Measuring the risk of institutional change in European financial markets

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Abstract Using a quantile function-based time series model, this paper illustrates a risk measurement to characterise the effects of institutional changes in major European financial markets. The paper presents examples based on major market indices to further address the influences behind the establishment of the European Central Bank. As this model allows more flexibility than classic generalised autoregressive conditionally heteroskedastic (GARCH) models, its validity and robustness are analysed theoretically and illustrated empirically through comparisons with multivariate GARCH models.

Keywords: *risk, institutional effect, European markets*

INTRODUCTION

With the recent acceleration of financial integration in various geographical areas, both positive and negative aspects of this trend have been well addressed (eg see Bordo *et al.*;[1] Soros;[2] Stulz;[3] and Williamson[4]). As institutions are widely accepted as one of the key factors behind long-term economic growth, academic researchers, practitioners and policy makers are naturally interested how changes in their settings affect the price behaviours of financial securities. A typical example is the formation of the European Central Bank (ECB) during the late 20th century, which helped economic integration in Europe and monetary policy stabilisation among EU member states, in addition to affecting risk issues and price behaviours in the European financial markets.

Unfortunately, it is not easy to accurately characterise asset price behaviours based on historical information unless some strict assumptions are made. Generalised autoregressive conditionally heteroskedastic (GARCH) process-based models have become widely accepted for the consideration of stochastic volatilities, however, the stationarity and distribution-related assumptions of such models may lead to biased or inaccurate results.[5–7] To improve accuracy, Jiang *et al.* have proposed a quantile function-based time series model which outperforms traditional GARCH models.[8] Its estimation accuracy and computational efficiency in capturing key features of financial time series have been highlighted by Jiang *et al.*[8] using individual stocks, and by Jiang and Wu using market indices in both mature and emerging financial markets.[9]

The present paper applies the model of Jiang *et al.*[8] to demonstrate how major financial markets were affected by the establishment of the ECB and the adoption of the euro. The advantage of this approach is that it uses the class of quantile distributions proposed by Jiang[10] as the basis of its time series model. This is because quantile distributions measure risk by simulating changing tail orders which have been shown empirically in the literature,[11] instead of modelling stochastic volatilities in GARCH models.[8] These features are illustrated by Jiang *et al.*, who use the maximum likelihood estimation and individual stocks in the US markets as examples.[8]

Adopting the Quantile-Quantile (Q-Q) estimation, Jiang and Wu[9] apply this quantile distribution-based model to highlight its robustness in both industrialised economies and emerging markets using the US and Chinese market indices as examples, respectively. In both instances, however, Jiang and Wu only examine the effects of financial events on the risk-taking behaviours of investors in local financial markets. As such, it is worth mentioning that the current study focuses on the effects of institutional changes on international financial markets in a certain geographical area, so as to further illustrate the robustness and generalisability of the model proposed by Jiang *et al.*[8] Furthermore, this study also highlights the influence of relaxing some key assumptions made in previous studies. The results show that the investment decisions made on the basis of this quantile function-based time-series model, whether or not the assumptions hold, are stable and reliable.

This study is expected to make multiple contributions to the literature on financial institutions and financial market analysis. First, it adds to the risk management literature by taking into account the effects of institutional changes. Secondly, it further illustrates the robustness and generalisability of the model proposed by Jiang *et al.*[8] in characterising financial market behaviours by applying it to international financial markets. Thirdly, the current study also contributes to the literature by using parameters estimated on the basis of Jiang *et al.*'s model to interpret the impact of the establishment of the ECB and the adoption of the euro so as to provide potentially crucial policy implications for European nations.

The following section discusses the theoretical basis for developing the time series model proposed by Jiang *et al.*,[8] and addresses the properties and advantages of this model. The paper then proceeds to analyse the effects of institutional changes on European financial markets, before drawing some conclusions and making recommendations for future studies.

METHODOLOGY

To better characterise properties, such as fat tails and tilting distributions, of observed information in the field of mathematical finance, Jiang has developed two classes of quantile function-based distributions.[10] The first of these — the Class I quantile function-based distribution — is constructed as follows:

$$q(\gamma;\alpha,\beta,\delta,\mu) = \begin{cases} \delta^{1/\alpha}\left\{log\dfrac{\gamma^{\beta}}{1-\gamma^{\beta}}\right\}^{1/\alpha}+\mu & if\ \dfrac{\gamma^{\beta}}{1-\gamma^{\beta}}>1 \\ 0 & if\ \dfrac{\gamma^{\beta}}{1-\gamma^{\beta}}=0 \\ -\delta^{1/\alpha}\left\{log\dfrac{\gamma^{\beta}}{1-\gamma^{\beta}}\right\}^{1/\alpha}+\mu & if\ 0<\dfrac{\gamma^{\beta}}{1-\gamma^{\beta}}<1 \end{cases} \quad (1)$$

where the values of parameters δ, α and β are positive. According to Jiang, the parameter α measures the volatility of the observed information, β is 'a tail balance adjuster', δ serves as 'a scaler parameter', and μ characterises the location of a distribution.[10]

Jiang also presents the Class II quantile function-based distribution characterised distributions with 'extremely unbalanced tails'. The corresponding quantile function for this is as follows:

$$q(\gamma;\alpha^{-},\alpha^{+},\delta^{-},\delta^{+},\mu) = -\delta_{-}^{1/\alpha_{-}}\left(log\frac{1}{\gamma}\right)^{1/\alpha_{-}} + \delta_{+}^{1/\alpha_{+}}\left(log\frac{1}{1-\gamma}\right)^{1/\alpha_{+}}+\mu \quad (2)$$

where the values of parameters α_{-}, α_{+}, δ_{-} and δ_{+} are positive. Note the Class II quantile function allows more flexibility than the Class I quantile function as the former has two separate parameters (α_{-} and α_{+}) to capture how fat the left and right tails are, respectively, and also has two separate parameters (δ_{-} and δ_{+}) to demonstrate the scaling on both sides.

Unfortunately, the Class II quantile function focuses more on distributions with extremely unbalanced tails which are not usually observed in financial markets. Jiang *et al.*[8] have therefore developed a time-series model to help characterise historical information in financial markets by assuming the log-returns of financial securities follow the probability illustrated by the Class I quantile function (1). As described by Jiang *et al.*[8] the time-series model not only has the advantages of the quantile functions in terms of explicit forms of distribution and density functions, but it also takes volatility clustering in financial markets into account by making use of special function forms of time-varying α_t and β_t. This allows the model to capture how fat the tails are and which side is heaviest in a dynamic framework, thereby illustrating how an event occurring on a specific date can affect future investment returns. To illustrate different categories of risk in financial markets, Jiang and Wu apply this model to financial market indices to consider both how the US market was affected by the Nasdaq collapse in 2000, and how the Chinese markets are affected by political risk.[9]

As presented in previous studies such as Jiang,[10] Jiang *et al.*[8] and Jiang and Wu,[9] the log-return of a financial security is a function of four time-varying parameters (α_t, β_t, δ_t and μ_t), such that:

$$LR = f(\alpha_t, \beta_t, \delta_t, \mu_t),$$

where LR denotes the log-return, δ_t and μ_t are assumed constant so that $\delta_t = \delta$ and $\mu_t = \mu$, and α_t and β_t are determined by accumulated information before time t. Using the maximum likelihood estimation and the Q-Q estimation, respectively, Jiang *et al.*[8] and Jiang and Wu[9] show the robustness and the validity of this quantile function-based time-series model in characterising the properties of financial securities' returns, such as volatility clustering, and fat and unbalanced tails.

EFFECTS OF INSTITUTIONAL RISK

Evidence from European financial markets

The economic unity of an increasing number of European countries is a common example of financial integration. Established in 1998 with headquarters in Frankfurt, Germany, the ECB is the key financial institution for economic and monetary union (EMU) in Europe, and is responsible for monetary policy throughout the Eurozone. The establishment of the ECB marked the second stage of EMU within Europe, in advance of the adoption of the euro currency and the creation of the European System of Central Banks. On 1st January, 1999, the euro was introduced, and the third stage of EMU had begun.

The impact of the ECB and the euro on financial markets has been extensively studied (eg see Feldstein,[12] Schroeder,[13] Bagella *et al.*[14] and Dominguez[15]). Using the model described previously combined with data from the period from 23rd December, 1998 to 15th December, 1999, the paper now addresses the effects of institutional risk within European financial markets by characterising the behaviours of two major indices in Europe: the UK's FTSE (Financial Times Stock Exchange) 100 and Germany's DAX (Deutscher Aktien Index) 30. The institutional risk in this study refers to the risk generated by the introduction of the euro at the beginning of 1999. The FTSE100 index is based on the 100 most capitalised companies listed on the London Stock Exchange, and DAX30 is based on the 30 major German companies listed on the Frankfurt Stock Exchange. Without loss of generality, the study uses 400 observations from 2nd January, 1997 to 10th August, 1998 as a clean period to provide a stable estimation of the marginal distribution, average values of parameters μ_t and δ_t, and initial values of α_t and β_t.

