

Chakraborty, Gourab; Chandrashekhar, G. R.; Balasubramanian G

Article

Measurement of extreme market risk: Insights from a comprehensive literature review

Cogent Economics & Finance

Provided in Cooperation with:

Taylor & Francis Group

Suggested Citation: Chakraborty, Gourab; Chandrashekhar, G. R.; Balasubramanian G (2021) : Measurement of extreme market risk: Insights from a comprehensive literature review, Cogent Economics & Finance, ISSN 2332-2039, Taylor & Francis, Abingdon, Vol. 9, Iss. 1, pp. 1-24, <https://doi.org/10.1080/23322039.2021.1920150>

This Version is available at:

<https://hdl.handle.net/10419/270082>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/4.0/>

Measurement of extreme market risk: Insights from a comprehensive literature review

Gourab Chakraborty, G. R. Chandrashekhar & G. Balasubramanian |

To cite this article: Gourab Chakraborty, G. R. Chandrashekhar & G. Balasubramanian | (2021) Measurement of extreme market risk: Insights from a comprehensive literature review, Cogent Economics & Finance, 9:1, 1920150, DOI: [10.1080/23322039.2021.1920150](https://doi.org/10.1080/23322039.2021.1920150)

To link to this article: <https://doi.org/10.1080/23322039.2021.1920150>



© 2021 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license.



Published online: 28 May 2021.



Submit your article to this journal [↗](#)



Article views: 3216



View related articles [↗](#)



View Crossmark data [↗](#)



Citing articles: 1 View citing articles [↗](#)



Received: 25 December 2020
Accepted: 17 April 2021

*Corresponding author: Gourab Chakraborty, Institute for Financial Management (IFMR), Affiliated to University of Madras, No: 196, TT Krishnamachari Rd, Alwarpet, Chennai 600018, India
E-mail: gourab.chakraborty@ifmr.ac.in

Reviewing editor:
David McMillan, University of Stirling, Stirling, United Kingdom

Additional information is available at the end of the article

FINANCIAL ECONOMICS | REVIEW ARTICLE

Measurement of extreme market risk: Insights from a comprehensive literature review

Gourab Chakraborty^{1*}, G. R. Chandrashekhar² and G. Balasubramanian¹

Abstract: The experience of past financial market turmoil suggests that in addition to eroding investor wealth, the severe consequences of rare extreme market events can spillover and impair the broader real economies. In this context, this paper is an evaluation of the methodological and empirical advances in the measurement of the extreme market risk. This paper argues that a major reason for the origin of such risks post 1980s has been the unintended consequence of asymmetric monetary policy to sustain the rise of financial markets. Thereafter, this review identified the value at risk (VaR) and VaR-based alternative expected shortfall (ES) as the principal measures of extreme market risk. The deficiencies in the standard modelling approaches for VaR-ES measures have led to several advanced estimation methodologies. However, the lack of identification of optimal methodology, in the internal models approach (IMA) regime where financial institutions (FI's) can choose suitable VaR-ES modelling technique incentivizes regulatory arbitrage and other inconsistencies. Therefore, this paper investigates the theoretical and empirical research literature on VaR and ES estimation for financial asset market prices. This paper finds that the extreme value theory (EVT) followed closely by the filtered historical simulation (FHS) are highly accurate methodologies. In addition, Mixture distributions, asymmetric and non-linear versions of the conditional quantile (CQ) approach, (volatility) asymmetry and long memory conditional volatility

ABOUT THE AUTHORS

Gourab Chakraborty is a graduating PhD student in Quantitative Finance area from the Institute for Financial Management and Research (IFMR), Chennai. His research interest lies in financial market risk measurement and asset pricing. He is also a Financial Risk management (FRM) Level II Candidate.

Prof G. Balasubramanian is the former dean of IFMR. His research interests are financial modelling and analytics.

Prof G. R. Chandrashekhar is currently a professor in the area of Data Science at IFMR. His research interest spans investigating strategic actions, unravelling complexity, and data-based exploration.

This literature review paper is a part of Gourab's PhD thesis. The alternative methodologies identified in this paper are being used in working papers to measure extreme market risk across asset classes and financial markets.

PUBLIC INTEREST STATEMENT

We live in an age of financialization, where economic policy is geared to sustain the rise of financial markets as drop in financial asset prices can wreak havoc for the real economy. Yet, arguably unintended consequences of policy action has led to higher instances of financial market turmoil since the 1980s, especially during the last decade since the global financial crisis (GFC) of 2008. Therefore, the measurement of extreme market risk is of paramount importance for financial institutions (FIs) and the regulatory authorities. While the current regulatory guidelines do not specifically mandate the FIs to measure this risk following any specific methodology, the scale of available methodologies is enormous. With this background, this study reviews the empirical literature for extreme market risk estimation methodologies. It finds that the few estimation approaches which can better explain the statistical properties of the extreme returns can superiorly measure extreme financial market risk.

models, especially those assuming skewed and leptokurtic distributions offer accurate VaR and ES measures.

Subjects: Economic Theory & Philosophy; Macroeconomics; Econometrics; History of Economic Thought; Finance; Public Finance; Banking; Insurance; Business History

Keywords: Expected shortfall; extreme market risk; extreme value theory; measurement; value at risk; estimation methodologies

JEL Classifications: B23; B26; B41; C13; C14; C18; C22; C52; G01; G15; G20

1. Introduction

In this paper, we review the literature on the measurement of extreme (financial) market risk, in particular for the estimation of Value at risk (VaR) and Expected Shortfall (ES). Mishkin (2009) and Orłowski (2012) suggest that extreme market events are unforeseen or rare, i.e. low frequency but high severity (LFHS) and refer to its risk as “tail risk”. From a statistical standpoint, LFHS market crises are tail events, i.e. outliers that lie in the tails of the distribution. While Kemp (2011) limits tails to the lower 10% quantile and beyond the upper 90% of a returns’ distribution, Smith (1987) offers a much stronger and narrower definition with tighter bounds—beyond 2.6 times standard deviation of asset returns away from the mean. The term “tail risk” concerns the “chances” - measured by the probability (estimated by empirical and theoretical probability distributions) and “consequences” - Value at Risk (VaR) and Expected Shortfall (ES) estimates of adverse returns in the tails of the returns distribution (Tolikas, 2008, 2014). Kemp (2011) suggest that the tail risk stems from fat tails, which is statistically referred to as (left skewed) leptokurtosis. Fat tails is an empirical regularity when asset prices have lower levels of volatility during ordinary market periods and considerably elevated volatility levels during market turmoil.

This paper aims to present a researcher in the field of extreme (market) risk measurement with a wide spectrum of methodologies to accurately measure and determine VaR and ES estimates; and acquaint him(er) with the contours of the maximum progress made in this area.

It is unsurprising that academic literature that proposes new VaR-ES models and backtesting methodologies with a prima facie aim to improve extant ones and compare the alternative VaR-ES estimation methods and backtesting techniques has expanded rapidly in the last two decade. This forms the primary motivation for this paper.

In the following sections, the review has tried to identify four broad themes that direct the research on measurement of extreme market risk and align the survey along these broad themes. These broad themes are - the origin of market tail risk¹ as perceived in the literature, the measurement frameworks of tail risk from the past, the weaknesses in the traditional tail risk measurement approaches in the past and the consequent evolution of newer models, and lastly, the impact of this evolution of tail risk measurement on the empirical literature. Figure 1 offers a schematic progression of this literature review.

The evolution of newer models and the impact on the empirical literature occur simultaneously. Hence, the studies aligned to these two latter themes have been consolidated. Accordingly, this review of literature can be aligned into three strands: antecedent, evolution of extreme risk measures and the consequent strand. This alignment guides the organization of the paper. Section 2 reviews the antecedent strand of literature on the critical nature of extreme market risks and highlights its importance of its measurement. Section 3 outlines the second strand of literature on the historical evolution of alternative extreme market risk measures. Section 4 reviews the consequent seminal and empirical literature on the alternative VaR and ES estimation methodologies. The conclusions are presented in section 5.

Figure 1. Alignment of the literature review along four broad themes.

Note: While the FHS is an improvement over the HS (a non-parametric) approach, FHS framework per se is a semi-parametric technique.

Source: Adapted from studies reviewed in section 4.2

Broad Theme 1: Origins of market tail risk (Section 2)

- Post 1980s ‘Financialization’
- Inordinate and pervasive influence of financial markets in real economy especially monetary policy.
- Tail Risk originates from unintended consequences of monetary policy.
- **Key Research Driver:** Extreme Market Events can cripple the real economy.

Broad Theme 2: How was tail risk measured in the past? (Section 3 and 4.1)

- A. Extreme Market Risk
Measures: Standard deviation, Sensitivity Analysis.
- B. Estimation of Value at Risk (VaR) and Expected Shortfall (ES) using 3 conventional methods: Gaussian Approach, Historical Simulation (HS) approach and Monte Carlo Simulation (MCS) technique

↓ (Overcome Weaknesses)

Broad Theme 4: Impact of alternative models in literature? (Section 4)

- Determination of accurate alternative methodologies.
- Accurate techniques such as POT-Hill Estimator, Kernel, S-Gt distribution, CF expansion, FHS and EVT are being extensively used in the tail risk empirical literature.

