Wavelet-Based Prediction for Governance, Diversi cation and Value Creation Variables

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Abstract

We study the possibility of completing data bases of a sample of governance, diversification and value creation variables by providing a well adapted method to reconstruct the missing parts in order to obtain a complete sample to be applied for testing the ownership-structure/diversification relationship. It consists of a dynamic procedure based on wavelets. A comparison with Neural Networks, the most used method, is provided to prove the efficiency of the here-developed one. The empirical tests are conducted on a set of French firms.

Key words: Wavelets, Time series, Forecasting, Governance, Diversification, Value creation.

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1 Introduction

The relationship relationship ownership-structure/diversification is of great interest in financial studies due to the role of diversification as a strategic choice affecting the capacity of firm development during long periods, its financing needs, its performance as well as related risks. Such a decision may cause some inter-actors interest conflicts and it may be imposed within its actionnarial structure. The main problem in studying the relationship ownership-structure/diversification is the necessity of conducting it on a complete data basis. So, with missing data, the study can not be well conducted and no conclusions can be pointed out correctly. This leads to a second problem consisting of completing data bases by reconstructing missing parts which induces also the third most difficult problem based on the fact that governance, diversification and value creation variables are short time series (One value on a year) leading any reconstruction to be difficult. This motivates our work here consisting of providing a well adapted method to reconstruct the missing parts on a sample of governance, diversification and value creation variables in order to obtain a complete sample to be applied for testing the ownership-structure/diversification relationship.

It is well known and often obvious that statistical or empirical tests are well conducted with complete sample datum. But, in many major cases, it may happen that some data are missing or can not be provided by the owner especially when dealing with fuzzy data, secured or coded data, etc. In these cases, the non availability may yield essential problems effecting the conclusions that can be conducted from empirical tests. Indeed, the incomplete file treatment places the statistician in front of difficulties in applying theoretical concepts. Furthermore, it can not generalize the discovered conclusions on all the population especially when dealing with important missing data parts. Otherwise, in multi regression analysis, some variables are non informative or redundant. Besides, the absence of data can eliminate the incomplete observations. The loss of information thus gotten can be considerable if numerous variables present missing values on different individuals. This problem therefore, of missing data should be managed with precaution in order to avoid all slanted in evaluating and analyzing results. The researches on this problem are growing up and different methods have been investigated in order to overcome the difficulties. From a practical point of view, especially for financial analysts and/or economists, it seems that the most effective idea is about the reconstruction of such data to obtain quasi-complete samples. Different methods have been proposed and tested, such as Neural Networks, Fuzzy Logic, Fourier Analysis, Autoregressive Models, etc. See for intense Miller (1990), Wodzisaw and (1996)), Karp et al (1988). However, these methods have not been efficient in all cases and in contrast they can lead to noised reconstructed data. Furthermore, it has been proved that such methods can not analyze all types of data. Let us comment them briefly and separately. Neural Networks approach has been widely used as an alternative for signal approximation since it provides a generic black-box representation for implementing mappings from an inputs' space to an outputs' one. The approximation accuracy depends on the measure of signal closeness. Neural Networks implementation is essentially based on key activation functions. So, the crucial point to obtain best approximations turns around how one should chose these functions. Almost all papers dealing with the subject are based on the assumptions that such functions are integrable, sigmoidal squashing, monotone, continuous and/or bounded. More precisely, there are not many choices of such functions but these are limited to sigmoid, tanh and Heaviside. Fuzzy Logic is based on two main principles. First, it requires to fix the input rules and to conduct data to satisfy or not these rules which is somehow ambiguous. Autoregressive Models are also based on one main hypothesis affirming that some dependence of present data on its history should exist. Fourier Analysis which consists in developing periodical phenomena in a superposition of oscillating ones based on sine and cosine with known frequencies and amplitudes, provides precious information on the analyzed signal. For example, for higher frequencies, the signal varies slowly conversely to low frequencies where it varies rapidly. But, the major problem is the fact that Fourier Analysis can not localize well the region of high or low variations. This lack in time and frequency localization lets researchers to think about new tools taking it into account. Recently, until the 80's, a new mathematical tool has been introduced issued from signal processing theory. It consists of Wavelet theory which has been proved to be a best candidate that refines the existing methods to be more adequate to data problems. The crucial idea in wavelet analysis consists in decomposing a time series into independent components with different scales well localized in time and frequency domains. So, wavelet analysis is until its appearance strongly related to scaling concept. Indeed, an analyzing basis is always obtained from a source function called mother wavelet by scaling and translation actions. Scaling analysis is firstly discovered in physics and next it has been increasingly applied to other disciplines especially in mathematics where theoretical concepts are developed and extended. In financial studies, scaling analysis have been applied for economic and/or financial data to prove the existence of scaling laws such as financial prices, exchange rates, etc. Scaling analysis of data gives useful information on the process that generates such data. Such process is the crucial point for understanding empirical and theoretical mechanisms that generate the data and in using the empirical scaling evidence as a stylized fact that any theoretical model should also reproduce. Several models have been proposed in the literature. However, they succeed in explaining some empirical cases, but fail in many others. Wavelet methods initially introduced in mathematics and physics have been applied in many fields such as finance. We want in the present paper to provide some contributions clarifying theses concepts, based on financial data samples. We propose to reconstruct missing data parts in order to obtain a complete basis. The completeness of missing data bases is already evoked by many authors such as Aminghafari et al (2007), Ben Mabrouk et al (2008), Karp (1988), Soltani (2002), etc, and the studies in such a subject are increasing. However, the classical methods such as Neural Networks, Fuzzy Logic, Fourier Analysis, Autoregressive Models suffer from important insufficiencies especially in causing noise components. Wavelet methods have been proved to be the most powerful tool in reconstructing missing parts already with eliminating the noise. This is a first motivation in the application of wavelet analysis in our study. A second motivation is due to the fact that wavelet algorithms are usually most rapid yielding thus an important gain in time and cost. Furthermore, it permits to overcome the non disposability data problem and/or the hard data access.

