The pattern of Euronext volatility in the crisis period: an intrinsic volatility analysis

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Abstract: - The pathology of the financial instability is inter alia characterized by structural changes in the market prices' volatility. Such changes are the expression of investor's uncertainty in regard to the market's dynamics and lead to systematic anticipation errors. The objective of this paper is to study the modifications in the most significant European index - EURONEXT, in the aftermath of financial crisis. The methodology consists in the estimation of the so called intrinsic volatility in index daily data, during pre and current crisis period. Also, it is a study on the structural changes in this volatility based on Quandt-Andrews Break point test. The main output consists in the thesis that for the financial crisis' period there are specific rapid adjustments in short run anticipations and the appearance of global picks in market dynamics.
Key-Words: - crisis, volatility, prices, structural changes
JEL: G01,G10, G15

Introduction

Recently, the risks to financial stability have subsequently increased with the sharp slowdown in financial and real international flows, credit deterioration and capital flight from illiquid and risky markets. In the same time, the emergent markets have lost a part of their recent progresses' advantages and there still remains a persistent probability of foreign investments' pullback from these markets. As a consequence, the global volatility of financial markets has increased with important shifting in the investor's behavior. More exactly, the pathology of the financial instability is inter alia characterized by structural changes in the market prices' volatility. Such changes are the expression of investor's uncertainty in regard to the market dynamics and lead to systematic anticipation errors. As noted in IMF *Global Financial Stability Report* for April 2009 (IMF (2009, xi)): "The current outlook is exceptionally uncertain, with risks still weighing on the downside. A key concern is that policies may be insufficient to arrest the negative feedback between deteriorating financial conditions and weakening economies in the face of limited public support for policy actions".

Overall, the volatility of the financial markets is a key variable which captures the interlinkages between the impact of informational asymmetries and prices adjustment mechanisms. A particular area of interest is the distinction between trend dependent volatility and “noise” / exogenous shocks’ related components. There is an extensive recent literature on this issue (see, for instance, Amihud & Mendelson, (1987, 1989, 1991); Theobald & Yallup (2004, 2005); Gerety & Mulherin, (1994); Damodaran, (1991, 1993)). All these are dealing with a complex set of aspects like the overreactions and “excessive” volatility, information processing and dissemination, prices adjustment towards their underlying intrinsic values and so on. Based on these studies, it can be argued that the trade heterogeneity may be seen as a key variable of the market volatility together with asymmetric information, different risk profiles of investors and the cumulated effects of “informational leverage”. The objective of the present study is to analyze the components of Euronext 100 Index’ volatility by involving a methodology proposed by Theobald & Yallup (2004, 2005) and modified under certain aspects - including data frequency, the estimation of partial adjustment factors and introduction of a baseline for the global volatility. Our results suggest that intra-daily use of this methodology could be changed to a “short-run” day to day one and, also, that the intrinsic and noise component of the index volatility are sensitive to the adopted volatility description and time changing.

The paper is structured as follows: Section 2 describes the theoretical framework and discusses some issues connected with the use of the methodology. Section 3 analyzes the data and the empirical results inside the adopted architecture of the case study. Some conclusions and further research directions are presented in Section 4.

The analytical framework

The global return volatility encompasses different components which reflect the informational adjustment mechanisms. Among them, there can be distinguished an *intrinsic* trend related component and a *noise* asymmetric information one. Thus, the total market volatility could be seen as a combination, not necessary linear one, between of intrinsic volatility, noise and partial adjustment factors. More exactly, the decisional processes by which the economic subjects are determine their financial assets portfolios implies frequent modifications of their structures according both with their inner anticipation mechanisms as well as with the new information arrived on the market. Such modifications affect the prices' mechanisms and determine both the "systematic" and "unsystematic" changes in this volatility.

