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Asset Pricing Model under Costly Information Evidence from the Tunisian Stock Market

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Abstract

The purpose of this paper is to propose a new model for price estimation in financial markets. This model considers costly information; investors must buy information in order to reach an optimal decision. We use entropy statistics to estimate information cost. Asset's price is supposed to be a linear function of its: previous price; information cost; exchanged quantity, and the risk-free rate of interest. We find that this model proves a very significant aptitude to anticipate future asset's prices of the Tunisian Stock Market over the period extending from 2002 to 2008. The proposed model allows both institutional and particular investors to predict future's asset prices on the basis of knowledge of the previous price, the information, the exchanged quantity and the risk-free rate of interest.

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Keywords: price estimation; price prediction; information cost; entropy statistics; linear interpolation

1. Introduction

The aim of several financial research studies is to propose models in order to estimate the asset's price in financial markets. The basic reference model for all these studies can be traced back to Bachelier, 1900 and is called the Random Walk Model (RWM). Indeed, the RWM supposes that the best estimator of the next price is the present price. Fama, 1965 referred to the RWM to propose the efficient market hypothesis. Some other authors, such as Engle, 2001; Skabar and Cloete, 2002 and Yamada and Honda, 2005 use several techniques (ARCH/GARCH, wavelets, neural network…) in order to estimate asset price.

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The objective of this paper is twofold: firstly, to estimate asset information cost; and secondly, to propose a new asset pricing model.

Several financial models suppose free information (Grossman, 1976; Glosten and Milgrom, 1985 and Biais, 1993). However, the information cost exists and it cannot be neglected. Indeed, whenever an investor wants to intervene to purchase and/or to sell, he/she faces the need to access the information which he/she judges to ensure an optimal decision. Actually the information cost is not only restricted to the purchasing of information, but also, and more specifically, involves the cost of analysis as well as the treatment and classification of information, a cost which is not to be neglected. Mohammed and Yadav, 2002; Peress, 2005 and Lundtafte, 2006, for example, emphasize the fact that the available information is not of the same quality. Investors are always in search of high-quality information, so they agree to pay additional costs.

The difficulty encountered at this level is how to estimate this cost. To help solve this problem, we propose to use entropy statistics.

The second purpose of the present paper is to propose a new model of asset price estimation. This model will be called Asset Pricing Model under Costly Information (APMCI).

In order to propose the APMCI, we suppose that asset's price is a linear function of its: previous price; information cost; exchanged quantity, and the risk-free rate of interest. Different languages for technical computing are used: MATLAB 7.0.1, SPSS 17.0.1 (Python) and EViews 5.0.

In this paper, we consider the Tunisian Stock Market (TSM) over the period extending between the years 2002 and 2008. We propose to divide this period into 2002-2005 and 2006-2008. The first period is aimed to provide primary results of asset price estimation. In order to exhibit the ability of the APMCI to predict future asset's price, we test the same relation over the period extending between the years 2006 and 2008 (the out of sample period).

The organization of this paper is as follows: we start with the estimation of the information cost (section 2). Section 3 presents theoretical asset pricing models. Section 4 defines the general form of the APMCI and the employed estimation method. Section 5 develops the different results and discussion. In section 6 we sum up the main conclusions.

2. Information cost estimation

2.1. Entropy Statistics

Entropy statistics is mainly used in financial market's researches (Chen, 2004; Peng, 2005; Pérez et al. 2006; Dadpay et al., 2007; Clarke, 2007; Gajdos et al., 2008; Sbuelz and Trojani, 2008; Zapart, 2009 and Safer Chakroun and Hamdouni, 2010).

Entropy statistics is meant to quantify the value of information (quantity which makes it possible to make a decision) by a random variable. In other words, according to entropy statistics, the value of information is a function of probability, which can take the following expression (Chen, 2004):

$$H(P) = -\log_b P \qquad (1)$$

- P: is the probability associated with a given event;
- b: is a positive constant, which is generally equal to 2.