Broad Theme 3: How is tail risk measured at present? (Section 4.2)

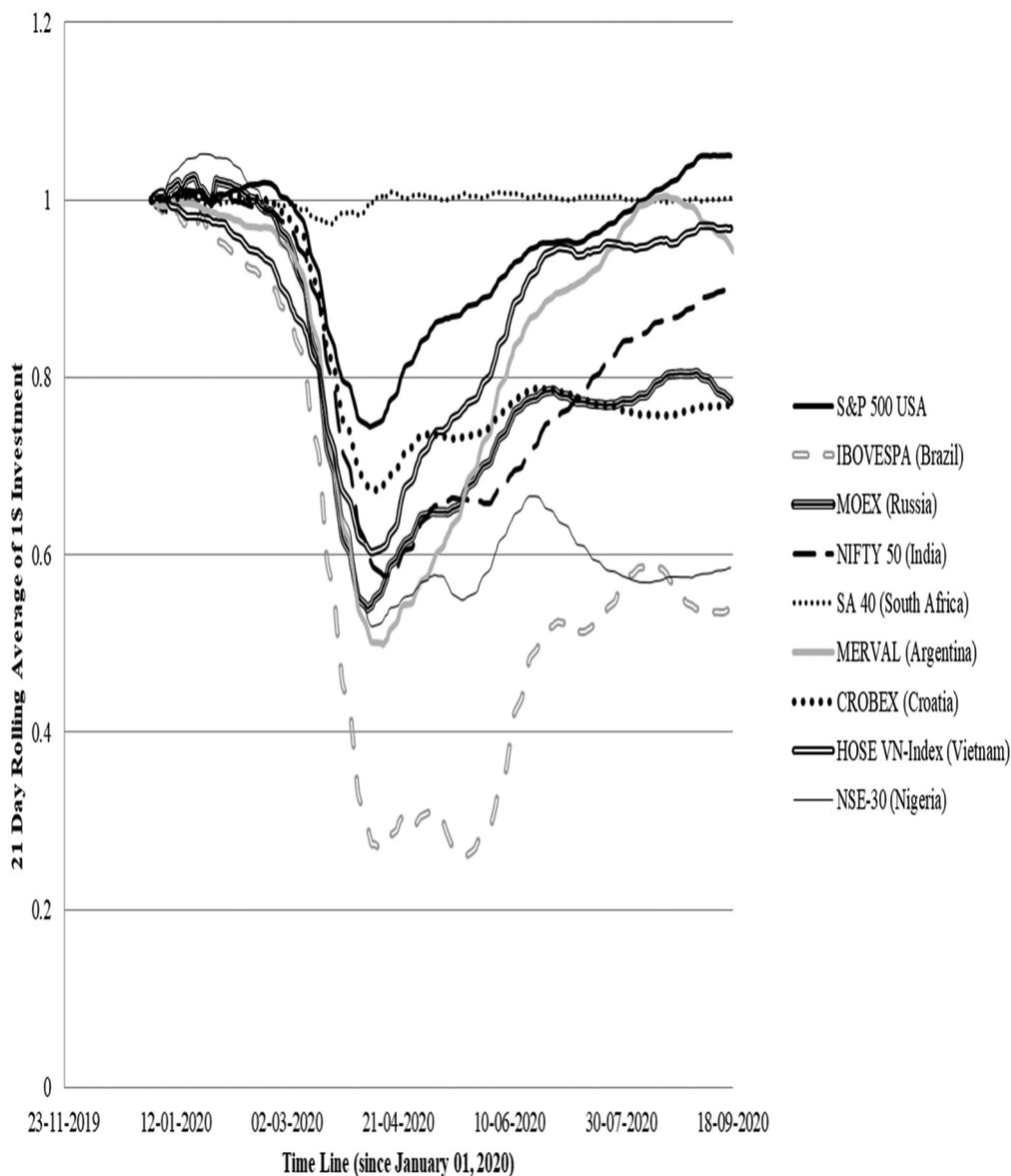
- Alternative Estimation Methodologies of VaR-ES.
- *Non-parametric*: Peaks over threshold (POT) – Hill Estimator, Kernel Smoothing
- *Parametric*: Skewed generalized t (S-Gt) distribution, Cornish-Fisher (CF) expansion.
- *Semiparametric*: Extreme Value Theory (EVT), Filtered Historical Simulation (FHS)

This paper argues, respectively, in section 2 that the increasingly frequent occurrence of extreme financial market events with debilitating consequences for the real economy since the 1980s and further argues in section 4.2 that the glaring weaknesses of the traditional tail risk estimation methodologies and the lack of identification of the optimal tail risk estimation methodology in the Basel guidelines are the principal drivers of research in tail risk measurement.

The key contributions of this paper are threefold. First, this paper argues that the origins of tail risk, especially post 1980s, can be attributed to the financialization. Second, it provides a comprehensive review that combines the origins of tail risk with the range of extreme market risk measures and estimation methodologies. Finally, it reviews a vast body of empirical literature

Figure 2. Performance of select post-Colonial equity indices during COVID19.

Source: Authors' estimation from market prices of indices and exchange rates available in Yahoo Finance and in investing.com



on the extreme market risk and categorically identifies the extreme value theory (EVT) as the most accurate methodology for extreme tails.

2. The origins of the extreme market risk, the high severity of rare extreme market events—need for its accurate measurement

In this section, this paper tries to trace the origins of tail risk - the first broad research driver - in the enormous and wide influence of financial markets on the real economy, especially economic policy making. This nexus is argued to encourage asset price bubbles, which subsequently bursts upon arrival of aggravating market information.

The March 2020 crash provides a relevant context to appreciate the importance of extreme financial market risk measurement. Studies such as Zhang, Hu and Ji (2020) and Wojcik and Ioannou (2020) which have evaluated the rapid asset price declines during COVID19 pandemic in mature financial markets and in China, indicate that while the unconventional monetary policy (UMP) appears to be

favoured response of central banks to mitigate the adverse economic impact of the pandemic, the undesirable consequences of the UMP are rather likely to aggravate the financial market risks.

This suggestion with regard to the monetary policy is consistent with the contention of Lian et al. (2018) and Cieslak et al. (2019) that UMP incentivizes destabilizing speculation in financial markets that may trigger unsustainable asset price inflation for 15 to 40 months (Gottesman & Leobrock, 2017), which culminates in extreme market events.

To elaborate, Figure 2 exhibits the 21 day rolling average value of a notional 1\$ investment in USA and 8 select emerging and frontier markets with that in the USA during COVID19 induced crash.

This figure suggests that investments stand to lose a substantial portion of their value during extreme market events and the time to recovery can be long. In fact, while the zoonotic origin of extreme markets is novel, nevertheless, the occurrence of rare yet extreme financial market events and the destruction of wealth in the aftermath, in the pre-COVID era, are extensively chronicled in financial history since the Dutch Tulip crisis in 1636.

A scrutiny of financial market history suggests that the steep financial asset price deflation in extreme market events, which affect multiple financial markets and asset classes are rare before the 1980s. This survey argues that a major driver of research into extreme market risk stems from the fact that while the post-1980s market disasters are rare such events are increasingly frequent.

To explain, the 1700s witnessed just 2 events - the South Street Sea bubble in 1720 and the crash from the end of “Seven Years War” in 1763. Thereto, the 1800s saw 4 extreme events - from the sovereign bond defaults during 1825–26 across Europe and Latin America through to the Panic of 1873 in the US, Austria and Germany. The 20th century prior to the 1980s saw only 3 extreme market episodes induced by the banking crisis - the panics of 1907 and 1929 (triggering the “Great Depression”) and the Spanish leg of the “Big Five Crises” in 1977. The reader may refer to Table A1 in the appendix for a chronological account of extreme market events till Covid19 induced March 2020 financial market crash.

To sum up, the financial markets worldwide have witnessed 10 extreme market events since 1600. However, the post 1980s era experienced 13 extreme markets events from the Latin American Debt Crisis of the 1980’s through East Asian financial crisis, Dot Com Bubble, global financial crisis, the Eurozone crisis and the COVID19 induced March 2020 Crash. (Cieslak et al., 2019; Coombs & Van Der Heide, 2020; Nageswaran & Natarajan, 2019).

An enquiry into the drivers of high incidence of extreme market risk since the 1980s highlights the exposure of broad stakeholders in an economy to financial markets is pervasive in an era of *financialization* of the physical economy. Tomaskov-Devey and Lin (2011) point out that since the 1980s, *financialization* has led to the substitution of active income from labor income with passive income from financial asset prices as the dominant component of national wealth. In fact, Cieslak et al. (2019) illustrate that while the unemployment in the US falls less when equity indices rise, it rises much more when market indices decline. Corporations and governments prefer to borrow via financial markets rather than banks. Financial Intermediaries (FI) earn greater share of their profits from trade of financial securities (securitized) loans, and market-linked products than from extending credit and other intermediation. Thus, financialization is characterized by substitution of credit risk with market risk. Karwowski et al. (2017) contend that as the financial markets rise to replace banking as the dominant source of funds, the need to implement asymmetric or unconventional monetary policy (UMP) via financial markets and sustain financial asset price inflation becomes a tacit policy objective.