One principal aim of the present work is to test the wavelet method in constructing missing data yielding prediction prospects and hence it may enable interesting functional regression complements. One motivation of our idea is to provide a longitudinal study to test the relation governance and diversification strategies. Indeed, some tests conducted with classical well known methods such as Neural Networks are developed and yielded non efficient results. This resolves the cross-section studies problem. Recall that the relation between diversification strategies and performance has already been the object of several studies such as Wernerfelt et al (1988), Amit et al (1988), etc. However, even-though, there are enough studies on such a subject, the results remains non concluding. See for instance Ramanujam et al (1989). A detailed study on such a subject will be provided later on complete sample data based on the theoretical results.

The present paper will be organized as follows. In the next section, some basics on wavelet analysis are reviewed, essentially those related to our application. In section 3, the proposed prediction method of financial series and so time series is developed based on wavelet estimators. It consists of a wavelet series learning algorithm consisting in acting dynamic wavelet estimators to build predicted values on short time series. The main crucial point that makes the method important is its simplicity in one hand especially for machine implementing and on the other hand, because of the fact that it acts on governance, performance and diversification variables. In such cases, the data is characterized by short time horizons which may effect negatively on empirical results. Indeed, in section 4, empirical results are provided already with eventual discussions based on comparisons with old methods such as Neural Networks. It is shown that predicted values and also reconstructed values of real data on Neural Networks are not adequate. We conclude afterwards.

2 Wavelet analysis review

Wavelet analysis has been practically introduced in the beginning of the 80's in the context of signal analysis and oil exploration. It gives a representation of signals permitting the simultaneously enhancement of the temporal and the frequency information (time-frequency localization). Its application comes to overcome the insufficiencies of Fourier Analysis. It consists in decomposing a series into different frequency components with a scale adapted resolution. The advantage that it presents compared to Fourier Analysis is the fact that it permits to observe and to analyze data at different scales.Wavelets analysis proposed initially by J. Morlet, is based on a concept somewhat different from the frequency one: the concept of scale. Instead of considering oscillating functions supported on a window, that can be shifted along the support of the analyzed signal, wavelet basis elements are copies of each other nearly compliant and only differ by their sizes (Daubechies (1992), Gasquet and Witomsky (1990)). Wavelet based methods are part of the most effective methods currently used. The starting point in wavelet analysis is to decompose a time series on scale-by-scale basis in order to control the series structure at different horizons. A wavelet basis is obtained from one source function ψ known as mother wavelet by dilation and translation operations. Each wavelet basis element is defined for $j, k \in \mathbb{Z}$ as a copy of ψ at the scale j and the position k,

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

The quantity 2^j designing the frequency of the series reflects the dynamic behavior of the series according to the time variable. This is why the index j is usually called the frequency. From a mathematical-physical point of view, the index k localizes the singularities of the series. In finance, or in data analysis the index k is used to localize the fluctuations and the missing data periods. Let for $j \in \mathbb{Z}$ fixed, W_j be the space generated by $(\psi_{j,k})_k$. Such a space is called the j-level details space. A time series $X(t)$ is projected onto W_j yielding a component $X_j^d(t)$ given by

$$X_j^d(t) = \sum_k d_{j,k}\psi_{j,k}(t) \tag{1}$$

where the $d_{j,k}$'s known as the wavelet or the detail coefficients of the series $X(t)$ are obtained by

$$d_{j,k} = < X; \psi_{j,k} > = \int_{\mathbb{R}} X(t)\psi_{j,k}(t)dt.$$

We will see later the impact of these coefficients in financial series analysis. In wavelet theory, the spaces W_j's satisfy the following orthogonal sum.