Consider, for instance, the micro-market financial model proposed by Amihud & Mendelson (1987). In this model, the decomposition of the global volatility could be done as:

$$\mathrm{var}\{R(t)\} = \frac{[g\nu^2 + 2\sigma^2]}{[2-g]} \quad (1)$$

$$\mathrm{cov}\{R(t),R(t-1)\} = \frac{g[(1-g)\nu^2 - \sigma^2]}{[2-g]} \quad (2)$$

Here *R(t)* is the observed (i.e. non-fully adjusting logarithmic return in period *t*), *g* the speed of adjustment factor, v^2 the intrinsic value return variance and σ^2 the noise related variance, with *var* and *cov* the variance and covariance operators, respectively. Obvious, when $g=1$ (there is a fully adjustment process) $\sigma^2=\mathrm{cov}\{R(t),R(t-1)\}$ from Eq. (2) and, given the observed total variance in Eq. (1), v^2 can be deduced. However, when $g\neq 1$, this simple decomposition is not valid and $\{\sigma^2,v^2\}$ are obtained by solving the equation system above.

Eqs. (1) and (2) can be rearranged to express the noise, σ^2, as:

$$\sigma^2 = (1 - g)\mathrm{var}\{R(t)\} - \mathrm{cov}\{R(t), R(t-1)\} \tag{3}$$

Correlatively, the *intrinsic* volatility, v^2, could be deduced as:

$$v^2 = \mathrm{var}\{R(t)\} + \frac{2\mathrm{cov}\{R(t), R(t-1)\}}{g} \tag{4}$$

Several questions could be raised in connection to such methodological approach. Among them: 1) is the *intrinsic* volatility following a random process?; 2) are the *intrinsic* and noise depending components independent?; 3) is the adjustment coefficient convergent on "long-run" to one? All these questions are derived from the fundamental issue of the nature of the adjustment mechanisms.

Overall, as Theobald & Yallup (2005: 407) notes: "Intra-daily volatility is related to the speed of adjustment of prices towards their intrinsic values. The decomposition of volatility into intrinsic and noise related components is demonstrated to be impacted by speeds of adjustment". However, in our view, "intra-daily" could be replaced by "short-time" without affecting the consistency of the explanatory framework. Of course, one of the main arguments against this consists in the assertion that the daily frequency covers the movements in the intraday volatility since the close to close returns could rest unchanged with important highly frequency changes. Still, we are arguing that, in the case of steady prices evolution trajectories, the adjustment coefficients for different intraday frequencies should slowly converge to the value of the daily ones. More exactly, they do not need to be the same, but should converge as shifting from high intra-daily to low daily frequencies.

Also, when the adjustment process is not complete, the partial adjustment factors need to be estimated. An estimator model in the presence of heterogeneous / "thin" trade could be the one proposed by Theobald & Yallup (2004):

$$\begin{aligned} R(t) &= g\mu + (1-g)R(t-1) + \sum_{i=0}^{q} w(i)L^{i}\{ge^{(t-i)} + u(t-i-1)\} \\ &+ (1-(1-g)L)z(t) \end{aligned} \tag{5}$$

This is an ARMA (1, q+1) process where q is the longest lag in the "true" (fully traded) returns affecting in an autocorrelation mechanisms the current observed returns, $w(i)$ is the proportion of the observed return deriving from "true" returns i periods previously, $z(t)$ is an error term from the heterogeneous / "thin" trading process and L the lag operator. It could be noticed that the choice of the AR(1) term implies the hypothesis that prices are I(1) processes which could be seen as a realistic ones. But if this does not hold and autocorrelations at higher lag order are more relevant and persistent, the model should be rewritten as an AR(k) one, with k > 1. Supplementary, if the optimal process which describes the prices dynamics is an AR (1) one, then the appeal to Eqs. (1) and (2) to estimate the intrinsic volatility and noise is not necessary feasible and the involvement of an GARCH model into the volatility processes is needed (for a more detailed discussion, see Theobald & Yallup (2005: 412-413)). In this case, it raises the problem of the "correct" GARCH specification. In this study, we will consider both the simple GARCH (r, s) specification as well as the so-called *Power ARCH (PARCH) Model*. This choice is motivated by the fact that power parameter δ of the standard deviation can be estimated, rather than imposed, and the optional γ parameters are added to capture the asymmetry of up to order τ which confers a higher flexibility of the volatility description:

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\ \delta} + \sum_{i=1}^{p} \alpha_i \left(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i} \right)^{\delta} \tag{6}$$

Here $\delta > 0, |\gamma_i| \leq 1, for\ i = 1, 2 \ldots \tau, \gamma_i = 0\ for\ all\ i > \tau\ and\ \tau \leq p$.

