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Noise traders or Fundamentalists? A Wavelet approach

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Abstract

According to market heterogeneity hypothesis, financial markets are characterized by the presence of heterogeneity of participants with different sensibilities to different time scales. Although Wavelet based Value at Risk is able to represent dealing frequencies of market participants, it doesn't explicitly take into account the presence of Noise traders and Fundamentalists. In this paper, we introduce a Wavelet Value at Risk model which make a clear distinction between the two categories of traders. Thus, WVaR of Fundamentalists shows good performance especially in a high volatility regime as the one which has occurred in 2008

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1. Introduction:

Financial markets are characterized by presence of a large heterogeneity of participants which impacts on their sensibilities to different time scales. Thus, time horizons heterogeneity is a major factor which must be embedded in VaR estimation.
The wavelet transform allows us to capture the high frequency volatility dynamics through fine scales, and the low frequency ones through coarse scales. Some authors have used the wavelet decomposition to estimate the VaR. Namely Hamburger(2003), and He,Xie,Chen,and Lai(2006).
In this article, our contribution to VaR estimation is twofold. We follow the JP Morgan Riskmetrics by assuming the conditional normality for the distribution for returns series with volatility modelled as an IGARCH(1,1).We also extend Hamburger (2003) and He et al.(2006) approach by considering the evolutionary competition between market participants according to their specific dealing frequencies. Thus, We consider short term dealing frequency for daily traders (Noise traders), and long-term dealing frequency for market participants who trade in a monthly frequency and more(Fundamentalists).
The article is organized as follows. The second section will be a brief overview of market heterogeneity hypothesis and evolutionary competition. In the third section, we will introduceWavelet Value at Risk(WVaR). In the fourth section, we will compute WVaR of CAC40,the French stock market index. In a fifth section, we will conclude.

2. Literature review:

2.1 Heteregeneous market hypothesis :

According to heterogeneous market hypothesis, there is a presence of heterogeneity in the traders (Müller et al.1997).The traders may differ in their perceptions of the market, risk profiles, informational sets, prior beliefs, institutional constraints, and other characteristics. These differences among market participants translate to their sensivity to different time horizons.Therefore, an interesting categorization of the market participants can be found in their characteristic time horizons and dealing frequencies.
On the side of high dealing frequencies, there are intraday speculators and market makers; on the side of low frequencies, there are the central banks and pensions funds.Short-term traders are constantly watching the market to reevaluate their current positions and execute transactions at a high frequency. Long term traders may look at the market only once a day or less frequently. Long-term traders are interested only in large price movements and these normally happen only over long time intervals. As a consequence, this evidence of market heterogeneity leads to a presence of different dealing frequencies, and thus different reactions to the same news in the same market. Each market component has its own reaction time to information, related to its time horizon and characteristic dealing frequency (Dacorogna et al., 2001). Thus, the volatility process has a scaling behaviour. We can distinguish the low frequency volatility(coarse) which capture the perceptions and actions of long term horizon traders, and a high frequency volatility(fine) which capture the expectations and decisions of short term traders (Gencay and Selcuk, 2004).
To further examine the volatility multifequency structure and identify the relative presence of market components, Müller et al.(1997) introduce an heterogeneous ARCH model (HARCH) which differs from all other ARCH-type processes in the unique property of considering the volatilities of returns over different time horizons.
We assume that the time-frequency analysis of wavelet transform is a pertinent statistical

tool for modelling volatility asymmetry rooted in financial market heterogeneity.

