Short Run Volatility and the Adjustment Processes on Financial Markets: An Analytical Framework and Empirical Study on NYSE Euronext Market

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Abstract: - The prices on financial markets are driven by fundamental determinants and exogenous shocks under the impact of new information. So, one of the critical issue is to isolate the different components of the global volatility in trend dependent volatility and “noise” / exogenous shocks’ related components. There are several methods for such decomposition. Among those, [12] and [13] highlight the interlinkages between the intradaily volatility and the speed of prices’ adjustment towards their intrinsic values. The objective of this paper is to discuss and modify their methodology by shifting from intradaily to “short-run” daily volatility, extending the estimation of the partial adjustment factors and introducing the idea of comparing the intrinsic volatility estimator with baseline volatility. The main result consists in providing some empirical evidences for the volatility estimators’ sensitivity to the adopted analytical framework in the case of NYSE Euronext market.

Key-Words: - Financial markets, Euronext 100 Index, intrinsic volatility, noise, GARCH, Power ARCH (PARCH) Models

1 Introduction

The volatility of the financial markets is a key variable capturing 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 Amihud & Mendelson [1987, 1989, 1991]; Theobald & Yallup [2004, 2005]; Gerety & Mulherin [1994]; Damodaran [1991, 1993]). All studies are dealing with a complex set of aspects like overreactions and “excessive” volatility, information processing and dissemination, prices’ adjustment towards their underlying intrinsic values etc. The objective of this study is to analyze the components of the Euronext 100 Index’ volatility by involving a methodology proposed by Theobald & Yallup [2004, 2005] modified under certain aspects as data frequency, estimation of the partial adjustment factors and introduction of an baseline for the global volatility. Our results suggest that intradaily appliance of this methodology could be changed to a “short-run” day to day one and that the intrinsic and noise component of the index volatility are sensitive to the adopted volatility description and are time changing.

The paper is structured as follows: Section 2 describes the theoretical framework and discusses some issues connected with the appliance 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.

2 The analytical framework

The global return volatility encompasses different components which reflect the informational adjustment mechanisms. Among them, there could be discriminate between an intrinsic trend related component and a noise asymmetric information one. Thus, the total market volatility can be seen as a combination, not necessary linear, between of intrinsic volatility, noise and partial adjustment factors. 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:

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

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

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 \(\sigma^2\) the noise related variance, with \textit{var} and \textit{cov} the variance and
covariance operators, respectively. Obvious, when \( g=1 \) (there is a fully adjustment process) \( \sigma^2 = \text{cov}(R(t), R(t-1)) \) from Eq. (2) and, given the observed total variance in Eq. (1), \( \nu^2 \) can be deduced. However, when \( g \neq 1 \), this simple decomposition is not valid and \( \{\sigma^2, \nu^2\} \) are obtained by solving the equation system above. Eqs. (1) and (2) can be rearranged to express the noise, \( \sigma^2 \), as:

\[
\sigma^2 = (1 - g) \text{var}[R(t)] - \text{cov}[R(t), R(t-1)]
\]

(3)

Correlatively, the intrinsic volatility, \( \nu^2 \) could be deduced as:

\[
\nu^2 = \text{var}[R(t)] + \frac{2 \text{cov}[R(t), R(t-1)]}{g}
\]

(4)

Within this framework, there can be identified several issues. A minimal list of these may include:

1. The selection of the data frequency;
2. The estimation of the partial adjustments factors;
3. The set of baseline volatility estimation.

First, as Theobald & Yallup [2005: 407] note: “Intradaily volatility is related to the speed of prices adjustment 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, “intradaily” could be replaced by “short-time” without affecting the consistency of the explanatory frame. 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 can rest unchallenged with important highly frequency changes. Still, we argue 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 intradaily to low daily frequencies.

