Modeling Risk Patterns of Russian Systemically Important Financial Institutions

Henry Penikas1, Irina Andrievskaya2, Richard Connolly3 and Sergey Aivazian4

1 National research university ‘Higher School of Economics’ (Moscow, Russia)
2 University of Verona (Italy)
3 University of Birmingham (United Kingdom)
4 Central Economic-Mathematical Institute (Moscow, Russia)

Abstract. The world financial crisis of 2008-2009 has shown that the existence of systemically important financial institutions (SIFIs) poses serious policy challenges to both developed and developing economies’ authorities. As for now there are different approaches to identifying SIFIs focused on contagion, concentration, correlation and conditions effects. The paper aims at testing a new approach to SIFIs’ identification based on the Russian banking data panel. It is hypothesized that SIFIs are characterized by unique behaviour in terms of risks undertaken. Automatic clustering procedure is being run to find homogeneous groups of banks in terms of their risk patterns. Risk patterns include proxies for credit, market, operational risk values for each bank in a sample. In order to reconstruct aggregate risk patterns for the banking clusters, copula models are used. Time variances in risk profile are accounted by identifying copula structural shift moment. The paper also tests a hypothesis about the key role of the institution’s size in determining systemic importance. Finally the effectiveness of SIFIs’ identification based on their risk profile is evaluated. When concluding, recommendations on SIFIs’ regulation in Russia are provided.

Keywords: Russia, systemically important banks, risk, copula, pattern

JEL Codes: C38, G20, G21, G28, G32

1. Introduction

Supervision and regulation of systemically important financial institutions (SIFIs) is a serious policy issue. It has received a lot of attention starting from the crisis 2008-2009 when several major US players provoked financial turmoil in the global economy.

SIFIs’ identification has long been considered a challenging task (e.g. (ECB, 2006)). Furthermore, there is still no adequate regulation in order to effectively deal with large conglomerates before and after their distress. A proper legal framework is required to prevent excessive risk-taking by large financial institutions.

When working out SIFIs’ regulation there arises the issue of systemic risk. It can be realized through interconnectedness of financial institutions, i.e. through the contagion effect. Thus, confidence loss in SIFIs might quickly spread through the whole financial system. That is why SIFIs’ identification and regulation is a crucial task for enhancing macroeconomic stability.

Several SIFIs’ definitions have been recently proposed. For example, “a financial institution can be considered to be systemically important if its failure or malfunction would have a significant, adverse impact on the financial system” (Praet, 2010). However, in (Thomson, 2009) the author argues that SIFIs’ definition is
not that simple and should be worked out considering different sources of systemic risk followed by differentiating the categories of systemic importance.

The size of a financial institution is often assumed to be the SIFIs’ prior determinant. However, as shown in (Zhou, 2010) it is not always a sufficient criterion. According to (FSB, 2010) “Every institution has a unique risk profile, making it impossible to solely rely on a one size-fits-all minimum capital requirement.” Small banks can also be systemically important when they form a part of a ‘herd’ (Adrian & Brunnermeier, 2010). This is referred to as “too many to fail” case in (IMF/BIS/FSB, 2009b), (Vom Acharya & Yorulmazer, 2007).

Approaches to SIFIs’ identification can be grouped in two blocks: qualitative and quantitative methods. It should be emphasized that most papers focus on developed economies or the global financial market. Moreover, many studies analyze theoretical models and provide calculations based on a banking sector model.

The qualitative assessment is based on several bank’s characteristics: size, substitutability, interconnectedness (or contagion), complexity of an institution (IMF/BIS/FSB, 2009b), leverage level, maturity mismatch (Adrian & Brunnermeier, 2010) and others. However, while the qualitative analysis stands as necessary, it does not provide sufficient criteria for SIFIs’ identification.

To get a deeper understanding quantitative methods have been worked out. They include an indicator-based methodology, a network analysis and an assessment of institutions’ contribution to systemic risk. For the indicator-based approach the survey (IMF/BIS/FSB, 2009b) provides a set of relevant measures. An example of using such a technique is presented in (ECB, 2006), (IMF, 2010a). The network analysis consists of contagion effect investigation (cf. (Furfine, 1999)) and a so-called centrality approach (cf. (Bech, Chapman, & Garratt, 2008), (von Peter, 2007)). The third type of the quantitative methodologies assesses the SIFIs’ contribution to systemic risk and includes two sub-approaches. The first one is the estimation of systemic risk and then its attribution to individual contributors (the “top-down” method; cf. (Segoviano & Goodhart, 2009), (Zhou, 2010), (Tarashev, Borio, & Tsatsaronis, 2010), (Huang, Zhou, & Zhu, 2010)); the second one is, by contrast, a “bottom-up” approach (cf. (Adrian & Brunnermeier, 2010)).

The above-mentioned methodologies could be used for determining capital requirements (cf. (Gauthier, Lehar, & Souissi, 2010)). Another way of assigning capital is proposed in (Vim Acharya, Santos, & Yorulmazer, 2010) where it is suggested to apply higher deposit insurance premiums to large banks. While in (ECB, 2010) a systemic tax is discussed.

A serious issue, while identifying SIFIs, is to understand their risk pattern. It is addressed in (Kuritzkes, Schuermann, & Weiner, 2003), (Rosenberg & Schuermann, 2006), (Elsinger, Lehar, & Summer, 2006). In (Kuritzkes, et al., 2003) the authors suggest a “building block” approach for aggregating risks and assume that all risks are jointly normally distributed. To avoid this assumption in (Rosenberg & Schuermann, 2006) a methodology using copulas is developed.

The crisis of 2007-2009 has raised serious policy debate with respect to the regulation of SIFIs. In the work (Morrison, 2009) it is argued that creation of a systemic risk regulator is the most effective way. While in (FSA, 2009) a so-called “living will” concept is considered. There are also different proposals with respect to limiting the size and restricting the activities of SIFIs (cf. (IIF, 2010)).

The aim of this paper is to test the efficiency of a new approach to SIFIs’ identification. The main hypothesis tested is that SIFIs’ risk pattern is unique thus providing a significant basis for identifying SIFIs.

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34 It is examined in more details in (Avgouleas, Goodhart, & Schoenmaker, 2010)
35 Risk pattern is a credit institution’s characteristic measured through a period of time. It incorporates the values of three material banking risks (credit, market and operational) for each time point.
The research focuses on the Russian banking system and is based on Russian banking data. Nonetheless, the results are considered to be relevant to both developed and developing countries.

2. Method

The methodology, employed in the current study, consists of 4 stages. The first one is the assessment of individual risks (namely, credit, market and operational) for each bank in every period. The second step is the cluster analysis of the whole banking system in order to determine the homogeneous banks’ groups in terms of their risk pattern. The third phase is the estimation of the structural shift moment in copula of joint risk distribution in each cluster. Finally, the regression analysis is carried out in order to test the hypothesis that the size of an institution determines its systemic importance. For the purpose of this study quarterly financial statements of all the Russian banks for the period 2004-2010 are used (25 quarters). The data is available on the website of the Central Bank of Russia.

2.1. Risk Measurement

The estimation of credit, market and operational risks, used in this paper, is described in details in (Andrievskaya, Penikas, & Pilnik, 2010). The approach for risk assessment is based on the methodology proposed in (Rosenberg & Schuermann, 2006). The credit risk return is calculated as the ratio of overdue indebtedness to the credit portfolio. The market risk return is estimated as the ratio of profits and losses from market-to-market revaluation to the amount of the trading portfolio. Operational risk return is calculated as the ratio of net income to the total assets.

2.2. Cluster Analysis

The cluster analysis is run to determine banks characterised by the same risk patterns. For the purpose the k-means clustering is used. The methodology for pattern dynamics analysis was firstly used to our knowledge by Aleskerov and Alper in 2000 (Aleskerov, Alper 2000). Recent findings are presented in (Aleskerov, Belousova, Serdyuk, & Solodkov, 2008). Clustering is done based on 75 variables as three risks are measured in 25 quarters. Each cluster is then analysed according to the banks’ characteristics. Initial K number is set to be 5.

It is important to mention that the clusters were determined in four steps. Firstly, 5 clusters were examined in terms of mean values, standard deviations, correlations, minimum and maximum values of individual risks. Then, based on the similarities authors undertook cluster consolidated. At the next stage the largest cluster containing 1108 banks out of 1206 observations was also partitioned in five clusters. Five clusters obtained were aggregated to three to have the most differentiating features. The final number of homogeneous groups equalled to five clusters.

2.3. Copula Structural Shift Identification

To test the hypothesis it is also necessary to examine the uniqueness of the received patterns in terms of the copula structural shift. In this paper an algorithm first presented in (Brodsky, Penikas, & Safaryan, 2010) is employed to estimate the moment of structural shift in copulas.

The copula is used to construct a joint distribution given the knowledge of marginal distributions. In the literature there are two main classes of tests with respect to copula- models. The first one includes parametric tests (e.g. for Gaussian copula (Malevergne & Sornette, 2003), for Clayton one (Shih, 1998), (Glidden, 1999), (Cui & Sun, 2004)). The second one - non-parametric, including the so-called blanket tests (e.g. (Fermanian & Scaillet, 2003), (Breymann, Dias, & Embrechts, 2003), (Dobric & Schmid, 2007), (Junker & May, 2005), (Genest, Quesy, & Rémillard, 2006)). While the analysis of the structural shift in copulas has

36 Data and program codes for R are available from the authors on request.
received much less attention. It was partly examined in such works as (Tsukahara, 2005), (Busetti & Harvey, 2011), (Harvey, 2008), (Remillard & Scaillet, 2009).

For the purpose of the current study the following procedure of determining the copula structural shift is used. There is a sample \( \{ X_1, \ldots, X_N \} \) of independent \( \text{d} \)-dimensional vectors and an unknown moment\(^3\) \( m = [\theta N] \) when the dependency among components \( X_{i_1}, \ldots, X_{i_d} \) of each vector \( X_i \) changes. Thus, the joint distribution function can be defined as:

\[
H(x_{i_1}, \ldots, x_{i_d}) = \begin{cases} 
\tilde{C}_1(F_1(x_{i_1}), \ldots, F_d(x_{i_d})), & 1 \leq l \leq m \\
\tilde{C}_2(F_1(x_{i_1}), \ldots, F_d(x_{i_d})), & m < l \leq m
\end{cases}
\]

(1)

where \( x_i = (x_{i_1}, \ldots, x_{i_d}) \) - realization of \( \text{d} \)-dimensional vector \( X_i \) in the moment \( l = 1, \ldots, N \); \( \tilde{C}_i (i = 1, 2) \) is a function of \( \text{d} \)-variables (copula). According to the Sklar theorem (cf. (Sklar, 1959, 1996)) the function \( \tilde{C}_i \) is determined as shown below:

\[
\tilde{C}(u \alpha) = F(F_{X^{(1)}}^{-1}(u^{(1)}), F_{X^{(2)}}^{-1}(u^{(2)}), \ldots, F_{X^{(d)}}^{-1}(u^{(d)})�)
\]

(2)

where \( u = (u^{(1)}, u^{(2)}, \ldots, u^{(d)}) \) is a value of the marginal distribution function of a random variable \( i (i = 1, \ldots, d) \) from the multidimensional random vector \( X = (X^{(1)}, X^{(2)}, \ldots, X^{(d)})^T \), whose joint distribution function is \( F_X \); \( \alpha = (\alpha_1, \alpha_2, \ldots, \alpha_k) \) is a vector of parameters of the copula function.

It should be emphasized that the structural shift is discrete, not continuous. The change of copulas takes place in different periods of time which depends on the frequency of data (for example, the change takes place on the next day if the daily data are used).

Thus, it is necessary to test the following hypothesis:

\[
H_0 : \tilde{C}_1 = \tilde{C}_2
\]

(3)

\[
H_1 : \tilde{C}_1 \neq \tilde{C}_2
\]

(4)

where \( \tilde{C}_1, \tilde{C}_2 \) are some copulas (not necessarily from the same copula-family).

And now an estimate of the structural shift moment \( m \) should be constructed, for which the probabilities of the first and the second type estimation errors would be small enough (tend to 0 with \( N \) increasing), while an estimate of the structural shift parameter \( \theta N \) would be consistent (tends to the true value with \( N \) increasing).

The proposed method is based on the non-parametric approach of comparison of empirical copulas \( D_i(u) \). These copulas are determined for each period of time \( l = 1, \ldots, N - 1 \) as the following:

\[
D_i(u) = \frac{1}{l} \sum_{i=1}^{l} I(U_{i,l} \leq u) - \frac{1}{l} \sum_{i=1}^{l} \prod_{j=1}^{d} I(U_{i,j} \leq u_j)
\]

(5)

\[
D_{N-l}(u) = \frac{1}{N-l} \sum_{i=l+1}^{N} I(U_{i,l} \leq u) - \frac{1}{N-l} \sum_{i=l+1}^{N} \prod_{j=1}^{d} I(U_{i,N-l} \leq u_j)
\]

(6)

\(^3\) The symbol \([ \cdot ]\) means the integer part.
where $u_j$ is the threshold of the partitioning net of the d-dimensional unit cube; $I(\bullet)$ is an indicator function, which equals 1 when the condition in the brackets is true; $U_{i,j} = (U_{i,1},...,U_{i,d})$ is the vector of the estimated empirical distribution functions where for each $j = [1,...,d]$ the below expressions are true:

$$U_{y,i} = \frac{l}{l+1}F_{y,i}(X_{y,i}) = \text{rank}(X_{y,i})(l+1), \quad 1 \leq i \leq l$$

$$U_{y,N-l} = \text{rank}(X_{y,i})(N-l+1), \quad l+1 \leq i \leq N$$

In order to find the moment $m$ the modification of the Kolmogorov-Smirnov statistics is employed (the modification takes into account the part of the sample before and after the shift moment $l$):

$$\Psi_{l,N-i}(u) = (D_{l}(u) - D_{N-l}(u))\sqrt{N(N-l)/N}$$

$$T_N = \max_{\{\beta N \leq l \leq (1-\beta)N\}} \sup_u |\Psi_{l,N-i}(u)|$$

where it is given that $0 < \beta < 1/2$ so that the following inequality holds $[\beta N] \leq l \leq [(1-\beta)N]$.

The estimate of the structural shift moment is constructed as the following:

$$m_N \in \text{Arg} \max_{\{\beta N \leq l \leq (1-\beta)N\}} \sup_u |\Psi_{l,N-i}(u)|$$

while the estimate of the structural shift parameter is defined as $\hat{\theta}_N = m_N/N$.

The maximum value of $T_N$ implies the copula structural shift moment.

### 2.4 Regression Analysis

In order to understand whether the size of an organization can determine its systemic importance the probit model is employed. The dependent variable equals 1 if a bank belongs to the group of systemically important institutions, and 0 in all the other cases. The explanatory variable is the amount of the bank’s total assets. The model also includes time dummy variable in order to allow for the time effect.

### 3. Results

Five distinctive patterns in terms of risk have been obtained due to cluster-analysis procedure (Fig.1, Fig.2). Each cluster represents a particular type of strategy, which, however, requires further analysis.

The first cluster consists of 8 banks, which are not the largest ones in the sector (only several of them are from the top 100 banks in terms of assets and on 01.12.2010 their share in total assets of the sector was 0.75%). They have the largest level of market risk in terms of mean value (-191%,) and standard deviation (4.57).