The estimated *intrinsic* volatility should be compared to a baseline in order to highlight the capacity of the involved methodology to discriminate between trend related movements in the volatility and noise related ones. For such baseline estimation, we are appealing to the *historical* volatility, $\sigma^{2\ hist}_{t}$ computed as a convex combination of volatilities over a *m* length moving window:

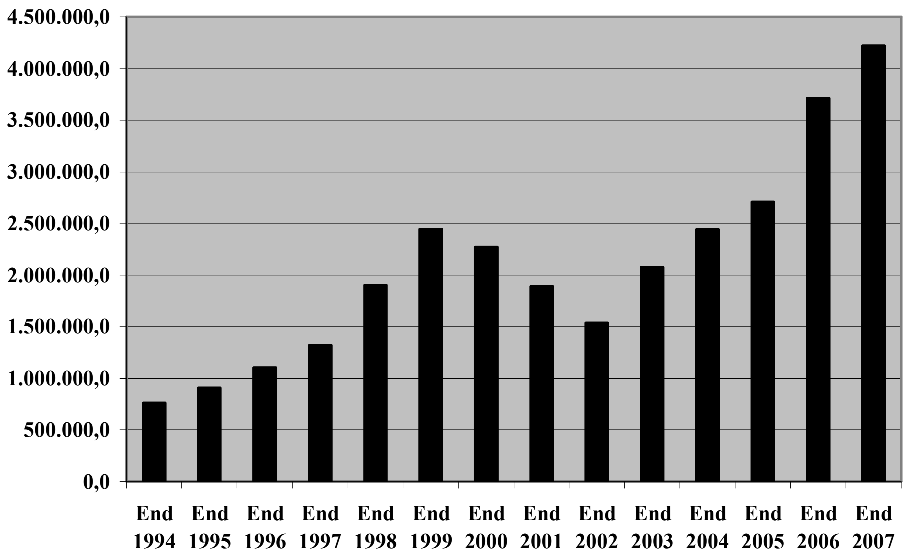
$$\sigma^{2\ hist}_{t} = \sum_{i=t-m}^{t} w_i \sigma^2_{\ i} \quad with\, w_i = \frac{i}{\sum_{i=1}^{m} i} \tag{7}$$

Our idea is that the *intrinsic* volatility could not systematically deviate from the baseline, since such a deviation will imply persistent autocorrelations in the noise component. Or, the existence of such autocorrelations is equivalent to the fact that the noise incorporates exogenous shocks which are absorbed in more than “one period” of time framework. In other words, it is necessary for *intrinsic* and baseline volatilities to have “the same shape”. The argument for such an assumption is quite a straight one: if the volatility decomposition in *intrinsic* and noise related components is a fair estimation, that the *intrinsic* values should be “as much as possible” close to the global volatility, with any deviation from this one being not systematically.

DATA AND EMPIRICAL RESULTS

In 2007, the merger between NYSE Group and Euronext (Pan-European exchange created from the merger of the equity and derivatives exchanges of Amsterdam, Brussels, Lisbon, London and Paris) has build up one of the largest global financial market.