$$\overset{\perp}{\bigoplus_{j\in\mathbb{Z}}} W_j = L^2(\mathbb{R}). \tag{2}$$

This means that the series $X(t)$ can be completely reconstructed via its detail components and that these components are mutually uncorrelated. But a famous starting point in financial studies before going on studying or detecting the instantaneous behavior of the series, is to describe its global behavior or its trend. This is already possible when applying wavelet analysis. Let us be more precise and explain the idea. The mother wavelet yields a second function called father wavelet or scaling function usually denoted by φ. For more details on the relationship ψ/φ the readers can be referred to Daubechies (1992), Gasquet (1990), Hardle et al (1996), etc. Similarly to ψ the scaling function φ yields dilation-translation copies

$$\varphi_{j,k}(t) = 2^{j/2}\varphi(2^j t - k).$$

Let V_j be the space generated by $(\varphi_{j,k})_k$. Under suitable conditions on ψ or equivalently on φ (Daubechies (1992)), the sequence $(V_j)_j$ is called a multi-resolution analysis (multi-scale analysis) on $\mathbb{R}$ and the V_j is called the j-level approximation space. It satisfies

$$V_j \subset V_{j+1}, \quad \forall\, j \in \mathbb{Z}. \tag{3}$$

This means that horizons j and $j+1$ can be viewed from from each other and so from any horizon $p \geq j+1$. In physics-mathematics this is called the zooming characteristics of wavelets. We have in fact a more precise relation of zooming,

$$f \in V_j \Leftrightarrow f(2^j.) \in V_0, \quad \forall\, j \in \mathbb{Z}. \tag{4}$$

This reflects the fact that, not only the signal f from horizon j can be seen in the horizon $j+1$ but either his contracted or delated copies. We will see later its relation to financial data. The sequence (V_j)'s satisfies also

$$\overline{\bigcup_{j\in\mathbb{Z}} V_j} = L^2(\mathbb{R}) \quad \text{and} \quad \bigcap_{j\in\mathbb{Z}} V_j = \{0\}. \tag{5}$$

The first part means that it covers the whole space of finite variance series. The second part means that there is no correlations between the projections or the components of the time series relatively to the different horizons. Finally the sequence $(V_j)_j$ satisfies a shift invariance property in the sense that

$$f \in V_j \Leftrightarrow f(. - k) \in V_j, \quad \forall\, k \in \mathbb{Z}. \tag{6}$$

This means that the multi-resolution analysis permits to detect the properties of the signal as well as its shifted copies. i.e, along the whole time support.

Finally, the following relation relates the W_j's to the V_j's,

$$V_{j+1} = V_j \oplus W_j, \quad \forall j \in \mathbb{Z}. \tag{7}$$

Under these properties, equations (1) and (2) yield, for $j \in \mathbb{Z}$ fixed, the following decomposition

$$X(t) = \sum_{j\in\mathbb{Z}} X_j^d(t) = \underbrace{\sum_{j\leq J-1} X_j^d(t)}_{X_J^a(t)} + \sum_{j\geq J} X_j^d(t). \tag{8}$$

Using equations (2) and (7), the component $X_J^a(t)$ is the projection of the series $X(t)$ onto the space V_J. Such a component is often called the approximation of $X(t)$ at the level J. It represents the global behavior of the series $X(t)$ or the trend at the scale J while the remaining part reflects the details of the series at different scales. Using the definition of the spaces V_j's, the component $X_J^a(t)$ which belongs to V_J can be expressed using the basis $(\varphi_{J,k})_k$ of such a space. Let

$$X_J^a(t) = \sum_{k\in\mathbb{Z}} C_{J,k}^a \varphi_{J,k}(t) \tag{9}$$

where the coefficients $C_{J,k}^a$, are obtained by

$$C_{J,k}^a =< X; \varphi_{J,k} >= \int_{\mathbb{R}} X_J^a(t)\varphi_{J,k}(t)dt.$$

It is proved in mathematical analysis that these did not depend on X_J^a but these are related directly to the original series $X(t)$ by

$$C_{J,k}^a =< X; \varphi_{J,k} > .$$

So that, the dependence on the indexation a will be omitted and these will be denoted simply by $C_{J,k}$ and are often called the scaling or the approximation coefficients of $X(t)$. The following relation is obtained issued from (8),

$$X(t) = \sum_{k\in\mathbb{Z}} C_{J,k}\varphi_{J,k}(t) + \sum_{j\geq J}\sum_{k\in\mathbb{Z}} d_{j,k}\psi_{j,k}(t). \tag{10}$$

This equality is known as the wavelet decomposition of $X(t)$. It is composed of one part reflecting the global behavior or the trend of the series and a second part reflecting the higher frequency oscillations and so the fine scale deviations of the trend.

To resume, in practice one can not obviously go to infinity in computing the complete set of coefficients. So, we fix a maximal level of decomposition J_{max} and consider the decomposition

$$X_{J_{max}}(t) = \sum_{k\in\mathbb{Z}} C_{J,k}\varphi_{J,k}(t) + \sum_{J\leq j\geq J_{max}}\sum_{k\in\mathbb{Z}} d_{j,k}\psi_{j,k}(t). \tag{11}$$

There is no theoretical method for the exact choice of the parameters J and J_{max}. However, the minimal parameter J does not have an important effect on the decomposition. But, the choice of J_{max} is always critical. One selects J_{max} related to the error estimates.