2.2. Information cost in the TSM

The sample selected for the purposes of the present study includes the assets quoted in the TSM and which were present over the two periods: 2002-2005 and 2006-2008.

The final sample consists of a total number of 35 assets and a total number of 47059 observations.

For a given asset, we compute the information cost which the investor has to spend at the beginning of the month.

Concretely, for a given asset, the quotation probability relating to one month is calculated. For this purpose, we use the binomial distribution given by:

$$P[X = x] = C_n^x p^x (1-p)^{n-x} \qquad (2)$$

- n: the total number of the working days in the TSM for a given month;

- x: the number of days when the asset is present for the same month;
- p: the success probability of the asset for the same month.

Table 1 (respectively Table 2) contains results of all assets in 2002-2005 (respectively 2006-2008). For example, for the asset *AB* on January 2002 we note: n=22, x=19 and p=19/22=0.863. The quotation probability is $P[X=19]$= 0.240 and the information cost is $H(0.2409)$=2.053. The same reasoning is applied for the remainder of the period. Then the average information cost for the asset *AB* corresponding to 2002-2005 is 2.300.

Table 1: Average Information Costs (2002-2005)

Asset	AB	ALKIMIA	ATB	ATL	BH	BIAT	BNA
Information Cost	2.300	2.169	2.244	2.032	1.669	1.384	2.335
Asset	BS	BT	BTEI	CIL	ELECTRO.S	GLS	ICF
Information Cost	1.730	1.076	1.356	2.354	1.001	2.035	2.107
Asset	MAZRAA	MG	MONOPRIX	SFBT	SIAME	SIMPAR	SIPHAT
Information Cost	2.264	1.670	2.198	0.134	1.835	1.958	0.382
Asset	SOTETEL	SOTRAPIL	SOTUMAG	SOTUVER	SPDIT	STAR	STB
Information Cost	0.347	0.462	2.207	2.230	1.754	2.054	1.033
Asset	STEQ	TUN LAIT	TUN LEASING	TUNINVEST	TUNISAIR	UBCI	UIB
Information Cost	0.661	1.856	2.033	2.403	0.558	2.327	1.105

Table 2: Average Information Costs (2006-2008)

Asset	AB	ALKIMIA	ATB	ATL	BH	BIAT	BNA
Information Cost	1.684	2.428	0.453	1.079	0.369	1.061	0.669
Asset	BS	BT	BTEI	CIL	ELECTRO.S	GLS	ICF
Information Cost	0.719	0.493	1.152	0.978	1.216	2.380	2.402
Asset	MAZRAA	MG	MONOPRIX	SFBT	SIAME	SIMPAR	SIPHAT
Information Cost	1.866	0.729	0.687	0.117	1.076	1.499	1.594
Asset	SOTETEL	SOTRAPIL	SOTUMAG	SOTUVER	SPDIT	STAR	STB
Information Cost	0.268	0.521	1.609	1.831	1.622	1.540	0.195
Asset	STEQ	TUN LAIT	TUN LEASING	TUNINVEST	TUNISAIR	UBCI	UIB
Information Cost	2.088	1.802	0.246	1.384	0.135	2.302	0.695

In a previous paper, Safer Chakroun and Hamdouni, 2010 show that information costs follow a Geometric Brownian Motion. Indeed, in order to establish this result, they estimate the Hurst parameter. The following figure summarizes the Hurst parameter's value for the 35 assets included in the studied sample.