According to the estimated results from the abovementioned period, the average value of δ_t for the FTSE100 and the DAX30 is 0.0026053 and 0.0059373, respectively. For the same period, the study also finds an average value of μ_t for the FTSE100 and the DAX30 of -0.020023 and 0.006267, respectively. As stated in the previous section, the parameter δ is a scaler parameter, while the parameter μ indicates the location of a distribution, and following previous studies[8,9] it is assumed that they are constant over time.

Using the information obtained from the above clean period, the distribution of log-returns is fit into the period from 23rd December, 1998 to 15th December, 1999. Figure 1 presents the FTSE100 and DAX30 α_t and β_t series, with each point on the horizontal axis representing two trading days over that period. As explained previously, the parameter α_t indicates the tail order and therefore measures how fat the tails are, while the parameter β_t characterises tail balance, which highlights the probability of making profits from investments. These two parameters indicate two aspects of the risk taken by investors following the introduction of the euro; this risk is a type of institutional risk as it is caused by an institutional change. Note that this model has a specification of distribution, which helps to accurately estimate the volatility of indices movement and how fat the left and right tails are.

The two α_t profiles shown in Figure 1 indicate that during the month in which the euro was adopted, ie January 1999, the risk carried by the FTSE index changed less dramatically than the risk carried by the DAX index. Unlike Germany, which was one of the first countries to adopt the euro, the UK did not adopt the euro; consequently, the adoption of the euro had a greater impact on the DAX market compared with the FTSE market. This illustrates that institutional change makes the market more volatile.

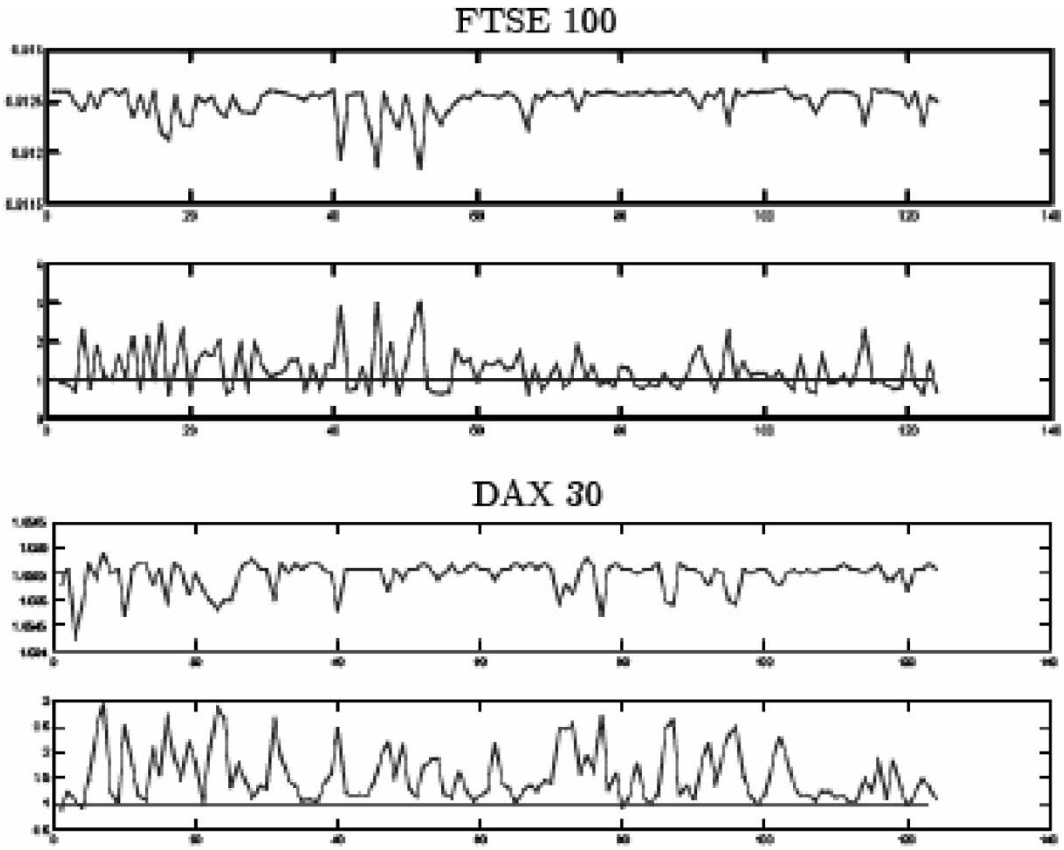

Figure 1: Estimated α_t (top) and β_t (bottom) profiles

The β_t profiles in Figure 1 also show the differences between the two markets. For instance, toward the end of the third month following the adoption of the euro, the risk shown in the FTSE100 α_t profile dropped significantly, while the β_t values during the same period increased significantly. This shows that, within this period, there was a dramatic increase in the likelihood of making profitable short-term investments in the FTSE100. Furthermore, according to Figure 1, the FTSE100 β_t values may have remained below one for much of the period between 23rd December, 1998 and 15th December, 1999 — a phenomenon seldom recorded in the DAX30 during the same observation period (recall that when $\beta > 1$, it is profitable when making a short-term investment). As such, this difference in the two β_t profiles sheds light on the positive side of financial integration by showing that adoption of the euro increases the likelihood of short-term investments being profitable.

Robustness tests

One issue which is worth noting is the validity of one of the assumptions made in prior research, and this assumption is that the values of the parameters δ and μ are constant over time. To test the robustness of the results presented above, this assumption is not relaxed due to the computational challenge this would entail. Instead, the whole initial estimation period is divided into two sub-periods, using 18th October, 1997 as the split point, and the parameter values are re-estimated using these two groups of information. This process helps to identify whether the assumption of constant δ and μ is reasonable.

Using 200 points within half of the initial estimation period (2nd January, 1997 to 17th October, 1997), it is possible to re-estimate the marginal distribution, values of parameters μ_t and δ_t, and initial values of α_t and β_t. Over this shorter period, the average (δ_t, μ_t) value sets of the FTSE100 and DAX30 are (0.0107, 0.0016) and (4.5126×10^{-5}, 0.02432), respectively. Thus, it is clear that the assumption of constant δ and μ does not hold, at least not in this case.

Fortunately, these results do not invalidate the analysis presented previously. Recall that the parameters δ and μ measure the scale and location of a distribution, respectively, and they help determine the value of q(0.5) in the quantile function shown in Equation (1). Note that according to the definition, if the value of q(0.5) is positive, the investment is more likely to be profitable; on the other hand, if its value is negative, then a loss becomes more likely. Thus, when relaxing the assumption of constant δ and μ, one can calculate the values of q over the period between 23rd December, 1998 and 15th December, 1999 using different (δ_t, μ_t) sets and corresponding α_t and β_t profiles.

Figure 2 presents the q(0.5) values of DAX30 over this testing period using the value sets of (δ_t, μ_t), (0.0059373, 0.006267) and (4.5126×10^{-5}, 0.02432) estimated above, respectively. The results show that the q(0.5) values, based on these two sets of (δ_t, μ_t) and their corresponding α_t and β_t profiles, are very similar, and the graph at the bottom of Figure 2 shows the difference between two q(0.5) value series. One can tell that the difference is between -3×10^{-3} and 2×10^{-3}.

Similar results for the FTSE100 are presented in Figure 3. Two graphs are based on two (δ_t, μ_t) sets, (0.0026053, −0.020023) and (0.0107, 0.0016), and their corresponding α_t and β_t profiles,