Second, when the adjustment process is not a complete one, then 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].

\[
R(t) = g\mu + (1 - g) R(t-1) + \sum_{j=0}^{q} w(i) L^j \{ge^{j-1} + u(t-i-1)\}
+ (1 - (1 - g)L) z(t)
\]

(5)

This is an ARMA \((1, \omega)\) process where \( q \) is the longest lag in the “true” (fully traded) returns affecting in an autocorrelation mechanisms the current observed returns, \( w(t) \) 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 can be noticed the choice of the AR \((1)\) term implies the hypothesis that prices are I(1) processes which can be seen as a realistic one. But if this does not hold and autocorrelations at higher lag order are more relevant and persistent, then the model should be rewrite 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 necessarily 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. Thus, we shall consider both the simple GARCH \((r,s)\) specification as well as the so-called Power ARCH \((PARCH) Model\). Its choice is motivated by the fact that power parameter \( \delta \) of the standard deviation can be estimated rather than imposed, and the optional \( \gamma \) parameters are added to capture asymmetry of up to order \( \tau \) which confers a higher flexibility of the volatility description:

\[
\sigma_{t}^{\delta} = \delta \sum_{j=1}^{q} \beta_{j} \sigma_{t-j}^{\delta} + \sum_{i=1}^{p} \gamma_{i} \left( \kappa_{i-1} - \sigma_{t-i}^{\delta} \right)^{\delta}
\]

(6)

Here \( \delta > 0, \gamma_{i} \leq 1 \), for \( i=1, 2, \ldots, \tau, \gamma_{i} = 0 \) for all \( i > \tau \) and \( \tau \leq p \). Third, the estimated intrinsic volatility should be compared with 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 at the historical volatility, \( \sigma_{t}^{\delta} \sim \sigma_{t}^{\delta} \) computed as a convex combination of volatilities over a \( m \) length moving window:

\[
\sigma_{t}^{\delta \text{hist}} = \sum_{i=t-m}^{t} w_i \sigma_i^{\delta} \text{ with } w_i = \frac{i}{m \sum_{j=1}^{m} j}
\]

(7)

We consider that the intrinsic volatility cannot systematically deviate from the baseline, since such a deviation implies 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” time framework. So, it is necessary for intrinsic and baseline volatilities to have “the same shape”. The argument for such an assumption is 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, any deviation from this one being not
3 Data and Empirical Results

The NYSE Group and Euronext merger in 2007 created one of the largest global financial markets. 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 represents more than 1/3 of the world's cash equity trading. Such a complex entity involves a heterogeneous market structure with various sources of global volatility.

The Euronext 100 Index is the blue chip index. It comprises the largest and most liquid stocks traded on Euronext. Each stock must trade more than 20% of its issued shares over the course of the rolling one-year analysis period. The index is reviewed quarterly through 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 wh it no significant higher lag autocorrelations so that the description of the lag returns as AR (1) processes is accurate.

It could be noticed that the tabulation of the data 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 wh it no significant higher lag autocorrelations so that the description of the lag returns as AR (1) processes is accurate.

Tab. 1. The log daily returns tabulation

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
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<tr>
<td>[6, 6.2)</td>
<td>0.04</td>
<td>0.00</td>
<td>0.09</td>
<td>0.06</td>
<td>0.06</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>[6.2, 6.4)</td>
<td>0.05</td>
<td>0.00</td>
<td>0.10</td>
<td>0.07</td>
<td>0.07</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<tr>
<td>[6.4, 6.6)</td>
<td>0.06</td>
<td>0.00</td>
<td>0.11</td>
<td>0.08</td>
<td>0.08</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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</tr>
<tr>
<td>[6.6, 6.8)</td>
<td>0.07</td>
<td>0.00</td>
<td>0.12</td>
<td>0.09</td>
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</tr>
<tr>
<td>[6.8, 7)</td>
<td>0.11</td>
<td>0.00</td>
<td>0.14</td>
<td>0.10</td>
<td>0.10</td>
<td>0.00</td>
<td>0.00</td>
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</tr>
<tr>
<td>All</td>
<td>0.19</td>
<td>0.00</td>
<td>0.21</td>
<td>0.11</td>
<td>0.11</td>
<td>0.00</td>
<td>0.00</td>
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</tbody>
</table>