Figure 1. Euronext market capitalization (millions USD)



Source: World Federation of Exchanges (2009)

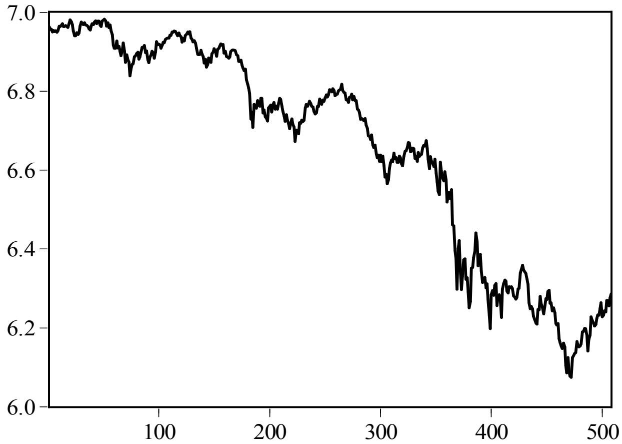
NYSE Euronext's nearly 4,000 listed companies represent a combined $30.5 trillion/ €20.9 trillion in total global market capitalization (as of Dec. 31, 2007). NYSE Euronext's equity exchanges transact an average daily trading value of approximately $141 billion/€103 billion (as of Dec. 31, 2007), which represent more than one-third of the world' cash equities/ equity trading. Such a complex composition involves a heterogeneous market structure with various sources of global volatility.

The Euronext 100 Index is the blue chip index. It includes the largest and most liquid stocks traded on Euronext. Each stock must trade more than 20 percent of its issued shares over the course of the rolling one year analysis period. The index is reviewed quarterly through a size and liquidity analysis of the investment universe. Euronext

Indices B.V. is the compiler of the index under the supervision of the independent Euronext Indices Steering Committee. Daily data on this index for a time span between 03 May 2007 and 30 April 2009 were collected from finance.yahoo.com (http://finance.yahoo.com/q?s=^N100). The use of index data rather than individual stock data avoids problems associated with, for example, bid-ask bounces and cross-sectional dependencies (see, for instance, Gerety & Mulherin (1994)).

The general statistical characteristics of the daily log returns (close to close) are reported in Table 1.

Table 1. The log daily returns tabulation



Return	Mean	Median	Max	Min.	Quant.*	Sum.	Std. Dev.	Skew.	Kurt.	Obs.
[6, 6.2)	6.15	6.15	6.20	6.07	6.15	184.47	0.04	-0.58	2.49	30.00
[6.2, 6.4)	6.29	6.28	6.40	6.20	6.28	678.81	0.05	0.36	2.34	108.00
[6.4, 6.6)	6.53	6.55	6.60	6.40	6.55	156.76	0.06	-0.88	2.30	24.00
[6.6, 6.8)	6.71	6.73	6.80	6.60	6.73	1047.03	0.06	-0.30	1.58	156.00
[6.8, 7)	6.92	6.92	6.98	6.80	6.92	1314.21	0.04	-0.70	3.11	190.00
All	6.66	6.75	6.98	6.07	6.75	3381.29	0.27	-0.59	1.91	508.00

*Quantiles computed for p=0.5, using the Cleveland definition.

It could be noticed that the tabulation of the data suggests that the hypothesis of independent and identical distribution could be rejected.

The correlogram (Table 2 in which the autocorrelations, the partial autocorrelations, the Ljung-Box Q-statistics and their p-values are reported) suggests that the dominant autocorrelation is manifested at lag 1 with no significant higher lag autocorrelations so the description of the lag returns as AR (1) processes is accurate.

Table 2. The log daily returns correlogram

Included observations: 508

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|********</td><td>.|********</td><td>1</td><td>0.991</td><td>0.991</td><td>501.40</td><td>0.000</td></tr>
<tr><td>.|********</td><td>.|. |</td><td>2</td><td>0.981</td><td>-0.011</td><td>994.14</td><td>0.000</td></tr>
<tr><td>.|*******|</td><td>.|. |</td><td>3</td><td>0.972</td><td>-0.001</td><td>1478.3</td><td>0.000</td></tr>
<tr><td>.|*******|</td><td>.|. |</td><td>4</td><td>0.962</td><td>0.007</td><td>1954.3</td><td>0.000</td></tr>
<tr><td>.|*******|</td><td>.|. |</td><td>5</td><td>0.952</td><td>-0.040</td><td>2421.4</td><td>0.000</td></tr>
</table>

Table 3 contains daily estimates of the adjustment speeds, total volatility, *intrinsic* volatility and noise induced volatility. In order to capture the structural changes in market dynamics induced by the global financial instability, two sub-sets were considered: a sub-set "A" between May, 03, 2007 and April, 23, 2008 and, respectively, a sub-set "B" for the April, 24, 2008 - April, 30, 2009. Sequential, a heteroskedastic ARMA model and two homoskedastic ARMA-GARCH were considered for the full set and the two sub-sets. The optimal specification of the model was choosing by using the Akaike info criterion.

Table 3. Speeds of adjustments and volatilities estimates- daily returns

Data partition	No day	Model	*g*	Variance var{R(t)}	Estimated *g*		g=1	
					σ^2	υ^2	σ^2	υ^2
Full set	510	ARMA(1,1)	0.9998	0.0743	-0.0739	0.2222	-0.0739	0.2222
Full set	510	ARMA(1,1) GARCH (3,1)	1.0021	0.0743	-0.0741	0.2219		
Full set		ARMA(1,1)	0.6084	0.0743	-0.0448	0.3174		

	510	GARCH (3,1)						
Sub set "A"	249	ARMA(1,1)	0.9999	0.0073	-0.0071	0.0216	-0.0071	0.0216
Sub set "A"	249	ARMA(1,3) GARCH (1,1)	0.8783	0.0073	-0.0063	0.023535		
Sub set "A"	249	ARMA(1,3) GARCH (3,2)	1.0011	0.0073	-0.0072	0.021539		
Sub set "B"	258	ARMA(1,0)	0.9997	0.0487	-0.0479	0.144490	-0.0479	0.1445
Sub set "B"	258	ARMA(1,3) GARCH (1,3)	0.9997	0.0487	-0.0479	0.144486		
Sub set "B"	258	ARMA(1,3) GARCH (1,3)	0.9997	0.0487	-0.0479	0.144491		

In the Table above, it can be noticed that there are no major in the adjustment speeds between the full set and the two sub-sets if the heteroskedastic ARMA model is involved; however, such changes occur in respect to the homoskedastic models' specifications. More exactly, in the first case, all three corresponding coefficients are close to one, suggesting an almost complete adjustment process. Nonetheless, for the heteroskedastic models, the coefficients are in general sub unitary (with the exception of the second one in the case of sample "A") and, in the case of the GARCH specification, for the full set and simple GARCH description components. Or, the sample "A" significant at a 5% level different from one thus indicating a under reaction in the prices adjustments. The existence of sub-samples' differences could reflect the increase in the global market volatility as an expression of the financial turbulence in progress over the analyzed period.

It can be observed that on March, 09, 2009 and April, 30, 2009 of intra-daily hourly data, there are some notable differences compared to the values of sample "B" adjustment coefficients and volatility components (Table 4). More exactly, if for the heteroskedastic ARMA model the adjustment coefficients are close to one, for the homoskedastic models the coefficients are significantly lower that the ones corresponding to the daily data. Of course, since this intra-daily sample does not completely cover the same time span as the sub set "B", a direct comparison is not possible.

Table 4.1. Speeds of adjustments and volatilities estimates- hourly

Model	*g*	Variance var{R(t)}	Estimated *g*		g=1	
			σ^2	υ^2	σ^2	υ^2
ARMA(1,1)	1.00008	0.00462	-0.00462	0.01386	-0.00462	0.01386
ARMA(1,1) GARCH(1,1)	0.84217	0.00462	-0.00389	0.01559		
ARMA(1,1) GARCH(3,1)	0.49858	0.00462	-0.00230	0.02315		

Even more, the two volatilities are cointegrated as is suggested by a Johansen test based on the assumptions of no deterministic trend in data- intercept (without trend) in the cointegration equation and no intercept in VAR (Table 4.2).