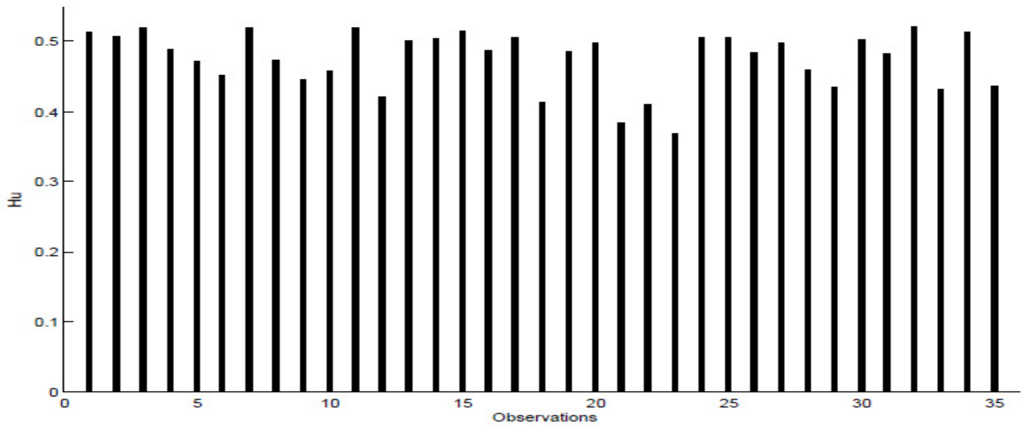

Figure 1: Hurst parameter

From this figure, it is possible to note that the values of *Hu* are equal to 0.5± ε, which makes it possible to confirm the existence of a geometric Brownian motion. In other words, the information cost follows a geometric Brownian motion similar to several other financial series, the most famous of which are the applications of Black and Scholes, 1973 for the valorization of the options prices.

Thus, the information cost can be formalized as follows:

$$X_t = X_0 \exp\left\{\left(b - \frac{1}{2}\sigma^2\right)t + \sigma B_t\right\} \tag{3}$$

With: b and σ: two constants; B: Standard Brownian motion.

3. Theoretical Asset Pricing Models

Various theoretical models have the same aim: estimate and predict stock prices. Skabar and Cloete, 2002, among others, recognize that approaches to forecasting the future direction of share market prices broadly fall into two categories—those that rely on technical analysis, and those that rely on fundamental analysis. While technical analysis uses only historical data (past prices, volume of trading, volatility, etc.), fundamental analysis is based on external information; that is, information that comes from the economic system surrounding the market. Such information includes interest rates, prices and returns of other assets, and many other macro- or micro-economic variables.

At this stage, we present two principal models of asset price estimation: the Random Walk Model and the GARCH Model.

3.1. Random Walk Model (RWM)

Bachelier, 1900 is the first who, in 1900, supposed the existence of random walk for stock prices and other speculative prices. Fama, 1965 proposes the following definition of Random walk: “A stock market where successive price changes in individual securities are independent is, by their definition, a random walk market. Most simply the theory of random walks implies that a series of stock price changes has no memory; the past history of the series cannot be used to predict the future in any meaningful way. The future path of the price level of a security is no more predictable than the path of a series of cumulated random numbers”. The RWM emphasizes, then, that the best estimator of the next price is the present price. Fama, 1965 referred to the RWM to propose the efficient market hypothesis.

Padhan, 2009 presents a synthesis of the prominent studies that have been concerned with the RWM. Indeed, using several correlation tests, Cootner, 1962; Fama, 1965 and Kendall, 1953, for example, find strong support to the random walk theory. They presume that the sample serial correlation coefficients computed for successive price changes is extremely close to zero, implying that successive changes in prices are independent. On the other hand, using the spectral analysis technique, Granger and Morgenstern, 1963 and Godfrey et al., 1964 among others, hold up the independent assumption of the random walk model. Several tests using serial dependence reject the random walk model e.g. Fama, 1976-1995 and Fama and French, 1988.

The RWM is represented as follow:

$$p_t = p_{t-1} + \varepsilon_t \tag{4}$$

- $t = 0, 1, \ldots, T$;
- p_0 : Initial value at time period zero ;
- ε_t : white noise process