2.2.Evolutionary competition:

De Long and al.(1990) make a clear distinction between two categories of market participants:
-The fundamentalists well informed, more rational, risk-averse, which base their trading rule on the fundamental value of asset prices given by the expected discount sum of future dividends.
-The noise traders, technical analysts or chartists less informed, boundedly rational, less risk averse. Their trading rule consists on observing past prices and extrapolating the historical trend.
The fraction of each trader type evolves over time and there exist an irregular switch between the two trading strategies according to their past realized profits. Once a certain threshold value of chartists is exceeded, the system becomes unstable and extreme returns occur. During this regime, prices deviate strongly from their fundamental values, creating bubbles or crashes. As a consequence, the fundamentalist strategy become more profitable, inducing more and more agents to switch from a noise to a fundamental strategy. This switching behaviour slowly brings prices back towards the fundamental value and is the stabilizing device of the system. Thus, the market is characterized by an irregular switching between phases of low volatility when prices changes are small, and phases of high volatility where prices changes due to random news are amplified and become large due the trend following trading rules (Kirman et al., 2002), Lux(1995).This interaction between noise traders and fundamentalists can create endogeneously a volatility clustering and a complex price behaviour which can be chaotic (Brocks et al.,1998).The short horizon traders can be identified with noise traders whereas the long run horizon traders with fundamentalists.

3. The Wavelet transform:

For most economic time series, the stationary assumption is too restrictive as they are affected by structural shifts, temporary shocks, or GARCH effect.
Wavelet transformation, in contrast to the familiar Fourier transform, enables us to relax this assumption by dividing the time axis into a sequence of successively smaller segments which are analysed individually. Specially, the discrete wavelet transform (DWT) which transforms a time series into frequency ‘’bands’’(segments of the time domain) that are referred to as ‘’scales ‘’ in wavelet analysis. The wavelet transform operates simultaneously on a range of scales. As the scale decreases, segments become narrower and inversely. A low scale corresponds to a large number of shorter time intervals, thereby capturing short duration/high frequency fluctuations, while a high scale corresponds to a smaller number of longer intervals, thereby capturing long duration/low frequency fluctuations. In other words there is an inverse relationship between frequency and scale (Priestley,1996).

3.1 Multiresolution analysis(MRA):

The name ‘’wavelet’’ is reputed to have come from the requirement that admissible functions integrate to zero, that is, they’’rise and fall’’ like ocean waves, above and below the x-axis.The suffixe ‘’let’’ suggests a local function , rather than a global one.(Grossman and Morlet, 1984).

There are two types of wavelets; father wavelets ϕ and mother wavelet ψ. The father wavelet
integrates to1 and the mother wavelet integrates to 0:

$$\int \phi(t)dt = 1, \int \psi(t)dt = 0 \qquad (1)$$

The father wavelets represent the smooth or low frequency parts of a signal, and the mother wavelets capture the details or high-frequency components. Thus, father wavelets and mother wavelets capture respectively the signal trend components and all deviations from this trend. A lot of wavelets families have been introduced. The most used empirically are orthogonal wavelets such as the Haar, Daublets, Symmlets and Coiflets (Daubechies,1992).

Wavelets consist on a two-scale dilatation equation. The dilatation equation of father wavelet $\phi(x)$ can be expressed as follows:

$$\phi(x) = \sqrt{2}\sum_k l_k \phi(2x - k) \qquad (2)$$

The mother wavelet $\psi(x)$ can be derived from the father wavelet by the following formula:

$$\psi(x) = \sqrt{2}\sum_k h_k \phi(2x - k). \qquad (3)$$

The coefficients l_k and h_k are called respectively the low-pass and high-pass filter coefficients.

Any function $f(t)$ in $L^2(\mathbf{R})$ to be represented by a wavelet analysis can be built up as sequence of projections onto father and mother wavelets generated from ϕ and ψ through scaling (stretching and compressing) and translation as follows:

$$\phi_{j,k}(t) = 2^{j/2}\phi(2^{-j}t - k) \qquad (4)$$

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^{-j}t - k) \qquad (5)$$

The wavelet representation of the signal or function $f(t)$ in $L^2(\mathbf{R})$ can be given as :

$$f(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \dots\dots + \sum_k d_{1,k}\psi_{1,k}(t) \qquad (6)$$

where J is the number of multiresolution components, and k ranges from 1 to the number of coefficients in the specified component.