Tab. 4.2. The Johansen cointegration test for historical baseline and *intrinsic* volatility

Sample (adjusted): 6 501
Included observations: 496 after adjustments
Trend assumption: No deterministic trend
Lags interval (in first differences): 1 to 4
Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	0.05 Critical Value	Prob.**
None *	0.049543	26.74975	12.32090	0.0001
At most 1	0.003113	1.546603	4.129906	0.2506

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.049543	25.20315	11.22480	0.0001
At most 1	0.003113	1.546603	4.129906	0.2506

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

1 Cointegrating Equation(s):	***Log likelihood***	5892.713

Normalized cointegrating coefficients (standard error in parentheses)

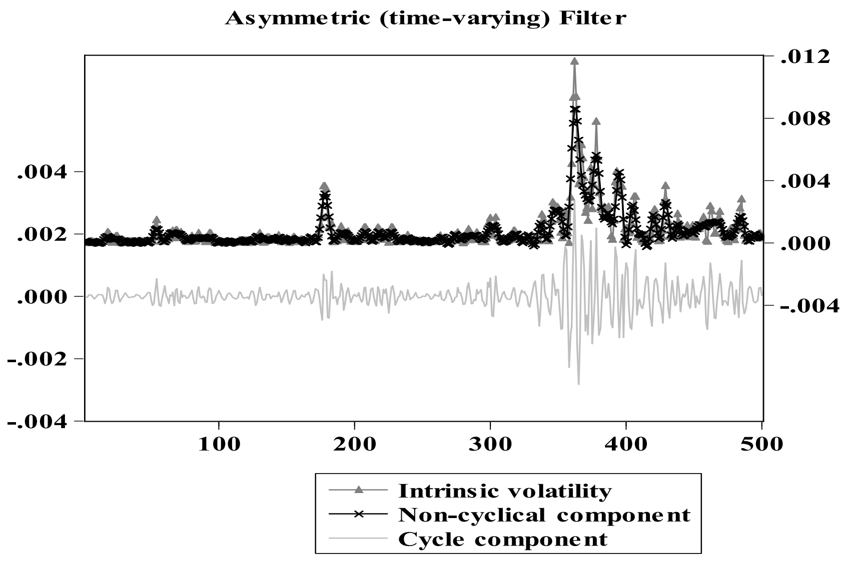
HISTORICAL	***INTRINSIC***
1.000000	-15.26642
	(1.34018)

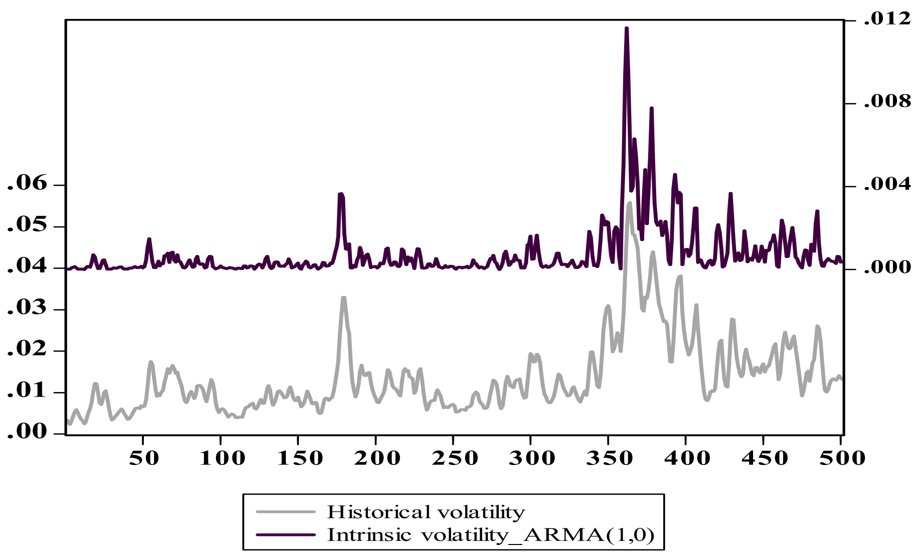
Adjustment coefficients (standard error in parentheses)

D(HISTORICAL)	0.002815
	(0.00735)
D(INTRINSIC)	0.008385
	(0.00276)

Overall, the *intrinsic* volatility and the baseline follows the same shape as these are displayed in Figure 2 for the heteroskedastic ARMA model estimation.