3.2. GARCH Model

The GARCH model introduced by Bollerslev, 1986 is an extension of the ARCH model introduced by Engle, 1982. The central focus of the GARCH model is that the variances of the error terms are not equal at all points or ranges of the data. Engle, 2001 notices: “The basic version of the least squares model assumes that the expected value of all error terms, when squared, is the same at any given point. This assumption is called homoskedasticity, and it is this assumption that is the focus of ARCH/GARCH models. Data in which the variances of the error terms are not equal, in which the error terms may reasonably be expected to be larger for some points or ranges of the data than for others, are said to suffer from heteroskedasticity. The standard warning is that in the presence of heteroskedasticity, the regression coefficients for an ordinary least squares regression are still unbiased, but the standard errors and confidence intervals estimated by conventional procedures will be too narrow, giving a false sense of precision. Instead of considering this as a problem to be corrected, ARCH and GARCH models treat heteroskedasticity as a variance to be modeled. As a result, not only are the deficiencies of least squares corrected, but a prediction is computed for the variance of each error term. This prediction turns out often to be of interest, particularly in applications in finance."

Several recent studies are still using the ARCH/GARCH model such as Fernandez and Muriel, 2009 and Leon and Sebastia, 2009.

The GARCH (*p,q*) model is defined as follow:

$$p_t = p_{t-1} + \varepsilon_t \tag{5}$$

$$\varepsilon_t = \tau_t z_t \tag{6}$$

$$z_t \to \mathrm{N}(0,1) \tag{7}$$

$$\tau_t^2 = \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \tau_{t-j}^2 \tag{8}$$

These two models (RWM and GARCH model) exhibit strong contributions to financial theories, but they present some insufficiencies during the empirical validations. To help solve this problem, we propose the following development.

4. Asset Pricing Model under Costly Information

In order to propose the Asset Pricing Model under Costly Information (APMCI) we suppose that asset's price is a linear function of its: previous price; information cost; exchanged quantity, and the risk-free rate :

$$p_t^i = f(p_{t-1}^i, c_t^i, Q_t^i, r_t) \tag{9}$$

- p_t^i (p_{t-1}^i): the price of the asset *i* at the instant *t* (*t*-1);
- c_t^i : the information cost of the asset *i* at the instant *t* ;
- Q_t^i : the exchanged quantity of the asset *i* at the instant *t* ;
- r_t : the risk-free rate of interest at the instant *t* ;

In order to estimate the different parameters of our model, we use the linear interpolation. Different languages for technical computing are used: MATLAB 7.0.1, SPSS 17.0.1 (Python) and EViews 5.0.

Linear interpolation is a method of curve fitting using linear polynomials. It can be defined as follow: "Some functions can be represented only numerically (by a table of values). Such functions are generally defined for some values of the domain variable *x*, but not for all such values. The process of linear interpolation allows us to estimate the value of a function *f* represented numerically, for any value *c* of *x* that lies between two values *a* and *b* in the domain for which *f* is defined." (Meijering, 2002).

In this case, the error of this approximation is defined as:

$$R_T = f(x) - p(x) \tag{10}$$

where *p* denotes the linear interpolation polynomial defined as:

$$p(x) = f(x_0) + \frac{f(x_1) - f(x_0)}{x_1 - x_0}(x - x_0)$$

(11)

Linear interpolation as described above is for data points in one spatial dimension. For two spatial dimensions, the extension of linear interpolation is called bilinear interpolation, and so on until obtaining the multilinear interpolation, which is used in the current study. In this case, if *n* points exist in the plane, (x_k, y_k), *k*=1, …, *n*, with distinct x_k's, there is a unique polynomial in *x* of degree less than *n* whose graph passes through the points. It is easier to remember that *n*, the number of data points, is also the number of coefficients, although some of the leading coefficients might be zero, so the degree might actually be less than *n-1*. There are many different formulas for the polynomial, but they all define the same function.

This polynomial is called the interpolating polynomial because it exactly reproduces the given data:

$$P(x_k) = y_k, \quad k = 1,\dots,n \tag{12}$$

5. Results and discussion

Remember that we noted in section 4 the following relation:

$$p_t^i = f(p_{t-1}^i, c_t^i, Q_t^i, r_t) \tag{13}$$

- p_t^i (p_{t-1}^i): the price of the asset *i* at the instant *t* (*t*-1);
- c_t^i : the information cost of the asset *i* at the instant *t* ;
- Q_t^i : the exchanged quantity of the asset *i* at the instant *t* ;
- r_t : the risk-free rate of interest at the instant *t* ;

We start by considering the case of the RWM (step 1), then we analyze the entire explicative variable (step 4).