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

Tab. 2. The log daily returns correlogram

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

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

<table>
<thead>
<tr>
<th>Data partition</th>
<th>No. days</th>
<th>Model</th>
<th>g</th>
<th>Variance var{R(t)}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full set</td>
<td>510</td>
<td>ARMA (1,1)</td>
<td>0.9998</td>
<td>0.0743</td>
</tr>
<tr>
<td>Full set</td>
<td>510</td>
<td>ARMA (1,1); GARCH (3,1)</td>
<td>1.0021</td>
<td>0.0743</td>
</tr>
<tr>
<td>Full set</td>
<td>510</td>
<td>ARMA (1,1); GARCH (3,1)</td>
<td>0.6084</td>
<td>0.0743</td>
</tr>
<tr>
<td>Sub set“A”</td>
<td>249</td>
<td>ARMA (1,1)</td>
<td>0.9999</td>
<td>0.0073</td>
</tr>
<tr>
<td>Sub set“A”</td>
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<td>ARMA (1,3); GARCH (1,1)</td>
<td>0.8783</td>
<td>0.0073</td>
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<td>Sub set“A”</td>
<td>249</td>
<td>ARMA (1,3); GARCH (3,2)</td>
<td>1.0011</td>
<td>0.0073</td>
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<tr>
<td>Sub set“A”</td>
<td>258</td>
<td>ARMA (1.0)</td>
<td>0.9997</td>
<td>0.0847</td>
</tr>
<tr>
<td>Sub set“A”</td>
<td>258</td>
<td>ARMA (1.3); GARCH (1,3)</td>
<td>0.9997</td>
<td>0.0847</td>
</tr>
<tr>
<td>Sub set“A”</td>
<td>258</td>
<td>ARMA (1.3); GARCH (3,3)</td>
<td>0.9997</td>
<td>0.0847</td>
</tr>
</tbody>
</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. In Table 3 it can be noticed that there are no majors differences 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. However, for the heteroskedastic models, the
coefficients are in general subunitary (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. The sample “A” coefficients are significant different at a 5% level from “I” thus indicating a underreaction in the prices adjustments. The existence of the sub-samples differences could reflect the increase in the global market volatility as an expression of the financial turbulence in progress over the analysed period.

It can be observed that on March 09, 2009 and April 30, 2009 of intradaily 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 for the homoskedastic models, the coefficients are significantly lower that the ones corresponding to the daily data. Obviously, since this intradaily sample does not completely covers the same time span as the sub set “B”, a direct comparison is not possible.

To test for the existence of such co-integrating relationships between the indices we will employ the methodology developed in Johansen [1988, 1995]. Thus, we will consider \( y \), a vector of non-stationary \( I(1) \) variables, \( x \), a \( d \)-vector of deterministic variables and \( \varepsilon \), a vector of innovations. Then, the data generating process for \( y \), \( y \) is a Gaussian vector autoregressive model of finite order \( k \), \( VAR(\kappa) \) which could be write as:

\[
\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + Bx_t + \varepsilon_t \tag{8}
\]

where:

\[
\Pi = \sum_{i=1}^{p} A_i - I, \quad \Gamma_i = -\sum_{j=1}^{r} (9)
\]

Granger’s representation theorem asserts that if the coefficient matrix \( \Pi \) has reduced rank \( r < k \), then there exist \( k \times r \) matrices \( \alpha \) and \( \beta \) each with rank such that \( \Pi = \alpha \beta' \) and \( \beta' y_t \) is \( I(0) \). The number of co-integrating relations (the co-integrating rank) and each column of \( \beta \) is the co-integrating vector. The elements of \( \alpha \) are known as the adjustment parameters in the VEC model. Johansen’s method is to estimate the \( \Pi \) matrix from an unrestricted \( VAR \) and to test whether one can reject the restrictions implied by the reduced rank of \( \Pi \).

The empirical time series may have nonzero means and deterministic trends as well as stochastic trends. Similarly, the co-integrating equations may have intercepts and deterministic trends. The asymptotic distribution of the LR test statistic for co-integration does not have the usual \( \chi^2 \) distribution and depends on the assumptions made with respect to the deterministic trends. Therefore, in order to carry out the test, one needs to make an assumption regarding the trend underlying the analysis data.