In the asymmetric monetary policy, central banks use (inter-bank) overnight rate rather than the money supply rate as the monetary policy instrument, and monetary policy is highly sensitive to financial asset price deflation. Central banks write real (monetary) put options by lowering overnight

rates to push up falling asset prices and write real (monetary) call options when reluctant to raise the overnight rates to arrest asset price inflation. In fact, overnight rates have lost efficacy at near zero levels. Therefore, central banks have been lately targeting (often lowering) the interest rates along the yield curve by dealing in (often buying) government and pseudo-government securities, as in quantitative easing (QE). A downward shift in the yield curve has contributed to corporate bond price inflation.

However, an accommodative monetary policy, especially UMP, signals that the central banks are implicitly underwriting the price inflation of liquid financial securities with higher ex-ante returns (ex. equities and bonds). Accordingly, the long-run capital investments which are illiquid and cumbersome appear less attractive against liquid financial securities. Also, the lower rate of interest signals less scarcity of goods and services in the future. Hence, the long-run investment may not return the expected profitability. In addition, an implicit central bank underwriting of risky securities in a lower interest rate regime lowers the opportunity cost of not investing in safer investments and induces savers to invest in more risky market-linked investment products. Therefore, these works argue that the asymmetric and unconventional monetary policies tend to cause more destabilizing speculation rather than long-term physical investments and that the monetary policy can be argued to be a major compounder of financial market fragilities leading to extreme market events.

An exploratory data analysis of the daily logarithmic returns during these extreme market episodes highlight that financial asset price deflation was usually greater than 3 standard deviations fall from the mean and the subsequent periods of recovery were protracted. Therefore, the fallout of these extreme market episodes can spillover into broader real economy and cripple it, especially the households.

The pervasive nature of financial market exposure and the severity of losses during extreme market events demonstrate that financial intermediaries (FI's) need to assign sufficient risk capital to protect themselves and the financial system against rare market catastrophes, and the elementary objective of the national and supra-national financial regulators and supervisory authorities is to improve the early identification of extreme market risk and mitigate the fallouts. Therefore, measurement of extreme market risk is an elementary responsibility for the former and of acute concern for the latter. Supranational consortium of financial regulators, such as the Basel Committee of Banking Supervision (BCBS), Bank of International Settlements (BIS) mandate the FI's to estimate VaR and lately ES (BCBS, 2019) derived market risk capital buffers; which are aimed set aside to absorb losses during future extreme market events.

3. Extreme market risk measures—Evolution, attractions and limitations

In this section, this paper tries to partly address the second and third broad themes of research on extreme market risk measurement. To be specific, this section reviews the strand of literature (Alexander, 2008; Aragonés et al., 2001; Berk & DeMarzo, 2012; Clare et al., 2013; Dowd, 2005; Ellis, 2017) that examines the evolution of extreme market risk measures over the years. The review along this broad theme finds that the extreme market risk measures have improved over the past three decades from the traditional standard deviation (SD) of asset price returns through to the recent alternatives of value at risk (VaR) and expected shortfall (ES).

Over time, the limitations in the naïve SD estimator were supplemented with *stop loss limits* during market trades. In addition, *gap analysis* examines the difference in net income due to asset and liability sensitivity towards interest rates. Moreover, *sensitivity metrics* consists of the first and second order mathematical derivatives of asset prices with changes in risk factors. These include “beta” for equities, “duration” and “convexity” for bonds, and “greeks” for options. Further, capital buffers such as *Margin Amount* and *Risk Capital* represent extreme market risk in terms of capital amount. These tools are devised to absorb the extreme market losses and protect the integrity of financial markets and banks, respectively.

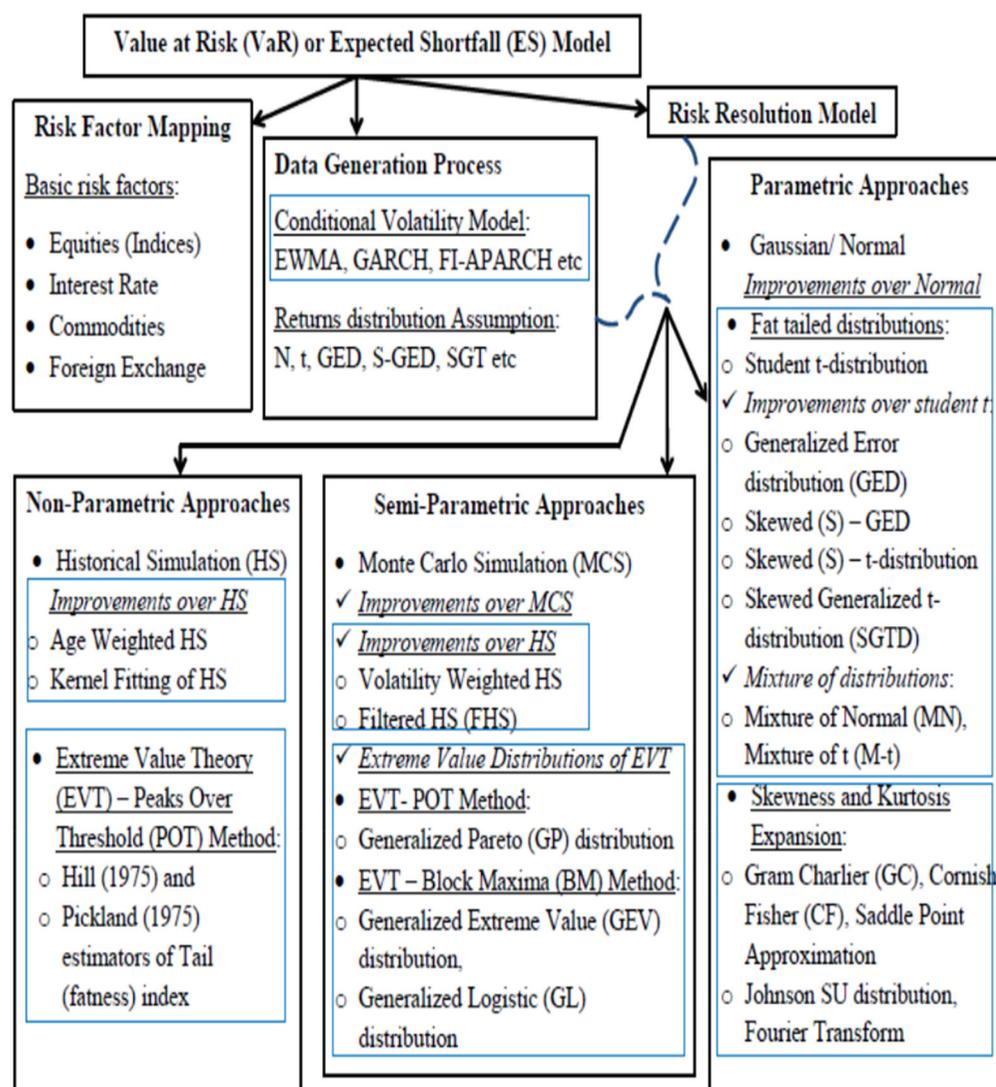
This review finds that several of these extreme risk measures also serve as the tools to absorb and mitigate the fallout of extreme market risks. Importantly, no single estimator is perfect and every alternative has its attractions and limitations. Nonetheless, all of these discussed measures represent mostly the consequences of loss and do explicitly summarize the chances (precisely the probability distribution) of loss.

This major limitation was overcome by Value at Risk (VaR) and the Expected Shortfall (ES), which are probabilistic statements of extreme losses. The VaR is a tail quantile that represents the probability boundary for extreme market losses. The ES measures the average of losses greater than VaR. The ES is also referred to as expected tail loss (ETL) and the Conditional VaR (CVaR).

A review of extreme market risk measures (as Dowd, 2005; Jorion, 2010) is likely to project the Value at Risk (VaR) as a highly popular metric and the Expected Shortfall (ES) as a superior

Figure 3. Hierarchical schema into the classification of VaR and ES models.

Source: Adapted from studies reviewed in section 4.2



alternative. However, the recent literature (Kou & Peng, 2014; Kellner & Rösch, 2016) is not

categorical and has argued to replace the ES with median shortfall (MS). The median shortfall (MS) estimates the median of losses worse than VaR; similar to ES which is the mean of the losses. MS for a particular confidence level (C_V) can be estimated as the VaR at confidence level $C_V' = 0.5 \cdot (1 + C_V)$. On balance, this section views VaR and ES as the most widespread (not necessarily sufficient) extreme risk measurement frameworks.

That said, the review of studies cited in this section and the ones discussed in the subsequent section indicate that while the VaR and ES despite are simple in theory, these measures are non-trivial to estimate in practice. In addition, the BCBS guidelines do not suggest any specific estimation methodology for VaR and ES estimations, rather advise the FI's to employ their "internal models"; subject to the qualification of the internal (VaR-ES) risk model in the backtesting of the VaR estimates. Against, this backdrop, the primary aim of the following section is to evaluate the alternative VaR and ES methodologies.

4. An evaluation of VaR and ES estimation approaches

In this section, the paper has tried to align the remaining sections of the literature review along the second and third broad theme of research and address the fourth theme that evaluates the effect of the tail risk estimation frameworks' progression on the empirical literature. This section suggests that three fundamental estimation methodologies of VaR and ES, the analytical procedures based on *Gaussian distribution*, non-parametric *Historical Simulation* (HS), and semi-parametric *Monte-Carlo Simulation* (MCS) (Best, 1999; Choudhry, 2013, page 32) suffer from major weaknesses that have spawned development and application of alternative estimation techniques over the past two decades.

4.1. Deficiencies in the three elementary VaR-ES estimation techniques and the need for advanced VaR-ES estimation methodologies

Overwhelming fraction of the consequent strand of literature highlights that the normal distribution fails to account for "fat tails" and other empirical regularities. The data imply that Gaussian distribution assigns unreasonably negligible probabilities to the tail events. For instance, the magnitude of the extreme price deviations during the 19 October 1987 flash crash and the East Asian financial crisis of 1998, and the LTCM crisis was 20 SDs away from mean returns; cannot occur according to Gaussian distribution. To sum up, the Gaussian VaR-ES framework has been documented to severely underestimate extreme market risk. This underestimation is profound for non-linear instruments with discontinuous payoffs like derivatives.

In addition, studies such as Hendricks (1996), Jackson et al. (1997), and Vlaar (2000) that applied the historical simulation (HS) approach, have found the HS derived VaR estimates found to outperform those from Gaussian approaches. These studies highlight the possible strengths of the HS technique. First, the empirical distribution accommodates fat tails. Second, no distributional assumption lends the theoretical flexibility to be applied to derivatives. Third, HS is intuitive and conceptually simple. Fourth, it is easy to produce confidence intervals for (non-parametric) VaR and ES estimates; and lastly, it is easy to implement and communicate the results. In addition, Huang and Tseng (2009) find the HS VaR to be marginally more accurate than the MCS VaR. This superior accuracy of the HS estimates can be attributed to higher matching of tail probabilities.

However, HS estimator is non-precise, i.e. estimates have high standard error, particularly for high confidence levels that represent the tails (rare events). Therefore, HS estimates are difficult to verify.

While MCS VaR estimates outperform Gaussian VaR estimates in backtesting (Pritsker, 1997; Bao, Lee, and Saltoglu, 2006), it is found to produce relatively inaccurate estimates compared to HS, Kernel smoothing, and CaViaR approaches (Huan, Lin, Chien, and Lin, 2004; Bao et al., 2006). Abad et al. (2014) too observed that it performs poorly than HS and (parametric) student t approaches. These studies document that the extreme value theory (EVT) approach is far more accurate and conservative than the MCS method.

The lacunae in the traditional approaches and the need to accurately characterize the extreme market risk have motivated the development of alternative VaR-ES estimation methodologies. A review of the studies examining the conventional approaches and ones applying the alternative techniques strongly suggest that the accurate measurement of extreme market risk acquires higher importance since it is often difficult to model unforeseen phenomena that usually lie outside the domain of available observations.

4.2. An evaluation of alternative VaR-ES estimation methodologies

This subsection critiques the best 64 known alternative methodologies for the VaR and ES estimation, based on different statistical (distribution) and econometric (volatility) methods. However, such a large number of approaches and methods complicate the selection of the methodology to measure VaR and ES. A systematic classification and comparison of different methods for risk measures will simplify the optimal selection. Figure 3 attempts to simplify this classification and comparison.

In the univariate risk metric estimation, the extreme risk model can be perceived to consist of 3 kinds of statistical models: risk factor mapping, the data generation process (DGP) and the risk resolution model. To explain, the estimation of VaR-ES measures for all assets (including non-linear/exotic) in a complex large portfolio can be a computational ordeal. Risk factor mapping replaces the current/market value of assets with exposures in a set of fundamental risk factors (equity market indices, yield curve, commodities, currency foreign exchange rates) by applying partial derivatives on an analytical pricing function (ex. Black Scholes formula) or by regression (ex. CAPM). In many instances, a working linear relationship is approximated between a (possibly non-linear) asset's market value and the primitive risk factors while risk mapping.

The data generation process (DGP) step augments the fitting of returns distribution with volatility clustering effects to better describe the evolution of returns series over time. It essentially states that conditional on assuming the evolution of the returns process, i.e. the conditional volatility model, the theoretical distribution is assumed for returns. The returns distribution is assumed to be parametric (in figure 1.2) or left as empirical. The parametric distribution can be fitted to the entire return distribution or in the tails. If the volatility clustering effects are not estimated then the risk model is referred to as “unconditional”.

The interaction of the risk mapping and data generation process lends itself to 3 broad risk resolution models: non-parametric, parametric and semi-parametric. The choice between these three components is intertwined. For instance, if returns distribution is empirical then the risk resolution model cannot be analytic but non-parametric or EVT for the tails. By contrast, if the returns are assumed to be independent and identical distributed (IID) then an unconditional risk resolution model is used.

4.2.1. Improvements over the standard Historical Simulation (HS) technique

A review suggests that Hill (1975) and Pickands (1975) type estimators are notable alternative non-parametric improvements over HS techniques. However, the Hill (1975) and Pickands (1975) type estimators estimate tail fatness of extreme returns filtered by the peaks over threshold (POT) approach from the returns distribution. It is noteworthy that the POT method is a constituent method to identify extreme returns also it also leads to parametric modeling of the extreme returns by the generalized pareto (GP) distribution. Moreover, the HS technique has been significantly improved by the non-parametric *age weighting* (Boudoukh et al., 1998) and the *kernel smoothing* (Huang and Tseng, 2007) and semi-parametric *volatility weighting* (Hull and White (HW), 1998a, 1998b) and the *filtered historical simulation* (FHS) approaches.

Empirical studies such as Barone-Adesi et al. (2002), Angelidis and Degiannakis (2005). Alexander & Sheedy (2008), and I. Roy (2011) find that the FHS approach is a highly accurate estimation approach with forecast accuracy comparable to that of extreme value theory (EVT) approach.

4.2.2. Parametric advances over the analytical approach based on Gaussian distribution

The insights from empirical studies on parametric improvements to Gaussian VaR-ES estimation can be classified into 3 broad buckets. The first strand searches for a suitable conditional (time-varying) volatility model, preferably with volatility asymmetry and long memory. The second direction tries fitting a skewed and fat-tailed parametric distribution that best explains the empirical returns distribution. The third strand aims to improve the Gaussian distribution by incorporating higher-order conditional moments - Skewness and Kurtosis.

As regards the first strand, the conditional volatility modelling can be compartmentalized into 3 categories:

- GARCH type models (Gonzalez-Rivera, Lee, and Mishra, 2004; Chen, Gerlach, Lin, and Lee, 2012; Sener, Baronyan., and Menguturk, 2012; Abad et al., 2014);
- Stochastic volatility (SV) family models (Lehar, Scheicher, and Schittenkopf, 2002; Fleming and Kirby, 2003; Clements, Galvao, and Kim, 2008; Gonzalez-Rivera et al., 2004; Chen et al., 2012);
- Realized volatility (RV) family models (Clements et al., 2008; Asai, McAleer, and Medeiros, 2012).

The following inferences are gathered with respect to the performance of parametric VaR and ES estimates with the performance of VaR and ES estimates based on conditional volatility models.

- First, the empirical works namely Asai et al. (2012), Chen et al. (2012) and Abad et al. (2014) suggest that the parametric distribution fitting of return distributions dominates over the conditional volatility model in the accuracy of VaR-ES estimates.
- Second, the exponentially weighted moving average (EWMA) process is inaccurate (Chen et al., 2012; Abad et al., 2014) for VaR-ES estimation.
- Overall, with minor departures (Gonzalez Riveria et al, 2004), the empirical findings suggest that the forecast accuracy of the VaR estimates based on the stochastic volatility (SV) family models and the GARCH family models are similar. There is no significant improvement in migrating from GARCH framework to SV approach (Chen et al., 2012).
- In general, the conditional volatility models with *leverage effect* and *long memory* such as fractionally integrated—*asymmetric power ARCH (FIAPARCH)* and Asai et al. (2012) realized volatility (RV) models are seen to provide highly accurate forecast estimates of VaR and ES. Giot and Laurent (2003) and Brownlees and Gallo (2011) observe that, although under a Gaussian distribution, an RV model is found to yield more accurate VaR estimates than a GARCH family model, regardless, under a skewed and leptokurtic distribution, such as the skewed (S)-t distribution, both competing frameworks produce similar levels of VaR forecast accuracy.

The second strand suggests that when asymmetric and fat-tailed distributions are considered, the accuracy of the VaR and ES estimates improve considerably:

- To elaborate, symmetric fat tailed distribution like the student t distribution fits the data better in the tails than the Gaussian distribution but is restricted by the symmetry assumption. Therefore, it can underestimate probability mass in the left tails and consequently offer inaccurate VaR and ES (Brooks and Persaud, 2003). In addition, the t distribution has no constraints on the maximum losses and can produce misleadingly high-risk estimates at higher confidence levels. Thus, tail risk estimates derived from t-distribution are unreliable. Moreover, the t-distribution is not stable and therefore the VaR estimates cannot be forecasted over longer horizons (Jorion, 2010).
- A group of studies have performed comparative evaluation of the statistical accuracy of the VaR estimates from the student t-distribution with those from the generalized error distribution (GED), skewed(S) version of GED (S-GED), skewed t-distribution (STD), and the skewed generalized t (SGT)

distribution. Notable studies include Angelidis et al. (2004), Huang et al. (2004), and Lin and Shen (2006), Maghyereh and Awartani (2012), and Assaf (2015). These studies find that while modeling the empirical returns distribution with the GED, S-GED, and the STD provide more accurate tail risk estimates over the t distribution, nonetheless the SGT distribution offers the most accurate results. In fact, these studies attribute the notable improvement of the latter three distributions over the t distribution to the distributional asymmetry. In addition, further insights obtained from this strand of literature are as follows:

- (i) Fan et al. (2008) find that the GARCH-GED process is superior to the GARCH-N model and the HS-(ARMIA forecast) for VaR estimation. In addition, Bali and Theodossiou (2007) note that the VaR measures derived from the GARCH-GED model are more accurate than the generalized t derived VaR estimates whereas the GARCH-SGED model outperforms those from the GARCH-GED model and GARCH-skewed t model in statistical backtesting. Nonetheless, the GARCH-SGT model outperforms the GARCH-SGED model in VaR and ES estimation. Lee et al. (2008) notes that the GARCH-SGED model is superior to the GARCH-GED model for extreme market risk estimation. However, in a study on real estate markets, Zhou and Anderson (2012) suggest that the VaR estimates obtained upon assuming that the extreme values of GARCH process filtered residuals follow the GP distribution and the FHS implied VaR estimates are not more accurate than the estimates from GARCH type GED process.
 - (ii) In contrast, Angelidis et al. (2004) finds that the GARCH, exponential (E)-GARCH and threshold (T)-GARCH models with t-distributed innovations perform superiorly in backtesting than their counterparts with GED innovations. Leverage effect or volatility asymmetry can be enhanced by EGARCH-t and AP-ARCH-t models instead of GARCH-t model. Su and Knowles (2006) exhibit that the improvement of GED and SGED over the student t distribution vis-a-vis the accuracy of VaR and ES estimates is marginal. In fact, Bali et al. (2008) find that the GED VaR can underestimate extreme market risk.
- This review has gained the following additional insights with regard to the Skewed “t” distribution:
 - (i) Studies with favourable assessment: Giot and Laurent (2003) find that the VaR and ES forecasts from the skewed t distribution are more accurate than the estimates with the gaussian and student-t distribution assumptions. In addition, Altun et al. (2018) suggest that the skewed t distribution provides more accurate VaR forecasts than the skewed N distribution. It also indicates that the backtesting performance of the skewed t VaR-ES models is similar to those corresponding to the GED and the SGED.
 - (ii) Studies with not a favourable assessment: Angelidis and Degiannakis (2005) highlight that capturing leverage effect or volatility asymmetry rather than the return distribution is more important for the accuracy of conditional VaR estimates. Moreover, Corlu et al. (2016) argue that generalized lambda (GL) distribution is a more suitable candidate than the skewed-t distribution.

This paper has received the following insights while reviewing studies which have investigated the skewed generalized t distribution in extreme market risk measurement:

- (i) *Features*: the SGT distribution is a skewed extension of the generalized t distribution (McDonald & Newey, 1988). The SGT nests several well-known distributions such as the generalized t (GT), the skewed t (ST) of Hansen (1994), the SGED of Theodossiou (2000), and the normal, Laplace, uniform, GED, and Student t distributions.
- (ii) *Advantages*: Hence, it can cater to highly diverse levels of kurtosis and skewness. Therefore, it can model the return distribution of a wide variety of assets. [Source: Harris et al. (2004), Bali and Theodossiou (2007), Bali et al. (2008), Cheng and Hung (2011), and Lin et al. (2014).] In fact, Lin et al. (2014) suggest that the accuracy of the SGT VaR models improves considerably if the tail fatness is estimated by the modified Hill estimator; the latter was proposed by Huisman et al. (2001).

(iii) *Disadvantages*: By contrast, Polanski and Stoja (2010) and BenSaïda and Slim (2016) find other parametric approaches outperform SGT models. The former observes that Gram and Charlier (GC) (24) expansion VaR and other GC expansion VaRs outperform SGT VaR at moderately high and extremely high tails. The latter, finds that, in equity indices, the Generalized Hyperbolic (GH) distribution explains the physical returns better than the SGT distribution. However, in exchange rates, the SGT distribution is a superior alternative.

This survey notes that the mixture distributions offer reasonably accurate VaR and ES estimates. To elaborate, the insights specific to the mixture distributions are as follows:

- Studies such as Venkataraman (1997), Hull and White (1998), and Alexander and Lazar (2006) report that the VaR and ES estimations obtained from models involving a mixture of distributions [normal (MN) and Student t (Mt)] are generally quite accurate. In particular, Su and Knowles (2006) observe that the accuracy of VaR models from GARCH-MN is comparable to that of Markov Switching (MS) model. In addition, GARCH-MN VaR model outperforms the VaR estimates from GARCH-N and GARCH-t models (Lee & Lee, 2011; Xu & Wirjanto, 2010). The accuracy is increased in the skewed and fat tailed mixture distribution VaR models (Alexander & Lazar, 2006; Miftahurrohmah et al., 2017) and in non-linear GARCH-mixture distribution VaR models (Nikolaev et al., 2013).

The third strand of literature examines the parametric adjustments that aim to augment the performance of the Gaussian approach with higher conditional moments (ex. skewness and kurtosis). These improvements are Cornish Fisher (CF) expansion, Gram Charlier (GC) expansion, and Saddle Point Approximation (SPA) on the one hand, and Johnson SU (distribution) and Fourier transformation:

- Early research from studies like Pitchler and Selitsch (1999) and Mina and Ulmer (1999) suggest that (uncorrected) Cornish-Fisher (CF) expansion is a highly fast technique that is less robust than MCS. These studies also highlight that GC expansion, Johnson's transformation and SPA have similar forecast accuracy performance with respect to CF technique. Fuss et al. (2007) suggest that CF expansion is a significant improvement over GARCH-N
- The CF VaR is found to deflate the artificially superior risk-adjusted returns by hedge funds/institutional investments (by S.D., Sharpe ratio, Semi-deviation, Gaussian VaR). Studies that share this finding are Favre and Galeano (2002); Amenc et al. (2003), Gueyie and Amvella (2006), Gueyie and Amvella (2006), Liang and Park (2010), and Boudt et al. (2013).
- Empirical studies like Tesfalidet, Desmond, Hailu, and Singh (2014) note that uncorrected CF VaR and ES estimates can be *non-monotonous*, i.e. extreme tails may provide lower values. A mathematical and simulation-based line of research originating with Jaschke (2002) investigates into the causes of *non-monotonicity*. Christoffersen (2003) and Giamourdis and Ntoula (2009) highlight that the CF VaR is *monotonic* and well-behaved when skewness and kurtosis parameters in the CF expansion formula have within their narrow domains of validity (DVs); for the skewness coefficient the domain of validity (DV) of is between $-/+ 1.2$.
- However, statistical improvements have been developed to overcome the (non-monotonic) deficiencies and obtain highly accurate risk estimates. To specify, Chernozhukov, Fernandez-Val, and Galichon (2010) proposes an increasing rearrangement formula to overcome the narrowness of the DV for the CF formula. Later, Maillard (2012) points out that the skewness and kurtosis parameters in the CF expansion are not the same as the corresponding empirical statistics and that most researcher confuse between the two pairs. It proposes a methodology to extract the formula coefficients (that satisfy the DV from sample estimates. Further, Amedee-Menasme, Fabric, and Maillard (2019) improve upon this extraction by providing analytical expressions for a range of empirical Skewness and Kurtosis values. The analytical formulae are derived using response surface methodology (RSM) polynomial regressions.

4.2.3. Insights from a review of advanced semi-parametric VaR-ES estimation techniques

In the semi-parametric framework, the improvements to the MCS technique have been methodological to improve its accuracy. These include the following:

- Delta-Gamma expansion (use full repricing in options which raises computational time) (Pritsker, 1997);
- Importance Sampling (IS), Stratified Sampling (SS) and improvements (Glasserman et al., 2000a, 2000b, 2001, 2002);
- Bootstrapped Algorithm (Siegl & West, 2001);
- Principal Component Analysis (PCA) (Antonelli & Iovino, 2002);
- Fourier Transform (FT) (Jin & Zhang, 2006);
- Convex Conservative Approximation (CCA) (Hong et al., 2014).