Figure 2. Historical baseline and *intrinsic* volatility - heteroskedastic ARMA specification





More exactly, Engle & Granger (1987) pointed out that a linear combination of two or more non-stationary series may be stationary. If such a stationary linear combination exists, the non-stationary time series are said to be co-integrated.

The stationary linear combination is called the *co-integrating equation* and may be interpreted as a “long-run” equilibrium relationship among the variables. To test for the existence of such co-integrating relationships between the indices, we shall employ the methodology developed in Johansen (1988, 1995).

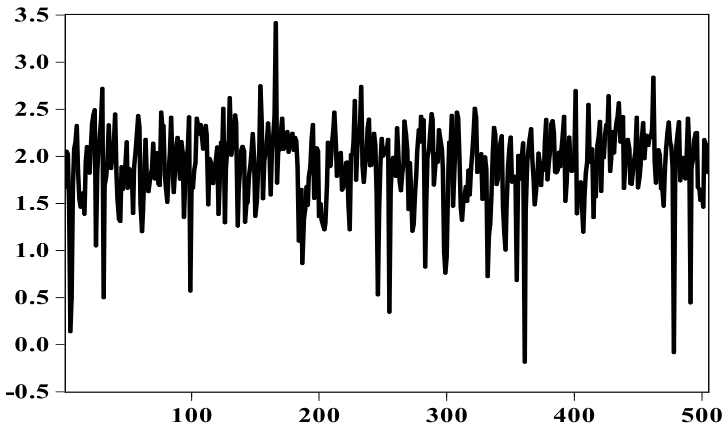
Of course, the empirical support for the existence of such co-integration relationship between the two forms of volatility does not necessary support the idea of a functional connection between them. The fact that the volatilities are “moving together” could be the effect of the global market conditions and does not imply a feedback between them.

Finally, it is interesting to compare this methodological framework with some alternative approaches. For instance, Damodaran (1993) develops an estimator for prices’ adjustment coefficients as a function of variances at varying differencing intervals and autocovariances. Brisley & Theobald (1996) have shown that the correct specification of this estimator for a differencing interval j is:

$$g(j)=\frac{2\operatorname{var}\{R(j,t)\}/j+2\operatorname{cov}\{R(k,t),R(k,t-1)\}/j}{\operatorname{var}\{R(j,t)\}/j+\operatorname{var}\{R(k,t)\}/k+2\operatorname{cov}\{R(k,t),R(k,t-1)\}/k}\quad(8)$$

As an example, for *j=1, k=5* the estimator looks like in Figure 3.

Figure 3. The Damodaran estimator



It could be noticed that such a variance / covariance estimator, estimated on a short-run time span, displays an important volatility with a minimum of -0.18 and a maximum of 3.42. So that, at least for this frequency of data, such a procedure leads to less robust estimation of adjustment coefficients.

Conclusion

The informational efficiency of the financial markets is inter alia expressed by their capacity to quickly adjust the new information and to correct the prices levels. If their mechanisms display a sort or other form of "efficiency", then the speed of adjustment should be "short enough". If, per a contrario, there is a low informational efficiency, then the level of this speed should reflect the lagged information effects and the translation of the effects of "long memory" processes in the prices' formation.

The purpose of this paper is to observe the *intrinsic* and noise related volatilities as well as the adjustment speeds on the NYSE Euronext market. It was found that all these variables are sensitive to the adopted volatility description and, as well, are changed in the overall time span. In order to enhance such conclusion, it is minimally necessary: (1) to repeat the proposed analysis by involving intra-daily data; (2) to compare the results for close to close volatility with the ones corresponding to open to open, since there could be expected some relevant differences between these due to the informational asymmetry; (3) to replicate the methodology for another market index in order to cover more market strata; (4) to check for the effects induced by the institutional and regulatory frameworks on prices' formation mechanisms.

In our view, this could be an important analytical research objective in the context of global financial instability, pessimistic expectations and high degree of uncertainty in regard to the future of the international financial system.

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