The multiresolution decomposition of a signal $f(t)$ into orthogonal components at different scales or frequency ranges can be defined as:

$$f(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \dots\dots + D_1(t). \qquad (7)$$

Where:

$$S_J(t) = \sum_k s_{J,k}\phi_{J,k}(t) \qquad (8)$$

.

$$D_j(t) = \sum_k d_{j,k}\psi_{J,k}(t) \text{ for j=1, 2,…, } J \qquad (9)$$

The functions(8) and(9) are respectively called the smooth signal and the details signals which constitute a decomposition of a signal into orthogonal components at different scales (Mallat, 1989).

3.2. Wavelet Value at Risk model:

Financial markets consists on heterogeneous participants: market makers, intraday traders,daily traders, short term traders, and long term traders. Consequently, prices are formed with influence from different types of investors characterized by different time horizons. Thus, Market risk has a multifrequency structure which must be embedded in VaR estimation.

The projection of the original returns time series $f(t)$ into the time scale domain with the chosen wavelet family as in (7):

$$f(t) = S_J(t) + \sum_{j=1}^{J} D_j(t) \qquad (10)$$

$S_J(t)$ refers to the decomposed time series using scaling function (father wavelet) at scale J

$D_j(t)$ refers to the decomposed time series using wavelet function at scales j up to scale J.

Thus, VaR can be estimated in the time-frequency domain as follows :

$$VaR\left[f(t)\right] = VaR[S_J(t)] + \sum_{j=1}^{J} VaR[D_j(t)] \qquad (11)$$

According to the preservation of energy property of wavelet transform, the variance for returns series is reconstructed from variance estimates at each scale j.

So as to compute the VaR at each time scale, we follow the convention used in financial risk modelling which consists on taking the mean value of returns series as zero. We also follow the JP Morgan Riskmetrics by assuming the conditional normality for the distribution for returns series with volatility modelled as an IGARCH(1,1) namely:

$$VaR_{t+1} = \sigma_{t+1}\phi^{-1}(\alpha) \qquad (12)$$

$$\sigma_{t+1}^2 = \lambda\sigma_t^2 + (1-\lambda)r_t^2 \quad , \quad 0 < \lambda < 1 \qquad (13)$$

Where is the confidence level of VaR, $\phi^{-1}(.)$ is the inverse function of cumulative distribution of normal distribution.

4. WVaR of CAC 40 index:

In order to estimate French stock market index CAC 40 Wavelet Value at Risk, we will use 3 sample sizes; respectively 500,1000, 2000 daily observations ending in December31, 2007.

4.1 Data :

The data consists of the daily closing prices for CAC40. Dickey-Fuller (1979) and Phillips and Perron (1988) tests show a presence of an unit root in the CAC40 time series.
We transform it by applying a first difference filter into a series of continuously compounded percentage returns by taking 100 times to log price relatives, i.e. $r_t = 100 * \ln(P_t / P_{t-1})$, where P_t is the closing price of the CAC40 index on day *t*.
In order to decompose the return time series, we choose the symlet 8 wavelet. The choice of this wavelet family was motivated by its ability to provide the best reconstruction quality of the signal and mimic the oscillations of financial data. The decomposition level is set to 6 as it enables us to preserve the signal quality and also reflect the main trading frequencies of heterogeneous participants of the market.
The Figure 1 shows the CAC 40 returns series wavelet decomposition and figure 2 shows the wavelet tree decomposition (see appendix).
The first detail level d1 is associated with the day traders activity, the detail levels d2 and d3 are associated with traders who adjust their portfolio in a bi-weekly frequency. The details d2, d3 and d4 levels correspond to the fund managers trading activity who adjust their portfolio at a monthly basis. The details [d2, d3, d4, d5, d6] and the approximation a6 represent the trading activity of mutual funds who reconsider their market position in a quarterly frequency.
Table I shows the parameters estimated $1-\lambda$ and λ (α and β) for IGARCH(1,1) model corresponding to detail time series of each decomposition level and the sixth approximation.

Table I. Multiscale IGACH estimated parameters

Sample size	Parameters	D1	D2	D3	D4	D5	D6	A6
500	α	0,167421	0,241303	0,397569	0,602799	0,707919	0,750162	0,779028
	β	0,832579	0,758697	0,602431	0,397201	0,292081	0,249838	0,220972
1000	α	0,202411	0,221189	0,386832	0,622441	0,699276	0,749529	0,768201
	β	0,797589	0,778811	0,613168	0,375759	0,300724	0,250471	0,231799
2000	α	0,196694	0,207519	0,390882	0,624887	0,711331	0,754194	0,777743
	β	0,803306	0,792781	0,609118	0,375113	0,288669	0,245806	0,222257

The results show the large differences between IGARCH(1,1) parameters corresponding to each frequency band (thus to a category of traders), which reveal the different generating processes of volatility specific to each decomposition level. It allows us to confirm strongly the heterogeneous market hypothesis.

4.2 WVaR:

Taking into account the market time horizons heterogeneity, the Wavelet Value at Risk can be computed as:

$$WVaR_t = VaR_t^{D1} + VaR_t^{D2} + VaR_t^{D3} + VaR_t^{D4} + VaR_t^{D5} + VaR_t^{D6} \qquad (14)$$

which can be expressed as:

$$WVaR_t = VaR_t^{daily} + VaR_t^{weekly} + VaR_t^{bi-weekly} + VaR_t^{monthly} + VaR_t^{quarterly} \qquad (15)$$

As short horizon traders can be identified with noise traders whereas the long run horizon traders with fundamentalists, we assume that VaR_t^{daily} corresponds to noise traders: **Noisy Wavelet VaR**(NWVaR) and $[VaR_t^{weekly} + VaR_t^{bi-weekly} + VaR_t^{monthly} + VaR_t^{quarterly}]$ corresponds to fundamentalists: **Fundamental Wavelet VaR** (FWVaR).

We thus get the following analytical formula at 99% confidence level:

$$\begin{aligned} NWVaR_t &= -2{,}33*(\sigma_t^{daily}) \\ FWVaR_t &= -2{,}33*(\sigma_t^{weekly} + \sigma_t^{bi-weekly} + \sigma_t^{monthly} + \sigma_t^{quarterly}) \end{aligned} \qquad (16)$$

4.2.1 Backtesting WVaR models :

In order to evaluate their out-of sample forecasting performance, we will use the time period from January 2, 2008 to December31, 2008. The sample size is 255 daily observations.

It corresponds to international financial crisis which occurs after the subprime crisis in USA and culminates by the Lehman Brother collapse in September 15, 2008. We will use a rolling window scheme. The WVaR models are computed respectively on the basis of 2000, 1000 and 500 daily returns, and then the window is rolled forward eliminating the first observation and including the next one for re-estimation of models. The procedure is then repeated until the last observation of the sample is reached.

4.2.2 Kupiec Test (1995)

Backtesting procedures are formal statistical methods which allow us to verify whether the VaR forecasts are in line with the realized losses.They involve exceedance observations, where an exceedance observation (tail loss) is a loss that exceed the VaR. The basic frequency test suggested by Kupiec(1995) test whether the observed frequency of exceedances is consistent with the frequency predicted by the VaR model. In particular, under the null hypothesis that the model is’’good”, the number of exceedance x given n observations follows a binomial distribution with probability p, where p is the tail probability or 1 minus the confidence level. In a likehood ratio form, the Kupiec test statistic under the hypothesis of correct unconditional coverage expressed as:

$$LR_{UC} = -2\ln\left(\frac{(1-p)^{n-x}\,p^{x}}{\left[1-\frac{x}{n}\right]^{n-x}\left(\frac{x}{n}\right)^{x}}\right) \quad (17)$$

is distributed as a chi-squared with one degree of freedom $\chi^2(1)$.

Table II shows the WVaR backtesting according to Kupiec test (1995).