3 Methodology

This section is devoted to present a wavelet based method to reconstruct missing data. The method consists in providing a prediction procedure able to predict a short time series on an arbitrarily set of extending values. Recall that most of the studies devoted to the prediction of time series are based on three main ideas. Firstly, the disposed sample data is known on a long time interval which is large enough than the predicted one. Secondly, the learning procedure is conducted on the whole time support which necessitates known data on this interval and thus a reconstruction or a prediction will not be of importance while the data is already known and it may be just for testing the accuracy of methods. Finally, forecasting time series is based on the disposition of a test sample. These facts are critical for many reasons. Firstly, the availability of long samples is not already possible. In contrast, for some situations such as the study of the relationship ownership-structure/diversification in our case, the samples are usually short. One has one main value on a year. Secondly, one sometimes seeks to predict on a long period more than the known one. Furthermore, when applying wavelet analysis to approximate and/or to forecast time series, the majority of the existing studies assume the presence of seasonality, periodicity and/or autoregressive behavior in the series or in the wavelet coefficients. See for instance Ben Mabrouk et al (2008), Soltani (2002) and the references therein. In the present paper, we provided a simple method leading to good prediction. The main important point in our method as it will be shown later, is the fact that it does not necessitate to test on the dynamic behavior of the series and/or its wavelet coefficients. This is essentially due to the fact that the considered series is short and its dynamics may not be important. However, the most positive point in the method is the fact that it necessitates only to compute the values of the source scaling function and the associated wavelet on a finite set of dyadic numbers.

Let $X(t)$ be a time series on a time domain $\mathbb{T} = \{0, 1, \ldots, N\}$. A recursive procedure is used which consists in applying firstly an estimator partially at short horizons to all the observations $(t_i, X_i)_{i=1,\ldots,N}$ to yield firstly the predicted value $\widehat{X}_{N+1}$ of $X(N+1)$. This last is then introduced as new observation to predict X_{N+2}. We then follow the same steps until reaching the desired horizon. Recall that the J-level wavelet decomposition of the series $X(t)$, $t \in \mathbb{T}$, is

$$X(t) = \underbrace{\sum_{k\in\mathbb{Z}} C_{0,k}\varphi_{0,k}(t)}_{X_\varphi(t)} + \sum_{j=1}^{J} \underbrace{\sum_{k\in\mathbb{Z}} d_{j,k}\psi_{j,k}(t)}_{X_{j,\psi}(t)}\,. \tag{12}$$

For $t = N + 1$, this yields

$$X(N+1) = \sum_{k\in\mathbb{Z}} C_{0,k}\varphi(N+1-k) + \sum_{j=1}^{J}\sum_{k\in\mathbb{Z}} d_{j,k}2^{j/2}\psi(2^j(N+1)-k). \tag{13}$$

This means that for evaluating the predicted value $\widehat{X}_{N+1}$, it suffices to do this for X_φ and the $X_{j,\psi}$'s. To attain this goal, it appears from (13) that it suffices to compute the values of the scaling function φ and the wavelet mother ψ on the integer grid $\{N + 1 - k\,;\, k \in \mathbb{Z}\}$ and $\{2^j(N + 1) - k\,;\, k \in \mathbb{Z}\}$ on the supports of φ and ψ. This motivates the use of Daubechies compactly supported wavelets which are well evaluated on the integer grid. (The values of the used scaling function and the wavelet associated are provided in the appendix). Next, $\widehat{X}_{N+1}$ is estimated as

$$\widehat{X}_{N+1} = \widehat{X}_\varphi(N+1) + \sum_{j=1}^{J} \widehat{X}_{j,\psi}(N+1). \tag{14}$$

where

$$\widehat{X}_\varphi(t) = \sum_{k\in\mathbb{Z}} \widehat{C}_{0,k}\varphi(t-k). \tag{15}$$

and similarly

$$\widehat{X}_{j,\psi}(t) = \sum_{k\in\mathbb{Z}} \widehat{d}_{j,k}\varphi(t-k). \tag{16}$$

with suitable estimators of the coefficients $\widehat{C}_{0,k}$ and $\widehat{d}_{j,k}$. The estimators are applied to avoid the presence may be of high dynamics in the series of wavelet coefficients and thus the possibility of noised parts and/or small ones. Such estimators lead to $\widehat{X}_{N+1}$ which will be added to the series and then we reconsider the initial step.

4 Results, interpretations and discussions

In this section, we develop empirical results based on the theoretical procedure developed previously. We propose to apply the step-by-step procedure described above to reproduce missing data parts of the data basis composed of performance and governance variables associated to French firms. The sample studied is composed of governance, diversification and value creation variables on a set of 69 French firms along the years 1995 to 2005. The wavelet method developed and Neural Networks are tested in order to conduct eventual comparison to prove the efficiency of our method. In fact, testing autoregressive procedure is not efficient here due to short time interval. It is known that for such cases the presence of autoregressive behavior is weak and may not be proved. Fuzzy Logic is also not suitable for the main reason of the absence of fuzzy data and the fact that it necessitates to fix the rules which is based on expecting the outputs which is ambiguous especially for governance, diversification and value creation variables considered here. Fourier Analysis necessitates the presence of periodicity which can not be expected for our variables. This motivates the comparison with Neural Networks. We just recall that we will not expose all the results because of the largeness of the sample but we restrict to some ones. Table 1 resumes the set of explicative variables.

Variable	French Abbreviation
Total assets	AT
Market Capitalization	CB
Sales	CA
Total Equity	KP
Total Debt	DT
Net Income	Rnet

Table 1
Analyzing Variables

The numerical results are provided using Daubechies compactly supported wavelets by applying a 4-level $DB10$ wavelet analysis and a hard threshold wavelet estimator with a threshold $\varepsilon = 0.75Max|d_{j,k}|$. The neural network forecasts are obtained by applying the well known software Alyuda Forecaster XL. Such forecaster a part of input data as a training set to find the best Neural Network and apply it by the next for the prediction. One main disadvantage in it is the necessary hypothesis of periodicity which may not be reel.

4.1 Reconstruction of existing data

Firstly, in order to test the efficiency and the performance of the proposed idea we applied it for the known parts of our data basis. A comparison is then conducted with reconstructed parts using Neural Network method. The results are exposed in the following tables where the effectiveness of the wavelet method appears. For each variable and each firm we fix the 5 or 6 first values to predict the 6 or 5 remaining ones. The tables 2-7 show the predicted values of the different explicative variables for the French firm ACCOR.

Year	Real Values	Wavelet Prediction	NN Prediction
1995	2799.22	...	...
1996	3146.46	...	...
1997	6086.85	...	...
1998	6504.18	...	...
1999	8707.07	...	...
2000	8820.38	8820.4	8694.861409
2001	8097.8	8097.8	8683.803108
2002	5733.19	5733.2	8672.965039
2003	7035.82	7035.8	8693.818931
2004	6455.4	6455.4	8699.095708
2005	9591.36	9591.4	8701.587759

Table 2
Comparison results: CB for the French firm Accor

Year	Real Values	Wavelet Prediction	NN Prediction
1995	3939.617175	...	...
1996	3482.397392	...	...
1997	3816.771372	...	...
1998	3262.152559	...	...
1999	4139.890318	...	...
2000	4305.977899	4306	3156.565015
2001	4087.818334	4087.8	4153.890745
2002	3812.589802	3812.6	3156.565015
2003	3816.340647	3816.3	4149.104216
2004	3839.705024	8339.7	3140.391532
2005	3828.989097	3829	4150.925829

Table 3
Comparison results: DT for the French firm Accor

4.2 Construction of missing data

As it is shown in tables 2-7, the wavelet predicted values (WPV) are more accurate compared to neural networks predicted ones (NNPV). This motivates the application of the wavelet procedure to reproduce the really missing parts

Year	Real Values	Wavelet Prediction	NN Prediction
1995	8343.839611	...	...
1996	8450.858822	...	...
1997	9725.027708	...	...
1998	9423.636001	...	...
1999	10865	...	...
2000	11954	11954	9410.595452
2001	12100	12100	8182.470332
2002	11275	11275	9317.530091
2003	10956	10956	8073.268155
2004	11510	11510	9342.956958
2005	12791	12791	8262.130542

Table 4
Comparison results: AT for the French firm Accor

Year	Real Values	Wavelet Prediction	NN Prediction
1995	2025.132745	...	...
1996	2459.764893	...	...
1997	2843.783968	...	...
1998	2873.968873	...	...
1999	3092	...	...
2000	3843	3843	3091.741598
2001	4139	4139	3091.735656
2002	3893	3893	309173147
2003	3587	3587	3090.331298
2004	3755	3755	3088.660429
2005	4301	4301	3088.112759

Table 5
Comparison results: KP for the French firm Accor

of our series taking in mind that the obtained values will be the best. The empirical tests are conducted on the French firm DMC for which we do not dispose of the data for the years 2000 to 2005. The results are exposed in tables 8-13.

Year	Real Values	Wavelet Prediction	NN Prediction
1995	4605.789709	...	...
1996	4251.498193	...	...
1997	4781.563426	...	...
1998	5554.175045	...	...
1999	6044	...	...
2000	6946	6946	6036.620238
2001	7218	7218	6034.605972
2002	7071	7071	6034.053505
2003	6774	6774	6043.649803
2004	7072	7072	6041.789193
2005	7562	7562	6040.57782

Table 6
Comparison results: CA for the French firm Accor

Year	Real Values	Wavelet Prediction	NN Prediction
1995	44.89044071	...	...
1996	163.7937425	...	...
1997	185.2322648	...	...
1998	259.4859474	...	...
1999	267.7294338	...	...
2000	431.8525675	431.8526	267.5776237
2001	473.6313588	473.6314	267.5647551
2002	372.713343	372.7133	267.6051109
2003	267.9924661	267.9925	267.6925082
2004	242.3262479	242.3262	267.6993183
2005	331.61336	331.6134	267.6998488

Table 7
Comparison results: Rnet for the French firm Accor

4.3 Performance and Value Creation Variables

The aim of this section is to inject the wavelet predicted or reconstructed variables into the equations yielding the endogenous variables. Two methods will be exposed. First, we provide the values of performance and value creation

Year	Real Values	Wavelet Prediction	NN Prediction
1995	198.76	...	...
1996	134.61	...	...
1997	127.02	...	...
1998	77.35	...	...
1999	45.75	...	...
2000	Unknown	101.32	45.42349633
2001	Unknown	116.75	45.42349633
2002	Unknown	74.04	45.42349633
2003	Unknown	83.4	46.39115105
2004	Unknown	61.42	46.18757939
2005	Unknown	57.36	46.2256794

Table 8
Comparison results: CB for the French firm DMC

Year	Real Values	Wavelet Prediction	NN Prediction
1995	140.1223053	...	...
1996	151.4085821	...	...
1997	136.6443018	...	...
1998	236.3393133	...	...
1999	203.168443	...	...
2000	Unknown	217.0818	217.0817999
2001	Unknown	124.8029	124.8028628
2002	Unknown	95.9582	95.95824202
2003	Unknown	85.8677	85.86766452
2004	Unknown	68.9464	68.94638019
2005	Unknown	76.0819	76.08186408

Table 9
Comparison results: DT for the French firm DMC

variables as endogenous variables, based on their explicit dependencies on the explicative variables reconstructed in the previous subsections. Secondly, we provide wavelet predictions of the endogenous variables using the wavelet procedure developed in section 2. A comparison between these values is also conducted as well as with a comparison with existing values for DMC firm and with Neural Network predicted values for the two firms. The performance

Year	Real Values	Wavelet Prediction	NN Prediction
1995	801.119586	...	...
1996	739.98753	...	...
1997	660.409143	...	...
1998	643.029955	...	...
1999	416.795613	...	...
2000	Unknown	339.1	415.8189638
2001	Unknown	236.7	415.8189638
2002	Unknown	178.3	415.8189638
2003	Unknown	163.4	421.4230757
2004	Unknown	120.6	435.9540594
2005	Unknown	120.6	496.7405454

Table 10
Comparison results: AT for the French firm DMC

Year	Real Values	Wavelet Prediction	NN Prediction
1995	355.053761	...	...
1996	276.694966	...	...
1997	221.660871	...	...
1998	131.563502	...	...
1999	30.794701	...	...
2000	Unknown	511.3528	29.39673892
2001	Unknown	482.7281	29.39673892
2002	Unknown	503.9588	29.39673892
2003	Unknown	568.4346	32.31103077
2004	Unknown	392.2119	36.16726538
2005	Unknown	189.8276	42.57971843

Table 11
Comparison results: KP for the French firm DMC

variables and value creation ones constituting the endogenous variables are listed in table 14 with their explicit expressions on the explicative ones. The empirical tests on DMC firm are provided in tables 15-18.

Year	Real Values	Wavelet Prediction	NN Prediction
1995	1085.437003	...	...
1996	948.690234	...	...
1997	906.461856	...	...
1998	818.041426	...	...
1999	667.879145	...	...
2000	Unknown	522.9	669.1731789
2001	Unknown	384.2	669.6223291
2002	Unknown	307.4	669.8566586
2003	Unknown	250.7	672.4642615
2004	Unknown	206	676.8128998
2005	Unknown	187.3	684.7212645

Table 12
Comparison results: CA for the French firm DMC

Year	Real Values	Wavelet Prediction	NN Prediction
1995	0.160322851	...	...
1996	-91.65018436	...	...
1997	-73.25569807	...	...
1998	-89.23636453	...	...
1999	-101.2818874	...	...
2000	Unknown	-82.9199	-102.3564978
2001	Unknown	-23.3818	-102.6829817
2002	Unknown	-3.7065	-102.6829817
2003	Unknown	8.1046	-102.5151181
2004	Unknown	-8.1113	-102.4520249
2005	Unknown	-11.7509	102.4326179

Table 13
Comparison results: Rnet for the French firm DMC

5 Conclusion

The study of the relationship ownership-structure/diversification is of great interest essentially for two main reasons. Firstly, the diversification constitutes a strategic important choice which strongly affects on the capacity of firm devel-

Variables	Abbreviations	Explicitness
Economic performance	Q	(CB+DT)/AT
Value creation	RMRS	CB/KP
Return on equity	ROE	Rnet/KP
Return on assets	ROA	Rnet/AT