Step 1: $p_t^i = f(p_{t-1}^i)$: Equation 1

Step 2: $p_t^i = f(p_{t-1}^i, c_t^i)$: Equation 2

Step 3: $p_t^i = f(p_{t-1}^i, c_t^i, Q_t^i)$: Equation 3

Step 4: $p_t^i = f(p_{t-1}^i, c_t^i, Q_t^i, r_t)$: Equation 4

The following table summarizes the results for each step (for the period 2002-2005).

Table 3: Estimation Results

MODEL	Non standardized coefficient		Standardized coefficient	t	Sig	Standardized coefficient			Collinearity statistics	
	A	Standard Error	Beta			Simple correlation	Partial	Part	Tolerance	VIF
1 Constant	0.006	0.005		1.386	0.166					
p(t-1)	1.000	0.000	1.000	5159.628	0.000	1.000	1.000	1.000	1.000	1.000
2 Constant	0.029	0.005		5.220	0.000					
p(t-1)	0.999	0.000	0.999	5121.263	0.000	1.000	1.000	0.991	0.983	1.017
C	-0.172	0.023	-0.001	-7.344	0.000	-0.130	-0.046	-0.001	0.983	1.017
3 Constant	0.023	0.006		4.123	0.000					
p(t-1)	0.999	0.000	0.999	5123.074	0.000	1.000	1.000	0.991	0.983	1.018
C	-0.161	0.024	-0.001	-6.832	0.000	-0.130	-0.043	-0.001	0.977	1.024
Q	1.816E-06	0.000	0.001	6.067	0.000	-0.016	0.038	0.001	0.993	1.007
4 Constant	1.001	0.203		4.932	0.000					
p(t-1)	0.999	0.000	0.999	5115.188	0.000	1.000	1.000	0.991	0.979	1.021
C	-0.156	0.024	-0.001	-6.620	0.000	-0.130	-0.042	-0.001	0.975	1.025
Q	1.774E-06	0.000	0.001	5.928	0.000	-0.016	0.037	0.001	0.992	1.008
R	-0.143	0.030	0.000	-4.821	0.000	-0.068	-0.030	0.000	0.993	1.008

Collinearity statistics indicate that the tolerance and VIF are close to 1, well within the required limits (tolerance> 0.3, VIF <3.3). This means that the explanatory variables are not correlated with each other, indicating good quality of the model.

From table 3, we notice that the equations which are statistically significant are the second, third and fourth equation.

In these cases, we calculate the AKAIKE (AIC), SCHWARZ (SC) and the average regression error values, noted in the following table.

Table 4: Average regression error value

Equation	2	3	4
AIC	1.195076	1.193721	1.192878
SC	1.196039	1.195004	1.194482
Average regression value	0.00622487	0.00934335	0.00617512

Previous results prove that the fourth equation almost perfectly reproduces the TSM's data. It is given by:

$$p_t^i = a + \alpha\ p_{t-1}^i + \beta\ c_t^i + \theta\ Q_t^i + \lambda\ r_t \quad (14)$$

- $a = 1.001$
- $\alpha = 0.999$
- $\beta = -0.156$
- $\theta = 1.774 * 10^{-6}$
- $\lambda = -0.143$

In order to support this finding, we provide the following figures for two assets: *SFBT* and *UBCI*.