These seminal studies have also backtested the model generated VaR and ES estimates and demonstrated significant improvement in statistical accuracy. However, this review failed to notice any empirical study that examines the comparative performance of these improvements with competing VaR-ES models.

In addition to these improvements, the Filtered Historical Simulation (FHS) method, the *conditional quantile* (CQ) approach [also known as the Conditional Autoregressive VaR (CAViaR)] and the extreme value theory (EVT) framework stand out as the preeminent semi-parametric improvements.

The conditional quantile (CQ) approach is based on directly modelling the quantiles of returns distribution rather than modelling the entire distribution. Given that the VaR and ES measures are tightly linked to the standard deviation of returns distribution that exhibits clustering, the CQ approach uses a conditional autoregressive specification to formalize VaR and ES clustering; volatility clustering often translates to autocorrelated distribution.

This literature review was able to find only a limited literature on CQ/CAViaR technique. For instance, Bao et al. (2006) and Polanski and Stoja (2010) observe that while the VaR-ES forecasts from the standard symmetric absolute value (SAV) version of the CQ approach are accurate in quieter markets/phases, the accuracy drops during market turbulence. However, the forecast accuracy increases substantially during market turmoil, especially at extreme confidence levels when asymmetric extensions of the CQ method that capture the leverage effect and other nonlinearities of returns are applied. Notable asymmetric versions which lead to greater accuracy in VaR and ES estimates are the asymmetric slope (AS), Indirect GARCH (1,1) (IG), combination of T-GARCH and Wong and Li (2001)'s Mixture ARCH model (Yu Li, and Jin, 2010) and the non-linear dynamic quantile (NLDQ)-AS extension (Gerlach, Chen, and Chan, 2011; Sener et al., 2012).

Finally, the extreme value theory (EVT) is a credible methodology in the field of probability theory that can be used to describe and forecast low frequency high severity events (LFHS). In the area of risk measurement, the EVT framework has been applied in the insurance industry, portfolio optimization, and in the measurement of operational risk (Wong, 2013). A major attraction of the EVT is that it characterizes the tails of the returns distribution and does not interfere with the modeling of the entire distribution. The true distribution of the returns is unknown and can be estimated only from empirical distribution, parametric density and semi-parametric approaches. To elaborate, if suitable assumptions are satisfied, then the tools in EVT can be used to characterize the extreme realizations of a given random process or distribution. The principles of EVT were founded by Fisher and Tippett (1928) who showed that the asymptotic distribution of the adequately scaled extreme realizations within a random sample from majority of the distributions can and usually do converge to one out of three extreme value distributions: generalized extreme value (GEV), generalized logistic (GL) and the

generalized pareto (GP) distributions. This powerful result allows the disregard of the exact form of the entire distribution of returns to estimate the extreme quantiles – VaR and ES measures. This characterization of few massive losses rather than a sequence of medium-sized losses is argued to mitigate the underestimation of VaR and ES. The former is of greater concern to protect investment values. This flexibility is further increased as the EVT can independently characterize the right and left tails of the asset returns distributions. Several of the reviewed studies in the EVT strand of literature cite Embrechts et al. (1997) and McNeil et al. (2005) as detailed and systematic reference materials for the EVT and its application in finance.

These works and the studies reviewed also highlight the limitations of EVT. For instance, basic EVT assumes that extreme values are realized from IID samples. Empirical returns are usually serially correlated. While the challenges to EVT modelling from this stylized fact can be overcome by few adjustments, there remains no agreement to the most suitable technique. In addition, a salient feature of EVT is the inevitable trade-off between the availability of a limited sample and the need to have vast numbers of realizations. The former is often realized as the EVT's domain of interest is extreme occurrences, which by definition should be rare. The latter is attributed to the requirement of asymptotic nature from theory. Therefore, the selection of the sample data can be a critical step in applying the EVT. Moreover, the scale parameter and to a greater extent the location or the threshold parameter of the theoretical EVT distribution are sensitive to the cut-off choice during the preparation of the sub-sample of extreme values. A lower value can induce bias while a higher value can induce standard error. Furthermore, multivariate EVT is more complex and can encounter far more computational impediments than the univariate EVT.

Koedijk et al. (1990) are an early application of the EVT that examines the fat-tailed nature of 8 European currency exchange rates against the dollar. This study examined the fat-tailed nature of financial returns especially initially applying the non-gaussian stable distributions with infinite variance and later using the student t-distribution and its extensions. Its findings suggest that the empirical distributions can be better described by the stable laws distribution than the t-distribution.

In a pioneering research, Longin (1996) defined an extreme return as the greatest or lowest return of an asset over a period. This definition stands out as what qualifies as extreme in financial markets is different from that in physical phenomena. Hence, the occurrence of extreme event is not contingent on any exogenous event. It implies that rational expectations may not hold and extreme returns may be realized without any major news.

The empirical literature on the use of EVT to study extreme market risk is quite extensive. In fact, this study could review a total of 52 empirical papers on EVT VaR and ES estimation. Therefore, we have classified the papers into four broad categories to render the comparative evaluation of EVT literature more organized and insightful.

(a) Comparison of performance of EVT models with alternative estimation methodologies: -

Select empirical Studies reviewed in this sub-strand are Ponwall and Koedijk (1999), Longin (2000), Bali (2003), and Da Silva and De Mendes (2003), Gencay and Selcuk (2004), Bekiros and Georgoukos (2005), Kuester et al. (2006), Tolikas et al. (2007), and Tolikas (2008), Marimoutou, Raggad, and Trabelsi (2009), Dimitrakopoulos et al. (2010), Kourouma et al. (2011), Chavez-Demoulin et al. (2014), Allen et al. (2015), Paul and Sharma (2017), and Fuentes et al. (2018).

These studies argue that the EVT framework is a strong modelling alternative over the Gaussian, student t, GED, S-GED, HS, and MCS frameworks; especially at extremely high tails (greater than 99% confidence level). Standalone, the GEV and GP distributions fit well with the returns distribution and in VaR backtesting. The FHS VaR comes close to the EVT VaR in forecast accuracy.

A narrow cohort of studies have tested and compared the performance the conditional EVT models with unconditional EVT models. These include Danielsson and De Vries (2000), Bystrom (2004), Kuester et al. (2006), and Samuel (2008), Marimoutou, Raggad, and Trabelsi (2009), and Zikovic and Filer (2013). Most of these studies support the hypothesis that conditional GEV and GPD-derived VaR and ES estimates are superior to those for unconditional GEV and GPD in terms of forecasting accuracy. However, Bystrom (2004) suggests that the improvement in the conditional estimates is marginal. In particular, Samuel (2008) infers that Markov Switching (MS) ARCH process can significantly improve statistical backtesting performance. Moreover, Zikovic and Filer (2013) find that GPD derived VaR estimates marginally outperform those estimated with the FHS approach.

(a) Fitting the EVT distributions to empirical distribution of extreme returns:-

Empirical studies that have tried to explain the empirical distribution of extreme returns with the theoretical returns report that:

(i)

In the developed markets, the GP distribution was found to fit the empirical returns distribution better than the Frechet distribution (a particular form of the GEV distribution) (Jondeau & Rockinger, 1999). In a similar finding, the GP distribution was found to be more accurate than the GEV distribution when fitted with the empirical returns (Walls and Zheng, 2006).

(ii)

For the past two decades, a new research agenda has emerged wherein the empirical works such as Gettinby, Sinclair, Power, and Brown (2004), Gettinby et al. (2006), Tolikas (2008), Tolikas and Gettinby (2009), and Tolikas and Fifield (2011), and Tolikas (2014) have modelled the extreme returns distribution with the theoretical GL distribution. Studies find that the GL distribution explains the physical distributions better than the GEV distribution.

(a) Modelling the extreme returns distribution with the peaks over threshold (POT) approach:-

The strand of EVT literature which identifies the extreme returns with the POT approach can be categorized into two sub-strands. The former sub-strand tries to describe the empirical distribution of extreme returns with the theoretical generalized pareto (GP) distribution whereas the latter uses non-parametric estimators of the tail-fatness index.

Select empirical studies that belong to the first sub-strand include Bali and Neftci (2003), Brooks et al. (2004), and Chan and Gray (2006), Ozun et al. (2010), Ren and Giles (2010), Karmakar (2013), Chou and Wang (2014), Wijeyakulasuriya and Wickremasinghe (2015), Dahlen et al. (2015), and Youssef et al. (2015), Kellner and Rösch (2016), Muela et al. (2017), Gkillas and Katsiampa (2018), and Liu et al. (2018). Unlike majority of these studies, Ren and Giles (2010) and Dahlen et al. (2015) did not employ the usual Hill scatterplots and the mean excess function to identify the threshold for extreme returns. The former introduced the media excess function (MEF) while the latter used average conditional exceedance rate (ACER) to identify the threshold.