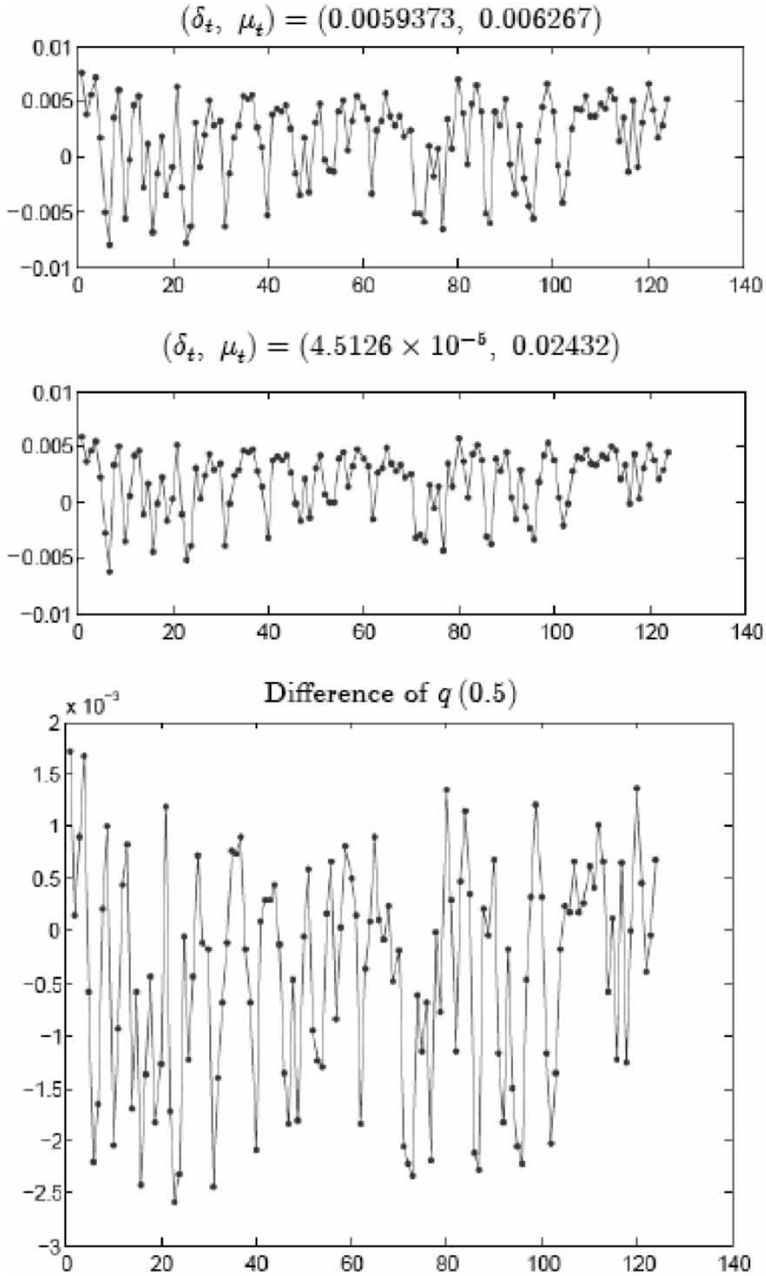

Figure 2: Value of q(0.5) based on DAX30 information

and their differences at corresponding time points are plotted at the bottom of Figure 3. The differences are between -1×10^{-3} and 3.5×10^{-3}. Thus, one can conclude that, while different sets of δ_t and μ_t parameter values are used, no qualitative change has been found regarding the investment decisions made according to the information carried by the quantile function. These show that, although the assumption of constant δ and μ over time should have been relaxed, fixing them does not affect the main analysis of this study.

In addition, as stated by Jiang *et al.*,[8] this time-series model outperforms the