Table II. Kupiec test outcomes

Confidence level	Model	Sample size		
		500	1000	2000
99%	NWVaR	85,93	139,64	85,93
	FWVaR	0,709	0,075	2,055
95%	NWVaR	47,99	108,38	84,66
	FWVaR	0,005	0,2646	0,6721

According to the Kupiec test, the FWVaR model is accepted at all confidence levels whatever the sample size is. However, NWVaR model is strongly rejected at all confidence levels and at all sample sizes.

It confirms the fact that noise traders execute transactions at a high frequency. They are generally intraday speculators who reevalute their positions and may liquidate them before the market closing. So, the VaR estimation is not a very interesting issue for this category of traders. As they can exacerbate volatility, a pertinent VaR computation must not take into account their contribution to market global volatility. Thus, for long term traders especially pension funds and central banks who deal at low frequencies, the Fundamental Value at Risk is more accurate according to the Kupiec test although in a high volatility regime as occurred in 2008.

5. Conclusion:

Financial markets are characterized by presence of large heterogeneity of participants which translates to their dealing frequency. The wavelet transform allows us the measurement of volatility at different temporal resolutions.

We thus introduced a new market risk model: the Wavelet value at Risk. The WVaR has the ability to extract information about the multifrequency market risk structure in accordance with the heterogeneous market hypothesis. It defines volatility components over differing time horizons which have different effects on current volatility. Consequently, it provides confirmatory evidence of heterogeneous components and support for the interpretation of such components as resulting from the presence of different traders types.

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Appendix

Figure1. Wavelet decomposition of CAC 40

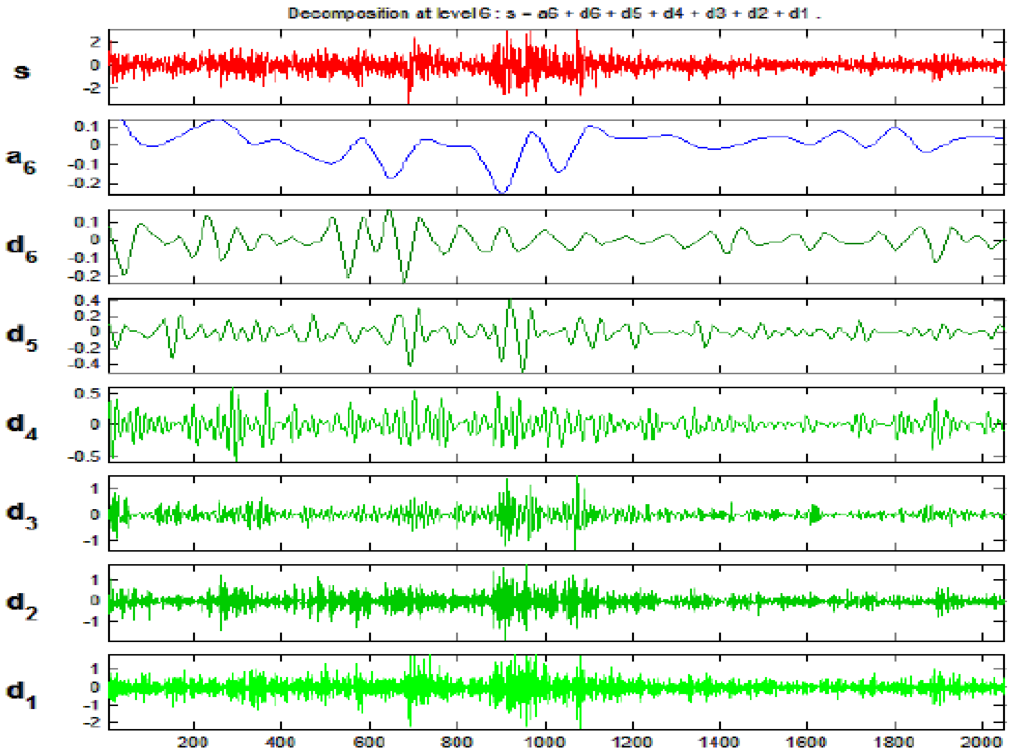

Figure 2. DWT wavelet tree