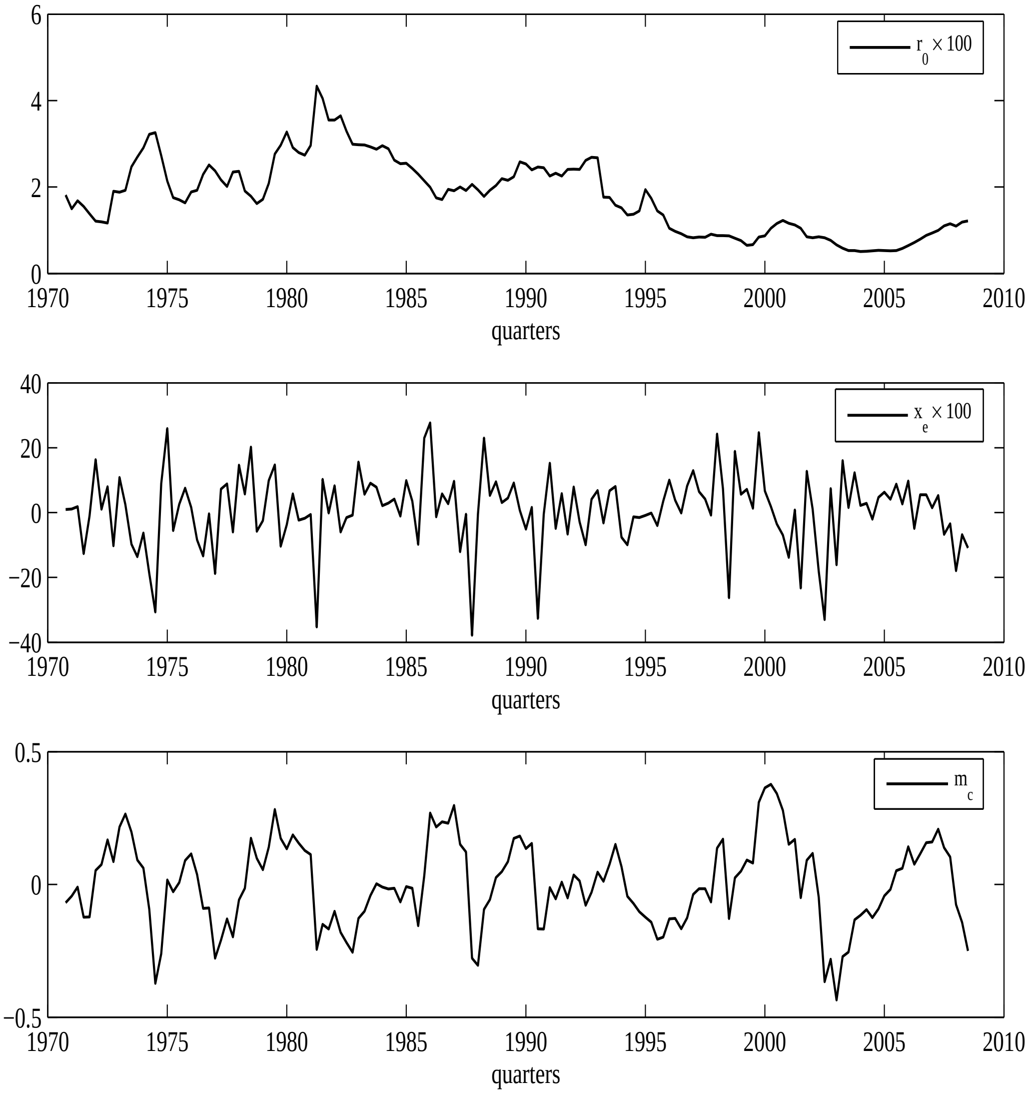

Figure 3: French data (1970Q4—2008Q4)

Table 3: VAR estimation results

	$m_{c,t}$	$x_{e,t}$
$m_{c,t-1}$	5.978	3.611
	(3.509)	(3.483)
	[0.09]	[0.30]
$m_{c,t-2}$	-11.019	-9.270
	(7.025)	(6.973)
	[0.11]	[0.18]
$m_{c,t-3}$	5.653	5.263
	(3.482)	(3.456)
	[0.10]	[0.12]
$x_{e,t-1}$	-5.212	-3.850
	(3.539)	(3.512)
	[0.14]	[0.27]
$x_{e,t-2}$	5.762	5.371
	(3.502)	(3.476)
	[0.10]	[0.12]
$x_{e,t-3}$	0.116	0.117
	(0.085)	(0.084)
	[0.17]	[0.16]
c	-0.006	-0.006
	(0.009)	(0.009)
	[0.51]	[0.52]
R-squared	0.60	0.24
Log-likelihood	129.99	131.09
Tests of residuals autocorrelation:		
LM-test	LM(4)=4.98	LM(8)= 4.08
	(0.29)	(0.39)
Box-Pierce	BP(4) = 7.66	BP(8) = 21.21
	(0.10)	(0.38)

Standard errors in ( ) and p-values of t-statistics in [ ].

Table 4: $VaR_k^{cr}(1-0.995^k)$ across investment horizon k

Years	mid-cycle	$-\sigma$ recession	$+\sigma$ expansion	a-cyclical
1	-0.33919	-0.21502	-0.44230	-0.44726
2	-0.29677	-0.13250	-0.42907	-0.47431
3	-0.29859	-0.12470	-0.43608	-0.47553
4	-0.31471	-0.14225	-0.45216	-0.47277
5	-0.32926	-0.15325	-0.46341	-0.46704
6	-0.33655	-0.16303	-0.47033	-0.45975
7	-0.33877	-0.16811	-0.47516	-0.45042
8	-0.33646	-0.16345	-0.47471	-0.43763
9	-0.33227	-0.15851	-0.47145	-0.42352
10	-0.32232	-0.14681	-0.46447	-0.40643
11	-0.31103	-0.13198	-0.45337	-0.38841
12	-0.29628	-0.11269	-0.44247	-0.36917
13	-0.27853	-0.09245	-0.42934	-0.34816
14	-0.25945	-0.06796	-0.41317	-0.32423
15	-0.23853	-0.04049	-0.39481	-0.30056
16	-0.21349	-0.01082	-0.37623	-0.27275
17	-0.18864	0.02168	-0.35502	-0.24346
18	-0.15971	0.05559	-0.33157	-0.21313
19	-0.13072	0.09511	-0.30862	-0.18065
20	-0.09695	0.13670	-0.28310	-0.14587