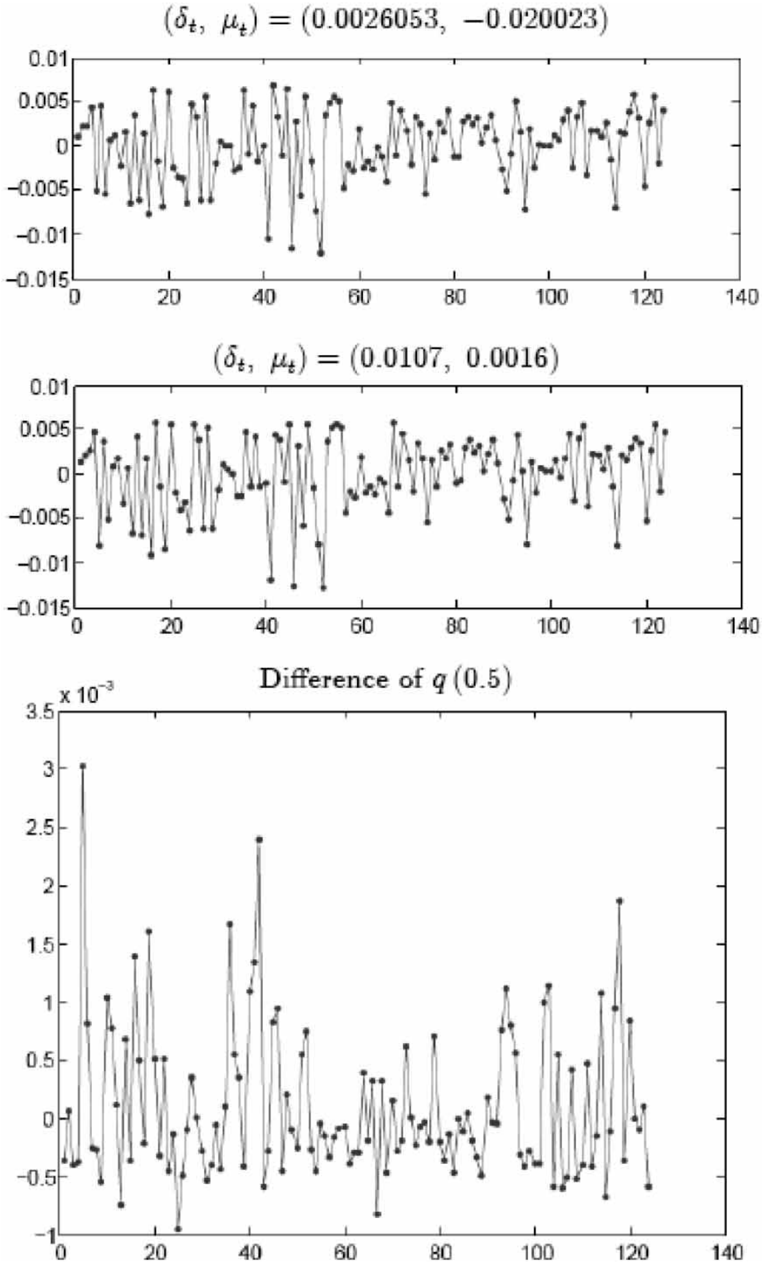

Figure 3: Value of q(0.5) based on FTSE100 information

traditional GARCH model as the quantile distribution has the advantages of being more flexible to capture detailed tail behaviours and can thus better fit distributions. To show this, the L_1 distance (the sum of the absolute differences of the coordinates between two points[16]) from the model of Jiang *et al.*[8] can be compared with that from the traditional GARCH model. The model which gives a smaller L_1 distance is considered to perform better in fitting distributions. This is supported by using the data from the above analysis and computing the L_1 distance from the model presented in Jiang *et al.*[8] and L_1

Table 1: L_1 distance from different models

Model	FTSE100	DAX30
Jiang *et al.* (2008)[9]	13.847	17.315
GARCH(1, 4)	39.798	69.446
GARCH(2, 3)	42.604	69.629
GARCH(3, 2)	43.650	69.704
GARCH(4, 1)	43.305	67.254

distances from various GARCH models. Results are presented in Table 1. It is clear that the L_1 distance from the quantile function-based model is much shorter than the L_1 distance from traditional GARCH models. Technically, these results demonstrate the good performance of this model in its estimation accuracy.

CONCLUSIONS AND FUTURE RESEARCH

During the first era of globalisation, integration of financial markets and international investments have been increasingly popular in the global economy, and resource reallocation and risk diversification are two of the major topics addressed in the literature. To illustrate these effects, the present study explores the institutional effects on the European financial markets, and on two typical financial market indices — the FTSE100 and the DAX30.

To provide a reliable analysis, the study applies the quantile function-based time-series model proposed by Jiang *et al.*[8] to investigate the impact of institutional risk on European financial markets following the introduction of the euro currency on 1st January, 1999. In previous studies, the model has been analysed analytically and illustrated empirically to show its validity and robustness by characterising the price behaviours of financial securities. Due to the analytical and computational advantages provided by the model and its theoretical basis, the results presented in this paper deliver intuitive and useful information which helps investors better understand risk issues in European financial institutions. To further ensure the validity of the analysis, the study has conducted robustness tests to gauge the impact of the constant-δ-and-μ assumption. The study finds that, even though this assumption does not necessarily hold when different periods are used to estimate their values, the main results about investment decisions show no qualitative impact.

Of the various possible directions for future research, two avenues hold particular promise. First, to analyse the influence of financial integration further, it would be interesting to examine the effects of institutional change on individual stocks and various industries. Secondly, high-dimensional computation methods can be further developed so that some assumptions made in the model can be relaxed. This may help the stability and robustness of the analysis significantly.

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