These studies suggest that the GP is a robust candidate distribution to describe the extreme returns distribution and the (POT)—GP distribution framework is a superior alternative over the HS, MC, EWMA and skewed GARCH approaches to model the VaR and ES measures.

Additional insights that are obtained from reviewing this sub-strand include:

(i) Youssef et al. (2015) found that long memory and volatility asymmetry process (ex. FI-APARCH) considerably improves the accuracy of the VaR and ES estimates.

(ii) In addition to volatility asymmetry, the incorporation of asset price seasonality (ex. in commodities) and jumps in the conditional volatility models leads to more accurate and conservative VaR and ES estimates. Chan and Gray (2006) advocate the use of seasonality while Ze-To (2008) and Liu et al. (2018) support the adjustment for jumps.

(iii) Kellner and Rosch (2016) determined that the ES measure carries more “Model Risk” than VaR, and measured the relatively greater model risk of ES over VaR.

(iv) Muela et al. (2017) observed that the GPD VaR is more conservative and accurate than uncorrected CF VaR in forecasts.

The second sub-strand of the EVT-POT literature that models extreme returns distribution with the non-parametric Hill Estimator of tail fatness index and its extensions, consists of studies such as Ponwall and Koedijk (1999), Huisman, Koedijk, Kool, and Palm (2001), Odening and Hinrichs (2003), Gencay and Selcuk (2004), Bao, Lee, and Saltoglu (2006), Walls and Zhang (2006), Bhattacharyya and Ritolia (2008), and Straetmans et al. (2008). The two common findings across the studies in this line of research are the following: -

- (i) These studies suggest that while the tail (fatness) index estimates from the POT-Hill type estimators are more stable than the tail index estimates for the POT-GP distribution, nonetheless the GP distribution derived VaR estimates are more accurate than the Hill-derived VaR estimates.
- (ii) In addition, Hill and modified Hill estimates’ derived VaR and ES measures have more forecast accuracy than the naïve HS VaR estimates.

In addition, few salient insights gained from individual studies are as follows: -

- (i) The Huisman et al. (2001) modification of the Hill (1975) tail fatness index estimator reduces the small sample size bias of rare extreme market events.
- (ii) Bao et al. (2006) observed that while the Conditional Quantile (CQ) or the Conditional Autoregressive VaR (CaViaR) approach is a close modeling alternative, the Hill estimate approach, GPD and GEV distribution-based method perform exceptionally well in providing accurate VaR and ES estimates during market stress periods.
- (iii) In an empirical study, on the US equity market, after 2001, Straetmans et al. (2008) found that pure new sectors (example PC’s, Biotech, Internet) have greater extreme market risk and correlated market risk than new-old sectors (Utilities, Bank, Insurance, Pharma).

The reviewed empirical literature on EVT comes across as heavily devoted to evaluating the left tails of returns distribution or equivalently the right tail of the loss distribution. In fact, this literature review could identify only 3 empirical works viz Gencay and Selcuk (2004), and Karmakar (2013), which have compared the left and right tail risks. The findings suggest that the left and right tail risks are statistically asymmetric. From a financial economics perspective, the findings indicate that the upside extreme rewards for a long position asset holder are lower than the downside extreme market risk. Equivalently put, the extreme market risks of a long investor appear to be higher than those for a short investor.

Moreover, an evaluation of the EVT literature suggest a nuanced common acknowledgement that while the EVT is a reliable and highly accurate (extreme market risk) estimation framework, the accuracy of the EVT-based risk estimates is likely to be comparable to that of risk measures from competing methodologies, especially at moderate tails. Actually, the EVT estimates may not be highly accurate for confidence levels lower than 99% (usually at 95%) and in few assets may be even perform worse than alternative models. However, the accuracy and reliability of the EVT quantile (i.e. VaR and ES) estimates improve as one moves farther into the tails, at higher confidence levels (ex. at 99% and beyond), where the estimates significantly outperform those of alternative approaches. In fact, Kuester et al. (2006) suggest that this observation is highly

relevant for conditional rather than for unconditional EVT models. Nonetheless, the results of the empirical EVT literature argue in favour of the estimation of VaR and ES measures in the conditional EVT framework. In this context, Bystrom (2004) argues that the unconditional VaR and ES measures are of greater relevance to long-run investment whereas the short-run traders need to pay attention to small-horizon risks measured by conditional estimates.

5. Conclusions

This article has argued that since the 1980s, financial markets have risen rapidly to acquire deep and widespread influence not just on financial intermediaries (FI's) but on the broader real economy: corporations, ordinary citizens, and quite interestingly on monetary policy. Therefore, in addition to dislodging financial markets and eroding investor wealth, the systemic risks of severe consequences of rare extreme market events can spillover and impair the wider economies, globally. The experience of past extreme financial markets supports this contention.

A review of literature leads to an understanding that overwhelming majority of the empirical research has measured extreme market risk with quantile estimators; predominantly with Value at Risk (VaR), and in recent past with Expected Shortfall (ES). This paper finds that the stark deficiencies in the three fundamental models, i.e. Gaussian, Historical Simulation and Monte Carlo Simulation, has spawned the development of several considerably improved alternative VaR-ES measurement frameworks, especially after the global financial crisis of 2008. However, the liberty of FI's in the internal models approach (IMA) of the Basel norms to use any statistically accurate VaR-ES methodology within an array of multiple approaches for risk measurement, and subsequent monitoring, control and reporting is strongly anticipated to promote *regulatory arbitrage*. Hence, the identification of the most suitable/accurate VaR-ES estimation model is the principal aim of this review, which presents the crucial insights gained from examining a wide range of VaR-ES models. It discusses the relative strengths and weaknesses of the modelling alternatives. Specifically, it finds that extreme value theory (EVT) is a highly accurate candidate framework to model the tails of the returns distribution where extreme market events are realized. The EVT methodology is followed closely by the filtered historical simulation (FHS). In addition, the non-parametric Hill (1975) and Pickands (1975) family extensions of tail fatness index estimators and the asymmetric and non-linear extensions of the semi-parametric Conditional Quantile (CQ) approach yield quite accurate estimates. Moreover, in the parametric framework, conditional volatility models that assume skewed and leptokurtic distributions - Skewed Generalized t (SGT), followed by the skewed generalized error and skewed t distributions - which can accommodate volatility asymmetry and long memory, provide superior VaR forecasts. This is best observed in the realized volatility (RV) models, followed by the FIAPARCH models in the GARCH family. In fact, few empirical works like Asai et al. (2012), Chen et al (2012) and Abad and Benito (2013) suggest that the choice of the theoretical return distribution dominates over the choice of the conditional volatility model in the accuracy of VaR-ES estimates. Lastly, the corrected Cornish Fisher (CF) approach can offer reasonably accurate VaR-ES estimates.

Acknowledgements

The authors wish to express their sincere gratitude for the valuable feedback received at the 1st Rajagiri Business School (RBS) Management Conference (RMC) 2020, to the session chair Prof. Rajesh Pathak, Goa School of Business and conference participants.

Funding

The authors received no direct funding for this research.

Author details

Gourab Chakraborty¹
E-mail: gourab.chakraborty@ifmr.ac.in
ORCID ID: <http://orcid.org/0000-0003-0944-9747>
G. R. Chandrashekar²
G. Balasubramanian¹

¹ Institute for Financial Management (IFMR), Affiliated to University of Madras, Chennai, India.

² Institute for Financial Management - Graduate School of Business (IFMR - GSB), Krea University, Chennai, India.

Disclosure statement

In accordance with Taylor & Francis policy and our ethical obligation as researchers, we report that this research has received no funding, and we have no financial or non-financial competing interest or conflict of interest.

Citation information

Cite this article as: Measurement of extreme market risk: Insights from a comprehensive literature review, Gourab Chakraborty, G. R. Chandrashekar & G. Balasubramanian, *Cogent Economics & Finance* (2021), 9: 1920150.