Table 14
Performance and value creation variables

Year	Real Values	Wavelet Predicted Values	Explicit Reconstruction with WPV
1995	0.807642223	...	...
1996	0.784400442	...	...
1997	1.018364335	...	...
1998	1.03636564	...	...
1999	1.182416964	...	...
2000	1.098072436	1.0981	1.0981
2001	1.007075895	1.0071	1.0071
2002	0.846632355	0.8466	0.8466
2003	0.990522147	0.9905	0.9905
2004	0.894448742	0.8944	0.8944
2005	1.049202494	1.0492	1.0492

Table 15
Comparison results: Comparison results: Tobin's Q for the French firm DMC

opment during a long period, its financing needs, its performance as well as the related risks. Secondly, such a decision may cause some inter-actors interest conflicts in the firm and it may be imposed within its actionnarial structure. The main problem in studying the relationship is the necessity of conducting it on a complete data basis. So, when having a missing data sample, the study can not be well conducted and no good conclusions can be pointed out. This motivates our work here based of constructing the missing data parts in order to obtain a complete sample to be applied for testing the ownership structure and diversification relationship. As it is well known nowadays, wavelet theory is the most powerful tool for filling this gap, we provided in the present work a wavelet based method to complete the missing parts of an incomplete sample composed of governance, diversification and value creation variables on a set of 69 French firms along the years 1995 to 2005. Some existing parts are also reconstructed in order to test the efficiency of our method. Having now a complete sample, we intend in an extending forthcoming work to apply the obtained full sample for the study of the original object, the relation between

Year	Real Values	Wavelet Predicted Values	Explicit Reconstruction with WPV
1995	1.382240254	...	...
1996	1.279171033	...	...
1997	2.140405203	...	...
1998	2.263135158	...	...
1999	2.815999353	...	...
2000	2.295180848	2.2952	2.2952
2001	1.956462914	1.9565	1.9565
2002	1.472692011	1.4727	1.4727
2003	1.961477558	1.9615	1.9615
2004	1.719147803	1.7191	1.7191
2005	2.230030226	2.2300	2.2300

Table 16
Comparison results: Comparison results: RMRS for the French firm DMC

Year	Real Values	Wavelet Predicted Values	Explicit Reconstruction with WPV
1995	0.06948208	...	...
1996	0.06557174	...	...
1997	0.08084057	...	...
1998	0.10349035	...	...
1999	0.11384217	...	...
2000	0.11631538	0.1163	0.1124
2001	0.11452042	0.1145	0.1144
2002	0.11045466	0.1105	0.0957
2003	0.07527181	0.0753	0.0772
2004	0.06364847	0.0636	0.0645
2005	0.07742385	0.0774	0.0771

Table 17
Comparison results: Comparison results: ROE for the French firm DMC

the properties of the structure and the diversification. We intend as well to join the determinants and the consequences of the diversification strategy.

Year	Real Values	Wavelet Predicted Values	Explicit Reconstruction with WPV
1995	0.00538007	...	...
1996	0.019381905	...	...
1997	0.019046965	...	...
1998	0.02753565	...	...
1999	0.024641457	...	...
2000	0.036126198	0.0361	0.0361
2001	0.039143088	0.0391	0.0391
2002	0.033056616	0.0331	0.0331
2003	0.025282262	0.0253	0.0253
2004	0.02105354	0.0211	0.0211
2005	0.025925523	0.0259	0.0259

Table 18
Comparison results: Comparison results: ROA for the French firm DMC

6 Appendix

We refer to [8] for the computation of the values of Daubechies father and mother wavelets. Recall that DB10 is supported on the interval $[0, 19]$. The grids $\varphi(n)$ and $\psi(n)$ for n integer in the support, are given in the following table. The values on the whose dyadic grid are obtained obviously using the 2-scale relation.

n	$\varphi(n)$	$\psi(n)$
1	3.354408256841158E-002	-1.668296029790936E-005
2	0.652680627783427	-1.413114882338799E-004
3	0.555223194777502	2.348833526687438E-003
4	-0.380687440933945	-1.203933191141380E-002
5	0.202266079588952	3.439149845726070E-002
6	-8.039450480025792E-002	-6.490697134847506E-002
7	1.740357229364825E-002	9.676861895219263E-002
8	1.788811154355532E-003	-0.176355684599155
9	-2.262291980513165E-003	0.563213124163635
10	3.861859807090320E-004	-0.658797645066142
11	7.746490117092401E-005	-0.359446985391733
12	-2.595735132421100E-005	-3.947780645895724E-002
13	7.455766803700000E-008	1.860748282571044E-003
14	1.064649412020000E-007	1.050025200672993E-004
15	-5.018348300000000E-009	-9.779523219362094E-006
16	1.350623000000000E-011	2.927524652329252E-008
17	9.591699999999999E-014	1.928006355576058E-010
18	8.000000000000001E-018	-3.615587627311547E-015

Table 19
Values of Daubechies 10, φ and ψ

References

[1] M. Aminghafari and J. M. Poggi, Forecasting Time Series Using Wavelets. International J. of Wavelets Multiresolution and Information Processing 5(5) (2007), 709-724.