To this pattern the concept of “too risky to fail” can be applied. Problems arising in such banks could have a significant negative impact on their counterparties. As well as the loss of confidence in these institutions could lead to a serious contagion effect. There have already been examples (e.g. Herstatt Bank) when the failure of a relatively small institution imposed significant losses on its counterparties (Thomson, 2009). There was an example in the Russian banking system as well. In 2004 the withdrawal of licences from only two small banks (Sodbusinessbank and Kredittrast bank) due to money-laundering issues (their total assets amounted to 0.29% of the total assets in the system) led to significant liquidity problems in many other banks.

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38 This statistics was only discussed in previous researches (e.g. (Tsukahara, 2005)). While the implementation was done only with respect to the statistics Cramér-von-Mises (cf. (Remillard & Scaillet, 2009))
including the major ones (Gaidar, Sinelnikov-Mourylev, & Glavatskaya, 2004). So, the 1st cluster could jeopardize the whole system.

The first cluster is characterized by the largest risk correlation. It is particularly high between market and operational (negative correlation) and credit and operational risks (positive correlation).

The analysis of the copula structural shift also confirms the uniqueness of the first cluster. Statistical inequalities in copulas are evident from December 2004 to September 2006 with test statistics reaching its maximum in December 2005. Besides, the unique local maximum is observed in September 2008 corresponding to the disastrous event of Lehman Brothers failure.

Fig. 1 Banks’ patterns in terms of risk levels

Fig. 2 Banks’ patterns in terms of risk correlations

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39 Notations used: rc – credit risk. rm – market risk, ro - operational risk.
40 Notations used: rc – credit risk. rm – market risk, ro - operational risk.
The second cluster consists of 90 banks, which are mainly retail oriented and inter alia include such large credit institutions as Sberbank, Alfabank, VTB24. It also contains quite a substantial number of regional banks. This group has relatively large mean value and standard deviation for market risk (-49% and 2.13 correspondingly). Furthermore, it has rather high negative correlation between market and operational risks and positive correlation between credit and operational risks. In terms of the copula structural shift this pattern also has a local maximum in September 2009 as it is for the first cluster (Fig.3). The local maximum is not observed for the last three clusters. This cluster should also be treated as of systemic importance and the concept of “too many to fail” can be applied.

The third cluster is composed of 125 banks, which are predominantly made up of banks specializing on some particular industries’ lending. This group is characterized by low levels of correlations among risks. And it is interesting to mention, that the correlation between credit and operational risks, though small (0.02), is positive. This cluster is a typical ‘median’ cluster.

The last two clusters include the rest of the banks. The risk levels of these groups are relatively small in terms of mean value and standard deviation. They differ with respect to correlation between market and operational risks: for the fourth cluster it is small and positive, while for the fifth – small and negative. All three last clusters are similar in terms of the copula structural shift moment, which appears in September 2006 corresponding to the event on Russia being granted the investment credit rating from all the reputable rating agencies of the world (Fig.4).
It is necessary to emphasize that according to the results of the regression analysis the hypothesis about the influence of the size of an institution on its systemic importance cannot be rejected. An increase of 1 bn. Rub in the bank’s size raises the probability for a bank to be included in the first two clusters by 7%. Moreover, in the 3rd and 4th quarters of 2009 the time effect becomes significant: the difference between risk patterns of banks from the first two clusters and from all the other clusters decreases. These results are in line with the conclusions made in the paper (Drehmann & Tarashev, 2011). The authors, using “bottom-up” and “top-down” methodologies for estimation of systemic importance and using the regression analysis, have shown that such measures as the size of a bank (total claims from non-banks creditors) and the amount of credits and borrowings on the interbank market are the reliable determinants of systemic relevance. This also confirms the effectiveness of the indicator approach.

The findings of this study have an important policy implication. The analysis has revealed the existence of 5 distinctive banks’ patterns, which might need differentiated supervision and regulation. For the first cluster special treatment of their trading activities might be applied. For the second pattern it is, in turn, essential to determine risk events, which have the most significant impact on the correlated portfolios of banks. This can be done using stress-testing techniques.

4. Conclusion

In this paper an approach to SIFIs’ identification has been proposed. The analysis is based on the Russian banking statistics. The main hypothesis is that SIFIs have unique risk patterns that might be traced due to cluster-analysis application. The banking groups obtained are indeed unique both in terms of marginal risk distributions, and in terms of risk distribution copula shift moments. Five distinctive banks’ patterns comprise, in our opinion, two SIFIs clusters: “too risky to fail” and “too many to fail” ones. The findings prove the efficiency of the proposed approach to SIFIs’ identification. The results have important policy implications. The obtained clusters require differentiated regulation and supervision. The design of the corresponding proposals is the issue of further investigation.

5. Acknowledgements

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References


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**Appendix. Descriptive statistics**

Table 1. Mean values, standard deviations, minimum and maximum values of individual risks in each cluster.

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Risk</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Credit</td>
<td>200</td>
<td>-0.0169</td>
<td>0.0475</td>
<td>-0.2655</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>Market</td>
<td>200</td>
<td>-1.9123</td>
<td>4.5693</td>
<td>-45.0368</td>
<td>2.8157</td>
</tr>
<tr>
<td></td>
<td>Operational</td>
<td>200</td>
<td>0.1025</td>
<td>0.1303</td>
<td>-0.0929</td>
<td>0.5085</td>
</tr>
<tr>
<td>2</td>
<td>Credit</td>
<td>2250</td>
<td>-0.0057</td>
<td>0.0188</td>
<td>-0.2706</td>
<td>0.0545</td>
</tr>
<tr>
<td></td>
<td>Market</td>
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<td>2.1333</td>
<td>-13.9322</td>
<td>20.2185</td>
</tr>
<tr>
<td></td>
<td>Operational</td>
<td>2250</td>
<td>0.1435</td>
<td>0.1487</td>
<td>-0.5654</td>
<td>0.7036</td>
</tr>
<tr>
<td>3</td>
<td>Credit</td>
<td>3125</td>
<td>-0.0073</td>
<td>0.0344</td>
<td>-0.6830</td>
<td>0.0190</td>
</tr>
<tr>
<td></td>
<td>Market</td>
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<td>1.3110</td>
<td>-9.9943</td>
<td>7.9024</td>
</tr>
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<td></td>
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</tr>
<tr>
<td>4</td>
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<td>-0.0049</td>
<td>0.0236</td>
<td>-0.9731</td>
<td>0.5498</td>
</tr>
<tr>
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<td></td>
<td>Operational</td>
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<td>5</td>
<td>Credit</td>
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<td>-0.0039</td>
<td>0.0255</td>
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<tr>
<td></td>
<td>Operational</td>
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<td>0.1317</td>
<td>-0.9045</td>
<td>0.9781</td>
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Table 2. Correlations between individual risks.

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Risk</th>
<th>Credit</th>
<th>Market</th>
<th>Operational</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Credit</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>Market</td>
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<td>1.000</td>
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</tr>
<tr>
<td></td>
<td>Operational</td>
<td>0.139</td>
<td>-0.322</td>
<td>1.000</td>
</tr>
<tr>
<td>2</td>
<td>Credit</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Market</td>
<td>-0.061</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Operational</td>
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<td>-0.227</td>
<td>1.000</td>
</tr>
<tr>
<td>3</td>
<td>Credit</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Market</td>
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<td>1.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Operational</td>
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<td>-0.057</td>
<td>1.000</td>
</tr>
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<td>Credit</td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>Market</td>
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<td>1.000</td>
<td></td>
</tr>
<tr>
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<td>Operational</td>
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<td>1.000</td>
</tr>
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<td>Credit</td>
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