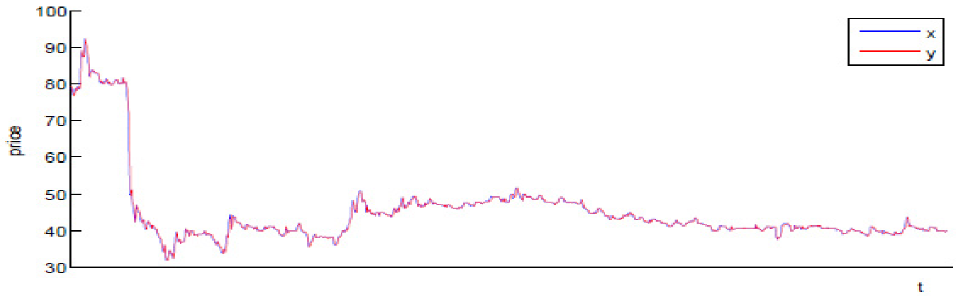

Figure 2: Comparison: Real Value (*x*) – Regression Value (*y*) (The asset: *SFBT*)

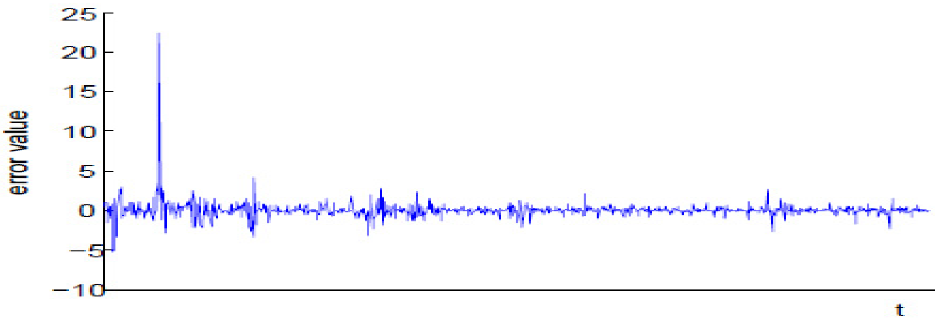

Figure 3: The error value (The asset: *SFBT*)

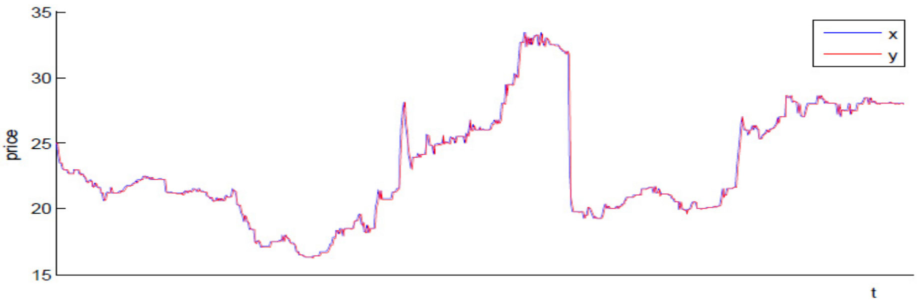

Figure 4: Comparison: Real Value (*x*) – Regression Value (*y*) (The asset: *UBCI*)

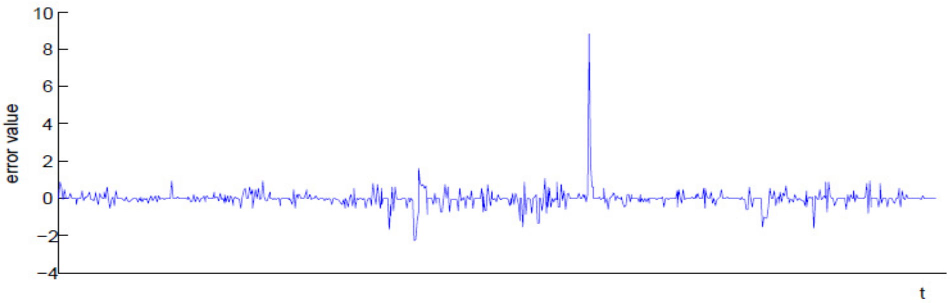

Figure 5: The error value (The asset: *UBCI*)

Figures 2 and 4 show that regression value of *SFBT* and *UBCI*'s price are almost the same as their real value. This result is generalized for the 35 assets included in our sample as described above. Figures 3 and 5 indicate that the error value is close to zero. Exceptions are observed when the asset's prices change unexpectedly for t to $t+1$.

These findings prove that the regression value of the asset's price is obviously the same as its true value.

In order to test the ability of the APMCI to predict the asset's future price value, we proposed to apply the APMCI represented by the equation (14) over the period extending between the years 2006 and 2008 (the out of sample period).

Comparing 2005's and 2008's market indicators, the TSM exhibit an important evolution. For example, the market capitalization increases from 3840MD (in 2005) to 8301MD (in 2008). Also, the stock market index (TUNINDEX) increases from 1615.12 (in 2005) to 2892.40 (in 2008).

In spite of this evolution, we find that the error term is equal to -0.02430, a finding which allows us to conclude that the APCMI exhibits a relatively strong capacity to predict the asset's future price value, which is very close to the real value.

The following figures illustrate the evolution of price's real value vs. price's regression value and the error value for the two assets *UBCI* and *SFBT* using 2006-2008 data.

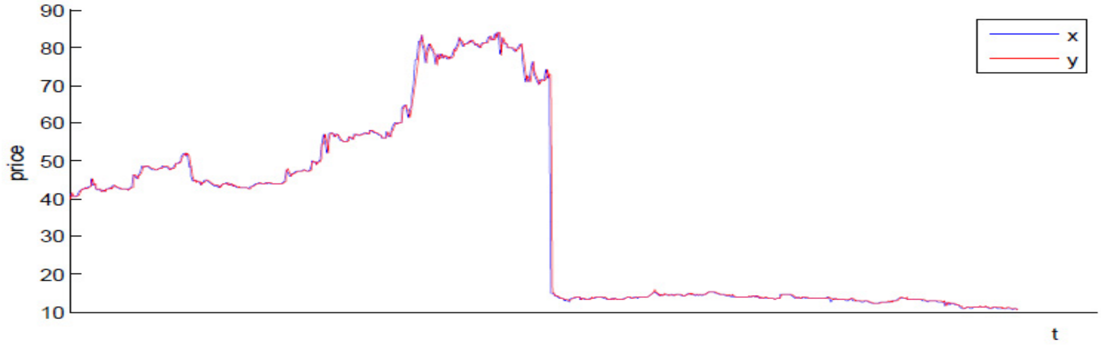

Figure 6: Comparison: Real Value (*x*) – Regression Value (*y*) (The asset: *SFBT*)

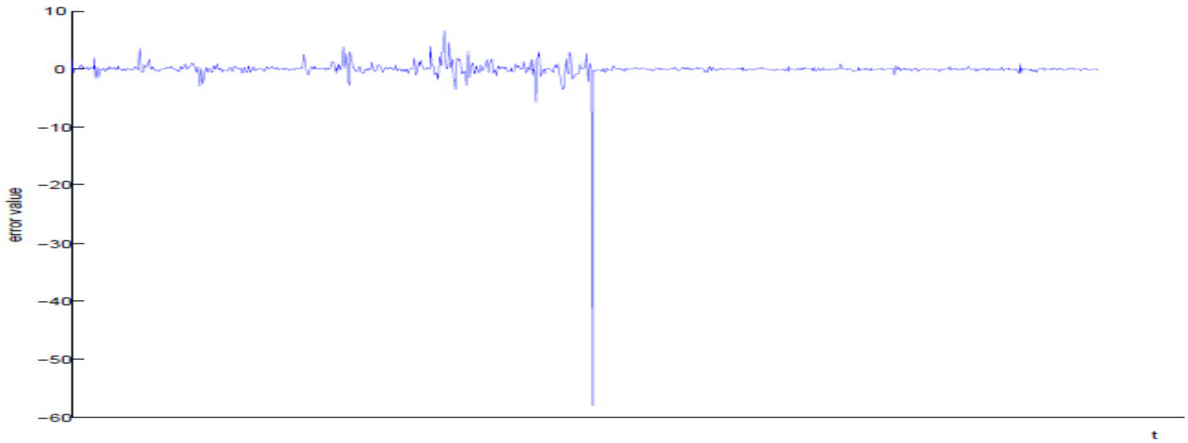

Figure 7: The error value (The asset: *SFBT*)

Figure 8: Comparison: Real Value (*x*) – Regression Value (*y*) (The asset: *UBCI*)

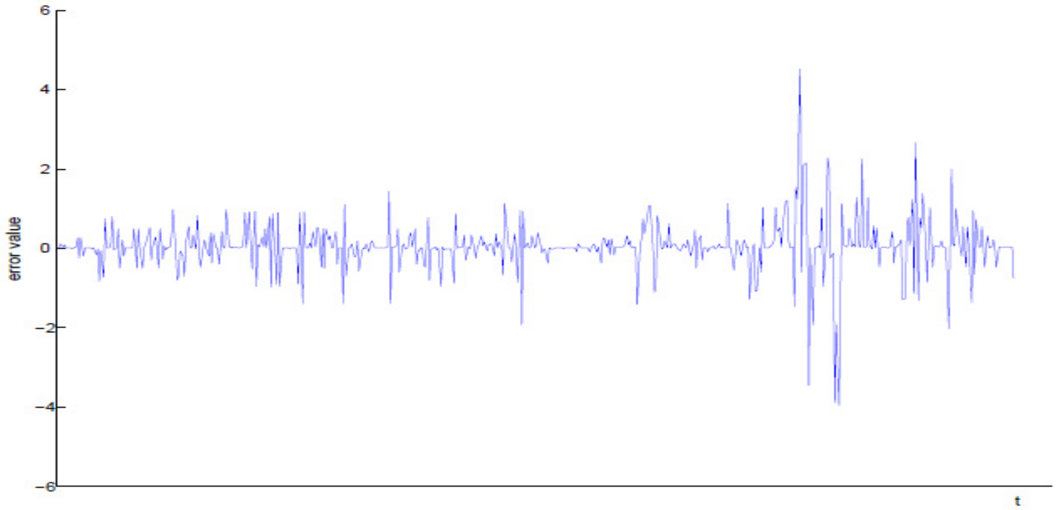

Figure 9: The error value (The asset: *UBCI*)

As we find during 2002-2005, these figures (for 2006-2008) indicate that the regression value of the asset's price is obviously the same as its true value. This result is generalized for the 35 assets included in our sample.

Accordingly to these findings, we can advance that the APMCI proposed in this paper display an interesting ability to reproduce market's data even with data that others have used initially for its formulation.

Then, on the basis of the asset pricing model proposed above, it is possible to advance the following comments:

- The relation between the price and the information cost is *negative*, which means that if the information cost increases, the asset's price decreases and vice versa. Falkenstein, 1996, for example, explains that asset's performance is negatively associated with transaction costs (and therefore, with information costs). Moreover, several authors, such as Kadlec and MCconnell, 1994; Forester and Karolyi, 1999 and Bellalah and Aboura, 2006, find a negative relationship between information costs and the expected return (and consequently the price).
- The relation between the price and the exchanged quantity is *positive,* which simply means that *the supply and demand law* is respected;
- The relation between the price and the risk-free rate of interest is *negative*. Indeed, we know that if the risk-free rate of interest increases, investors will demand risk-free assets (such as Treasury bill, bonds …) more than risky assets (stocks). Then risky asset's prices will decrease.

6. Conclusion

In this paper we have provided evidence that information in financial markets is costly. Entropy statistics provides a solution to estimate information costs. Then, we have proposed an Asset Pricing Model under Costly Information (APMCI). We have found that asset's price is a linear function of its: previous price; information cost; exchanged quantity, and the risk-free rate. The error term is equal to 0.00617 over the period 2002-2005. In order to test the ability of the APMCI to predict the asset's future price value, we proposed to reconsider 2006-2008's period data (the out of sample period). We have found that, in spite of TSM's evolution between the end of 2005 and the end of 2008, the APCMI exhibits a relatively strong capacity to predict the asset's future price; the error term is equal to -0.02430. Therefore, we can conclude that the APCMI exhibits a relatively strong capacity to predict the asset's future price. This result indicates that the APMCI can reproduce market's data even with data that others have used initially for its formulation.

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