[2] B. Aktan, A. Ben Mabrouk, M. Ozturk and N. Rhaiem, Wavelet-Based Systematic Risk Estimation An Application on Istanbul Stock Exchange. International Research Journal of Finance and Economics 23 (2009), 33-45.

[3] E. Barnes and H. Brown, The diversification Puzzle: Revisiting the value impact of diversification for UK firms. Journal of Business Finance and Accounting, 33(9-10) (2006), 1508-1534.

[4] Baudat and F. Anouar, Kernel-based methods and function approximation.

International Joint Conference on Neural Networks, Washington, DC July 15-19, 2001, 1244-1249.

[5] A. Ben Mabrouk, N. Ben Abdallah and Z. Dhifaoui, Wavelet Decomposition and Autoregressive Model for Time Series Prediction. Appl. Math. Comput. 199(1) (2008), 334-340.

[6] A. Ben Mabrouk, Z. Dhifaoui and H. Kortas, A wavelet support vector machine coupled method for time series prediction. International Journal of Wavelets Multiresolution and Information Processing, 6(6) (2008), 851-868.

[7] A. Ben Mabrouk, H. Kortas and S. Ben Ammou, Wavelet estimators for long memory in stock markets. International J. of Theoretical and Applied Finance 12(3) (2009), 297317.

[8] M. L. Ben Mohamed, On some nonlinear problems, Wavelet approach, Thesis in Mathematics, Faculty of Sciences, Monastir, 2007.

[9] C. Bontemps, Prévision stochastique de trajectoire: procédure paramétrique et non paramétrique. Rapport de DEA Informatique Fondamentale et Parallelisme, Ecole Nationale de l'Aviation Civile, 1997.

[10] G. Charreaux, Structure de propriete, relation d'agence et performance nanciere. Revue Economique, 42(3) (1991), 521-552.

[11] I. Daubechies, Ten lectures on wavelets. CBMS-NSF Regional Conference Series on Applied Mathematics, Vol. 61, SIAM, Philadelphia, PA, 1992.

[12] A. Delios and Z. J. Wu, Legal Person Ownership, Diversification Strategy and Firm Profitability in China. Journal of Management and Governance, 9 (2005), 151-169.

[13] C. Gasquet and P. Witomsky, Analyse de Fourier et Applications, Filtrage, Calcul numérique, Ondelettes. Masson, 1990.

[14] R. Gencay, F. Seluk and B. Whitcher, An Introduction to Wavelets and Other Filtering Methods in Finance and Economics. Academic Press, 2001.

[15] [14] W. Hardle, G. Kerkyacharian, D. Picard and A. Tsybakov, Wavelets, Approximation and Statistical Applications. Seminar Berlin-Paris, 1996.

[16] C. R. Harvey, Predictable risk and returns in emerging markets. Review of Financial Studies 8(3) (1995), 773-816.

[17] J. S. Karp, G. Muehllehner and R. M. Lewitt, Constrained Fourier Space Method for Compensation of Missing Data in Emission Computed Tomo Graphy. IEEE Transactions on Medical Imaging, 7(1) (1988), 21-25.

[18] R. Lagnado and S. Osher, A technique for calibrating derivative security pricing models: Numerical solution of an inverse problem. The Journal of Computational Finance 1 (1997), 13-25.

[19] L. H. P. Lang and R. M. Stulz, Tobin's Q, corporate diversification, and firm performance. Journal of Political Economy, 102(6) (1994), 1248-1280.

[20] R. Liva and F. d'Alché-Buc, Modèle dynamique a noyaux pour la prévision des series temporelles non linéaires. In Actes de la Confrence Apprentissage CAp'03, Laval, 2003.

[21] S. Mukerjee, E. Osuna, and F. Girosi, Nonlinear prediction of chaotic time series using support vector machines. In IEEE NNSP'97, Ameila Island, FL, USA, 24-26 Sept, 1997.

[22] D. B. Percival and A. T. Walden, Wavelet Methods for Time Series Analysis. Cambridge University, 2000.

[23] F. Perdreau, Désengagements et recentrage en France 1986-1992. Finance Contrôle Stratégie, 1(2) (1998), 137-165.

[24] S. D. Prowse, Institutional investment patterns and corporate financial behaviour in the United States and Japan. Journal of Financial Economics, 27(1) (1990), 43-66.

[25] M. Singh, N. Wallace and J. A. Suchard, Corporate diversification strategies and capital structure. Quarterly Review of Economics and Finance, 43 (2003), 147-166.

[26] S. Soltani, On the use of the wavelets decomposition for time series prediction. Neurocomputing, 48 (2002), 267-277.

[27] S. Thomsen, T. Pedersen and H. K. Kvist, Blockholder Ownership: eects on firm value in market and control based governance systems. Journal of Corporate finance, 12 (2006), 246-269.