The mentioned assumption for testing the cointegration between the volatilities is equivalent to:

Overall, the intrinsic volatility and the baseline follow the same shape, as these are displayed in Fig. 1 for the heteroskedastic ARMA model estimation.

Even more, the two volatilities are cointegrated as 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).

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.

Fig. 1. Historical baseline and intrinsic volatility - heteroskedastic ARMA specification
\[ \Pi y_{t-1} + Bx_t = \alpha \left( \beta y_{t-1} + \rho_0 \right) \]  

(10)

In order to estimate the number of co-integration relationships, two tests could be employed:

The trace statistic tests the null hypothesis of \( r \) co-integrating relations against the alternative of \( k \) co-integrating relations, where \( k \) is the number of endogenous variables, for \( r = 0, 1, \ldots, k-1 \). The alternative of \( k \) co-integrating relations corresponds to the case where none of the series has a unit root and a stationary VAR may be specified in terms of the levels of all of the series. The trace statistic for the null hypothesis of co-integrating relations is computed as:

\[
LR_r (r | k) = -T \sum_{i=1}^{k} \log (1 - \lambda_i) \tag{11}
\]

where \( \lambda_i \) is the \( i-th \) largest eigenvalue of the \( \Pi \) matrix.

The maximum eigenvalue statistic tests the null hypothesis of \( r \) co-integrating relations against the alternative of \( r+1 \) co-integrating relations. This test statistic is computed as:

\[
LR_{\max} (r+1 | k) = -T \sum_{i=1}^{k} \log (1 - \lambda_{i+1}) = LR_r (r | k) - LR_r (r+1 | k) \tag{12}
\]

Thus:

Tab. 4. The Johansen cointegration test for historical baseline and intrinsic volatility

<table>
<thead>
<tr>
<th>Hypothesized</th>
<th>Trace</th>
<th>0.05</th>
</tr>
</thead>
<tbody>
<tr>
<td>None *</td>
<td>0.049543</td>
<td>25.20315</td>
</tr>
<tr>
<td>At most 1</td>
<td>0.003113</td>
<td>1.546603</td>
</tr>
</tbody>
</table>

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)

<table>
<thead>
<tr>
<th>Historical</th>
<th>Intrinsic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.000000</td>
<td>-15.26642</td>
</tr>
<tr>
<td>(1.34018)</td>
<td></td>
</tr>
</tbody>
</table>

Also, it can be noticed that there are some structural breaking points in the evolution of the intrinsic volatility as an expression of market patterns’ changes. For instance, by using the Quandt-Andrews Breakpoint Test of intrinsic volatility, it appears that the end of September 2008 is a major structural change point and the null of no such points over the analysis time span could be rejected (Table 5). The idea behind the Quandt-Andrews test is that a single Chow Breakpoint Test is performed at every observation between two observations, \( \tau_1 \) and \( \tau_2 \). The \( k \) test statistics from those Chow tests are then summarized into one test statistic for a test against the null hypothesis of no breakpoints between \( \tau_1 \) and \( \tau_2 \). The individual test statistics can be summarized into three different statistics: the Sup or Maximum statistic, the Exp Statistic, and the Ave statistic (see Andrews [1993] and Andrews & Ploberger [1994]).

4 Conclusion

The purpose of this paper is to observe the intrinsic and noise related volatilities as well as the adjustment speed in the NYSE Euronext market. It was found that all these
variables are sensitive to the adopted volatility description and that 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 intraday 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 them due to the informational asymmetry;
3. to replicate the methodology for another market index in order to cover more market strata.

A specific interest for further research could be represented by the developing of discrimination methodology for the adjustment processes and heterogeneous / “thin” trade effects. As Theobald & Yallup [2004: 91] note: “In assessing the efficiency of markets, it is, of course, important to distinguish between an adjustment effect and a thin trading effect. The presence of the latter could distort inferences regarding the efficiency of a particular market”. Such a methodological cut-off could better clarify the functional mechanisms behind the prices’ adjustments and could capture more accurate the effects of markets heterogeneity.

References: