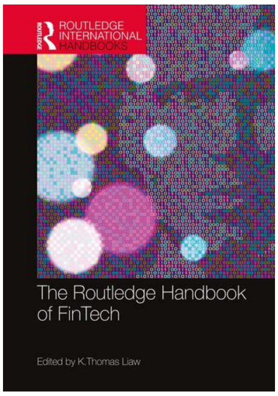

The Routledge Handbook of FinTech

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MARKET RISK FOR ROBOT ADVISORY

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1 Robot advisory and market risk

The Financial Stability Board (FSB) in its two recent reports (FSB 2017a, 2017b) identifies three common drivers of FinTech: (i) shifting consumer preferences on the demand side; (ii) evolving technology, and (iii) changing financial regulation on the supply side. The first concerns higher customer expectations for convenience, speed, cost and "user-friendliness", the second concerns advancement in technology, mainly related to big data and mobile technology, and the third regards the increased frequency of changes in regulatory and supervisory requirements. The same factors have also spurred the adaptation of artificial intelligence (AI) in financial services.

Automated consultants, known as robot advisors, are considered the main application of AI in financial services. In particular, robot advisors build personal portfolios on the basis of specific algorithms that take into account information of investors filling out online questionnaires drawn up according to instructions provided by the Markets in Financial Instruments Directive (MiFID) directive. Information concerns age of investors, risk tolerance and aversion, investments and income.

The European Supervisory Authorities joint report (2017) defines the phenomenon of automation in financial advice as "a procedure in which advice is provided to consumers without, or with very little human intervention and with providers relying on computer-based algorithm and/or decision trees." In practice, robot advisors build personalised portfolios for investors, on the basis of algorithms that take into account investors' information such as age, risk tolerance and aversion, net income, family status. Obtaining this information is a legal requirement and robot advisors employ online questionnaire to receive it in order to match "expected" (investors' risk profile resulting form the questionnaire) and "actual" risk (portfolio risk) of investors.

The literature on the measurement of expected risks in robot advisory is very limited. For example, Kim et al. (2016) compare the relative advantages of automated consulting of robot advisors with respect to more classical financial advising, from different perspectives, including fees and risks (associated with age). Scherer (2016) shows, within a tree model approach, the key investor features that can predict financial market participation.

In this chapter we do not measure expected risk of investors but we assume that for a specific value of the risk assigned by the robot advisor on the basis of the result of the MiFID questionnaire it is possible to provide personalized portfolios managing the actual risk especially that linked to the centrality of assets included in the financial investment.

The advantages associated with automatized advice may be offset by the greater risks that are brought on board, among which the risks of making unsuitable decisions (due to lack of information or reduced opportunities) and risks of errors and functional limitations of the tool (European Supervisory Authorities, 2017).

As is the case with big data analytics, there are several regulatory requirements that already exist and apply to automated advice, among which: the Markets in Financial Instruments Directive (MiFID), the Insurance Distribution Directive (IDD) and the Mortgage Credit Directive (MCD) (European Supervisory Authorities, 2017). However, some risks are yet to be fully considered and measured. Among them, we believe the following are the most relevant: (i) compliance risk – mismatch between expected and actual investment risk class; (ii) operational risk – errors in the functioning of the algorithms, and (iii) cyber risk, hacking or manipulation of the algorithms.

As for big data analytics, the increased risks connected with the use of robot advisory platforms can be mitigated by an appropriate analysis of the data they generate. In this respect, robot advisors generate, in an automated way, a large amount of data, which can be leveraged not only to improve the service, making it more personalized, but also to reduce compliance risk and, in particular, the risk of an incorrect profile matching between expected and actual risk classes.

We investigate two particular aspects of market risk associated to robot advisory and financial technologies. The first one proves how random matrix theory (RMT), an approach deriving from the econophysics field, together with correlation network clustering can be used to construct investment portfolios of Exchange Traded Funds (ETFs) that correctly take high dimensional correlations into account. The second one pertains measuring interconnectedness of Bitcoin exchange markets for price discovery purposes. In other words, the aim is to determine which are the market exchanges leading the Bitcoin price formation process and which are those that rather follow changes in prices of leading platforms and adjust their prices consequently.

The above approaches are useful to quantify and/or prioritise compliance risks and market risks associated with the application of artificial intelligence methods in finance and can thus be employed to offer an "automated" risk management tool, for both RegTech and SupTech purposes.

The chapter is organized as follows: Section 2 presents clustering algorithms applied to the correlation matrix filtered through random matrix theory and empirical results, Section 3 investigates connectedness and price discovery in crypto field with a generalized Vector Error Correction model (VECM) including some empirical results.

2 Asset allocation through hierarchical correlation models

2.1 The problem

The hierarchical organization behind financial markets represented as a complex network can contribute to solving the portfolio optimization problem.

A large amount of research work has contributed to the study of portfolio optimization, using alternative methods with respect to the original one defined by Markowitz (1952). These methods include neural networks, genetic algorithms, random matrix theory filtering and hierarchical clustering. Among them, the latter are the most efficient methods for the selection of financial assets for optimal portfolios construction.

We propose a portfolio strategy based on RMT filtering of the original correlation matrix, leading to an improved hierarchical correlation tree.

Therefore, first we "filter" the empirical correlation matrix of financial assets using the RMT approach (Plerou et al., 2002) and using the deriving distance matrix to compute the Minimum Spanning Tree (Mantegna, 1999). Then, we extend Markowitz's approach changing the optimization function itself, taking into account the centrality of assets coming from the Minimum Spanning Tree (MST) according to the work of Výrost and colleagues (2019).

Random Matrix Theory represents one of the main tools able to separate the "signal" part of a correlation matrix from the "noise" one, and the information on assets centrality prevents risk of ingent portfolio losses due to contagion, especially during crisis periods.

2.2 Empirical application and results

The data we consider here is a collection of 92 Exchange Traded Funds daily returns belonging to different classes according to the classification of the ETFs reported by the Italian Stock Exchange over the period from March 2017 to February 2018 (T= 250) as shown in Table 20.1.

Table 20.2 describes summary statistics for each ETF class: mean, variance, kurtosis and skewness of the returns' distribution, to describe their location and variability. Values of kurtosis and skewness confirm some stylized facts of returns distribution that tends to be Non-Gaussian and heavy tailed.

Moreover, Table 20.2 reports that the mean of ETFs is around 0 and ETFs belonging to the class of Emerging-Equity Market, regardless the specif geographical area considered, show highest values of standard deviation.

We compute the "filtered" correlation matrix for the N financial assets comparing eigenvalues spectral density of the empirical correlation matrix to those of a same size random correlation matrix, which distribution is known as shown by Marčenko and Pastur (1967).

Then, we draw the MST associated to the distance matrix that perfectly replicates the classification of the Italian Stock Exchange as shown in Figure 20.1.

Table 20.1 ETFs by asset classes

	ETF Class	*Number of ETFs*
1	Aggregate bond	4
2	Commodity	8
3	Corporate–euro	11
4	Corporate–not euro	3
5	Corporate–high yield	2
6	Corporate–world	1
7	Emerging equity–Asia	30
8	Emerging equity-America	10
9	Emerging equity–East Europe	4
10	Emerging equity–world	17
11	Equity–Europe	1

Note: Number of Exchange Traded Funds for each class according to the classification of the Italian Stock Exchange

Table 20.2 ETF classes summary statistics

ETF class	*Mean*	*St. dev*	*Kurtosis*	*Skewness*
1	0.000181	0.001896	0.658933	0.001896242
2	0.00029	0.00601	0.664302	0.006010002
3	7.21E-05	0.001041	1.143563	0.001041386
4	0.000213	0.002877	0.257732	0.002876562
5	0.000292	0.001345	2.941169	0.001344703
6	0.000301	0.002074	0.072985	0.002074447
7	0.000967	0.007933	3.152594	0.007932573
8	0.000895	0.012863	18.25085	0.012863393
9	0.001142	0.012657	0.88198	0.012656785
10	0.00106	0.006452	2.210931	0.006452237
11	0.000191	0.005868	1.703763	0.005868344

Note: Summary statistics for ETF classes compositions: mean, standard deviation, kurtosis and skewness expressed in absolute values computed for the dataset.

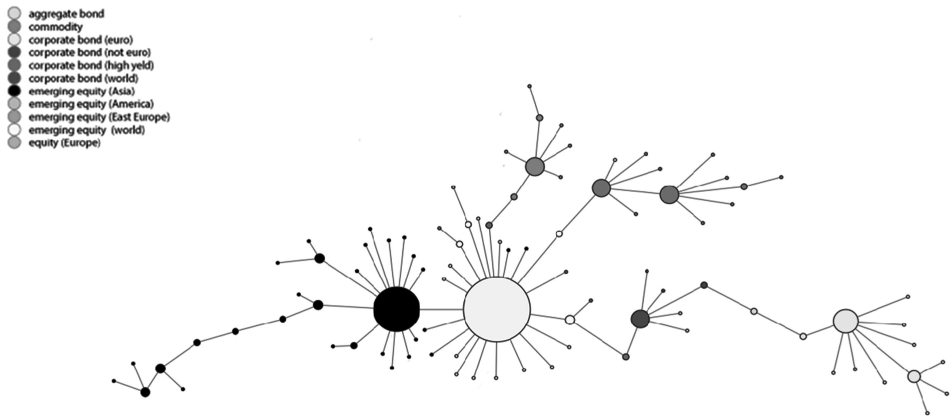

Figure 20.1 Minimum Spanning Tree drawn from the RMT filtered correlation matrix

Note: The vertices indicate the ETFs, the width represents the value of node degree. Colors indicate the different classes as reported in the legend.

From the MST shown in Figure 20.1 we calculate eigenvector centrality of nodes represented by ETFs, in order to insert this measure in our portfolio construction model. Centrality of assets in the portfolio model is weighted according to the individual risk aversion level (λ) obtained from the online Robot Advisory questionnaire: a higher value of λ is associated to a more risky financial subject. For λ equal to zero the portfolio variance is higher in the case of unfiltered covariance matrix. Portfolio variance results for λ different from zero are reported in Table 20.3.

Table 20.3 shows that the filtered covariance matrix leads to a portfolio less risky in terms of variance for different values of λ. In conclusion, when the random matrix approach is applied, we obtain a tree representation of ETFs which is interpretable, and reflects expert based classifications. In terms of portfolio allocation, our empirical findings show that the RMT filtering leads to a less risky portfolio. In addition, when the network centrality

Table 20.3 Portfolio summary results for filtered and unfiltered covariance matrix (absolute values)

	λ	*Filter?*	σ^2
1	0.003	YES	0.00039
2	0.03	YES	0.00096
3	0.003	NO	0.096
4	0.03	NO	0.096

parameters are included as constraints in the Markowitz optimisation, we obtain a further reduction in the risk of a portfolio, for a given value of returns. Furthermore, the model is able to incorporate risk aversion, specified by the investors.

3 Measuring price discovery and connectedness of Bitcoin exchange markets

3.1 The problem

Prices of the same good may vary consistently across trading platforms, hence so do stock price returns. The study of return connectedness is key to assess market risk and, in particular, to understand which are the market exchanges whose shocks in price are transmitted to the others; or which are those that receive shocks from the others and adjust their prices consequently. In other words, the study of connectedness across market exchanges is fundamental for price discovery purposes, that is, to determine the leader–follower relationships between markets. This is crucial when analysing nascent markets with peculiar features, such as the cryptocurrency one.

The econometric measure used in order to investigate connectedness and price discovery is an extension of the Diebold and Yilmaz (2012) methodology with a generalized Vector Error Correction model (VECM). To the best of our knowledge, this is the first application of such a technique to measure connectedness of exchange platforms, particulary of Bitcoin.

The methodology employed allows us to study market exchange connectedness at different levels: pairwise and system-wide, as well as both from a static and time-varying point of view, accounting for the common stochastic trend driving the fundamental Bitcoin price.

Therefore, in this context the contribution is twofold and: from a methodological viewpoint, we contribute to the econometric literature – particularly concerning price discovery and connectedness of market exchanges – by employing an extension of the Diebold and Yilmaz (2012) connectedness measurewhich relies on VECM rather than Vector Autoregressive (VAR) models. The model helps to shed further light on price discovery in Bitcoin markets, extending the conclusions in Giudici and Abu-Hashish (2019) and Pagnottoni and Dimpfl (2019) and, in particular, characterizing which are the leaders and followers in price formation among the considered exchanges, along time.

3.2 Empirical application and results

For our empirical analysis we consider what is arguably the most relevant cryptocurrency that exists today: Bitcoin. We examined Bitcoin exchange prices denominated in USD on a daily basis during a time-frame from 18 May 2016 to 30 April 2018 Data were collected from https://www.investing.com/crypto/bitcoin and through the CryptoCompare API.

We considered eight Bitcoin exchanges, i.e. Bitfinex, Coinbase, Bitstamp, Hitbtc, Gemini, ItBit, Kraken, Bittrex, in order to achieve heterogeneity of trading volume and geographic location.

We derive several spillover measures, among which the Net Spillover Index. The Net Spillover Index measures the difference between the total spillover contribution of a market exchange *i* to all the others, and the total spillover contribution of all other market exchanges to the same exchange *i*. A graphical representation of the daily Net Spillover Index for the period 22 September 2016 to 30 April 2018 is provided in Figure 20.2.
In Figure 20.2 we notice that the dynamics of exchange return connectedness are sensible and time-varying. The most relevant peaks correspond to. the points in time in which we have a strong misalignment in Bitcoin prices of the analyzed exchanges. Those misalignments are likely due to exits and entrances of big players in the market.

From the spillover analysis, one may draw conclusions on the lead–lag relationships among the analysed Bitcoin exchanges. In this regard, results point to the fact that Bittrex, Bitfinex appears to be the exchange receiving the least and contributing the most to others in terms of return spillovers over time, immediately followed by Coinbase. In both cases, the magnitude of their influence varies over time.

Kraken is the exchange most influenced by others. From the beginning of May 2017, its contribution to others starts declining, whereas the one transmitted by others begins to rise. It is interesting to notice that Kraken's follower behaviour begins with the surge in Bitcoin prices, a day in which exchanges connectedness are arguably expected to experience some changes. This marks the beginning of a "follower phase" for Kraken, which lasts until the end of the sample, where we see its net contribution converging to its previous values.

In conclusion, the measures proposed monitor market connectedness and risk at an exchange level. Moreover, they can assess which market exchanges are informationally

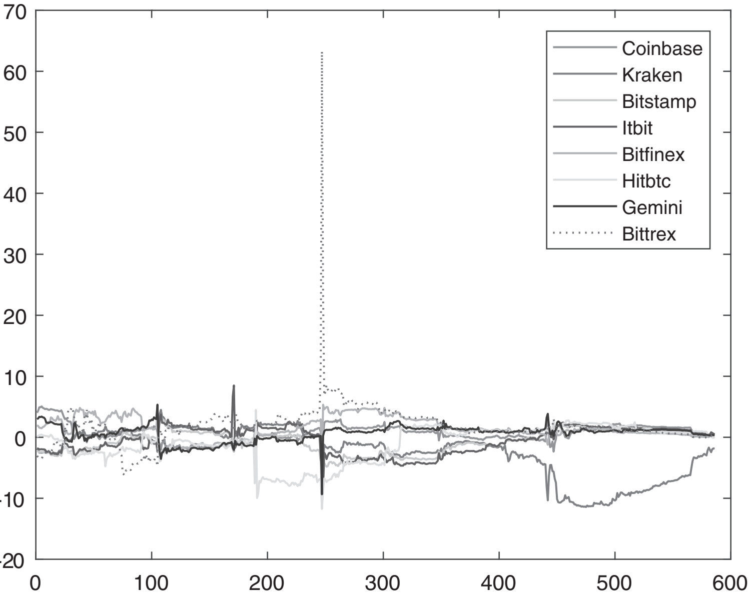

Figure 20.2 Dynamic net pairwise Spillover Indexes associated to the 8 analysed market exchanges

Note: The Spillover Indexes are expressed in percentage terms (y axis) over time (x axis). The time period ranges from 22 September 2016 to 30 April 2018. They measure the difference between the gross shocks transmitted from one market exchange to the others and the gross shocks received from others by the same exchange.

dominant in the Bitcoin price formation process. Without loss of generality, these models can be applied to the cryptocurrency market in general, as well as to traditional asset classes, for the same purposes of risk measurement and price discovery.

Conclusions

In this work, we show how hierarchical clustering and spectral methods can be combined in order to highlight stronger correlations between financial asset returns. Relevant information, embedded in the edges of financial assets, is extracted by replacing completeness of network of the distance matrix by sparseness of the minimum spanning tree, which includes fewer but more important links. These tools not only enable detection of the hierarchical organization behind the ETF's market but also, if employed in asset allocation strategies, improve the profile of risk/return of portfolios obtained. In fact, the inclusion of network centrality parameters and random matrix filter in the Markowitz optimization function allows us to reach a further diversification of portfolio risk for a specific value of returns.

We believe that our proposal could be relevant, especially for regulators tasked with measuring and preventing the under estimation of compliance risks coming from the adoption of robot advisory financial advising. Moreover, the use of connectedness measures allows the characterization of the leaders and followers in price formation among the considered exchanges at different levels: pairwise and system-wide, as well as both from a static and time-varying point of view.

In this work network measures employed are fundamental for two purposes: for the construction of asset allocation model and the detection of mechanisms of price information among new financial products such as Bitcoin Exchanges, with a generalized Vector Error Correction model.

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