Note

1. In this paper, the terms “tail risk” and “extreme market risk” have been used synonymously.

References

- Abad, P., Benitob, S., & López, C. (2014). A comprehensive review of value at risk methodologies. *The Spanish Review of Financial Economics*, 12(1), 15–32. <https://doi.org/10.1016/j.srfe.2013.06.001>
- Alexander & Sheedy, E. (2008). Why VaR models fail and what can be done. Macquarie University Applied Finance Center Research Paper no. 34.
- Alexander, C. (2008). *Market risk analysis* (Vol. ume IV, Value-at-Risk Models). John Wiley & Sons Ltd.
- Alexander, C., & Lazar, E. (2006). Normal mixture GARCH (1,1): Applications to exchange rate modelling. *Journal of Applied Econometrics*, 21(3), 307–336. <https://doi.org/10.1002/jae.849>
- Alexander, C., & Sheedy, E. (2008). Developing a stress testing framework based on market risk models. *Journal of Banking & Finance*, 32(10), 2220–2236. <https://doi.org/10.1016/j.jbankfin.2007.12.041>
- Allen, D., Singh, A., & Powell, R. (2015). EVT and tail-risk modelling: Evidence from market indices and volatility series. *The North American Journal of Economics and Finance*, 26(C), 355–369. <https://doi.org/10.1016/j.najef.2013.02.010>
- Altun, E., Tatlidil, H., Ozel, G., & Nadarajah, S. (2018). Does the assumption on innovation process play an important role for filtered historical simulation model? *Journal of Risk and Financial Management*, 11(7), 2–13. <https://doi.org/10.3390/jrfm11010007>
- Amédée-Manesme, C. O., Barthélémy, F., & Maillard, D. (2019, March). Computation of the corrected cornish-fisher expansion using the response surface methodology: Application to VaR and CVaR. *Annals of Operations Research*, 281(1), 423–453. <https://doi.org/10.1007/s10479-018-2792-4>
- Amenc, N., Martellini, L., & Vaissé, M. (2003). Benefits and risks of alternative investment strategies. *Journal of Asset Management*, 4(2), 96–118. <https://doi.org/10.1057/palgrave.jam.2240097>
- Angelidis, T., Benos, A., & Degiannakis, S. (2004). The use of GARCH models in VaR estimation. *Statistical Methodology*, 1(2), 105–128. <https://doi.org/10.1016/j.jstamet.2004.08.004>
- Angelidis, T., & Degiannakis, S. (2005). Modeling risk for long and short trading positions. *The Journal of Risk Finance*, 6(3), 226–238. <https://doi.org/10.1108/15265940510599838>
- Antonelli, S., & Iovino, M. G. (2002). Optimization of Monte Carlo procedures for value at risk estimates. *Economic Notes*, 31(1), 59–78. <https://doi.org/10.1111/1468-0300.00072>
- Aragones, J., Blanco, C., & Dowd, K. (2001). *Incorporating stress tests into market risk* (pp. 44–49). Risk Week.
- Asai, M., McAleer, M., & Medeiros, M. (2012). Modelling and forecasting noisy realized volatility. *Computational Statistics & Data Analysis*, 56(1), 217–230. <https://doi.org/10.1016/j.csda.2011.06.024>
- Assaf, A. (2015). Value-at-risk analysis in the MENA equity markets: Fat tails and conditional asymmetries in returns distributions. *Journal of Multinational Financial Management*, 29(3), 30–45. <https://doi.org/10.1016/j.mulfin.2014.11.002>
- Bae, T., & Iscoe, I. (2012). Large-sample confidence intervals for risk measures of location scale families. *Journal of Statistical Planning and Inference*, 142(7), 2032–2046. <https://doi.org/10.1016/j.jspi.2012.01.008>
- Bali, T. (2003). An extreme value approach to estimating volatility and value at risk. *The Journal of Business*, 76(1), 83–108. <https://doi.org/10.1086/344669>
- Bali, T., Mo, H., & Tang, Y. (2008). The role of autoregressive conditional skewness and kurtosis in the estimation of conditional VaR. *Journal of Banking & Finance*, 32(2), 269–282. <https://doi.org/10.1016/j.jbankfin.2007.03.009>
- Bali, T., & Neftci, S. (2003). Disturbing extremal behavior of spot rate dynamics. *Journal of Empirical Finance*, 10(4), 455–477. [https://doi.org/10.1016/S0927-5398\(02\)00070-1](https://doi.org/10.1016/S0927-5398(02)00070-1)
- Bali, T., & Theodossiou, P. (2007). A conditional-SGT-VaR approach with alternative GARCH models. *Annals of Operations Research*, 151(1), 241–267. <https://doi.org/10.1007/s10479-006-0118-4>
- Bao, Y., Lee, T., & Saltoglu, B. (2006). Evaluating predictive performance of value-at-risk models in emerging markets: A reality check. *Journal of Forecasting*, 25(2), 101–128. <https://doi.org/10.1002/for.977>
- Barone-Adesi, G., Giannopoulos, K., & Vosper, L. (2002). Backtesting derivative portfolios with Filtered Historical Simulation (FHS). *European Financial Management*, 8(1), 31–58. <https://doi.org/10.1111/1468-036X.00175>
- Basel Committee on Banking Supervision (BCBS). (2019). *Standards: Minimum capital requirements for market risk*. BIS.
- Bekiros, S., & Georgoukos, D. (2005). Estimation of value-at-risk by extreme value and conventional methods: A comparative evaluation of their predictive performance. *Journal of International Financial Markets Institutions and Money*, 5(3), 209–228. <https://doi.org/10.1016/j.intfin.2004.05.002>
- BenSaïda, A., & Slim, S. (2016). Highly flexible distributions to fit multiple frequency financial returns. *Physica A: Statistical Mechanics and Its Applications*, 442, 203–216. <https://doi.org/10.1016/j.physa.2015.09.021>
- Berk, J., & DeMarzo, P. (2012). *Corporate finance*. Pearson Education.
- Best, P. 1999. *Implementing value at risk* Chichester. John Wiley and Sons.
- Bhattacharyya, M., & Ritolia, G. (2008). Conditional VaR using EVT - Towards a planned margin scheme. *International Review of Financial Analysis*, 17(2), 382–395. <https://doi.org/10.1016/j.irfa.2006.08.004>
- Boudoukh, J., Richardson, M., & Whitelaw, R. F. (1998). The best of both worlds: A hybrid approach to calculating value at risk. *Risk*, 11(5), 64–67.
- Boudt, K., Carl, P., & Peterson, B. G. (2013). Asset allocation with conditional value-at-risk budgets. *Journal of Risk*, 15(3), 39–68. <https://doi.org/10.21314/JOR.2013.258>
- Brooks, C., Clare, A., Molle, J., & Persaud, G. (2004). A comparison of extreme value approaches for determining value at risk. *Journal of Empirical Finance*, 12(2), 339–352. <https://doi.org/10.1016/j.jempfin.2004.01.004>
- Brownlees, C., & Gallo, G. (2011). Shrinkage Estimation of Semiparametric Multiplicative Error Models. *International Journal of Forecasting*, 27(2), 365–378. <https://doi.org/10.1016/j.ijforecast.2010.04.005>
- Bystrom, H. (2004). Managing extreme risks in tranquil and volatile markets using conditional extreme value theory. *International Review of Financial Analysis*, 13(2), 133–152. <https://doi.org/10.1016/j.irfa.2004.02.003>
- Chan, K., & Gray, P. (2006). Using extreme value theory to measure value-at-risk for daily electricity spot prices. *International Journal of Forecasting*, 22(2), 283–300. <https://doi.org/10.1016/j.ijforecast.2005.10.002>

- Chavez-Demoulin, V., Embrechts, P., & Sarady, S. (2014). Extreme-quantile tracking for financial time series. *Journal of Econometrics*, 181(1), 44–52. <https://doi.org/10.1016/j.jeconom.2014.02.007>
- Chen, C., Gerlach, R., Lin, E., and Lee, W. (2012). Bayesian Forecasting for Financial Risk Management, Pre and Post the Global Financial Crisis. *Journal of Forecasting*, 31(8), 661–687. <https://doi.org/10.1002/for.1237>
- Chen, C., Gerlach, R., Lin, E., & Lee, W. (2012). Bayesian Forecasting for Financial Risk Management, Pre and Post the Global Financial Crisis. *Journal of Forecasting*, 31(1), 661–687. <https://doi.org/10.1002/for.1237>
- Cheng, W., & Hung, J. (2011). Skewness and leptokurtosis in GARCH-typed VaR estimation of petroleum and metal asset returns. *Journal of Empirical Finance*, 18(1), 160–173. <https://doi.org/10.1016/j.jempfin.2010.05.004>
- Chernozhukov, V., Fernandez-Val, I., & Galichon, A. (2010). Quantile and Probability Curves Without Crossing. *Econometrica*, 78(3), 1093–1125. <https://doi.org/10.3982/ECTA7880>
- Chou, H., & Wang, D. (2014). Estimation of tail-related value-at-risk measures: Range based extreme value approach. *Quantitative Finance*, 14(2), 293–304. <https://doi.org/10.1080/14697688.2013.819113>
- Choudhry, M. (2013). *An introduction to value-at-risk*. John Wiley & Sons Ltd.
- Christoffersen, P. (2003). *Elements in financial risk management*. Academic Press.
- Cieslak, A., Morse, A., & Vissing-Jorgensen, A. (2019). Stock returns over the FOMC cycle. *Journal of Finance*, 74(5), 1–57. <https://doi.org/10.1111/jofi.12818>
- Cieslak, A., & Vissing-Jorgensen, A. (2018, September 1). SSRN. The Economics of the FedPut Retrieved December 13, 2019, from: https://papers.ssrn.com/sol3/papers.cfm?Abstract_id=2951402
- Clare, A., Seaton, J., Smith, P. N., & Thomas, S. (2013). Breaking into the blackbox: Trend following, stop losses and the frequency of trading—The case of the S&P500. *Journal of Asset Management*, 14(3), 182–194. <https://doi.org/10.1057/jam.2013.11>
- Clements, M., Galvao, A., & Kim, J. (2008). Quantile Forecasts of Daily Exchange Rate Returns from Forecasts of Realized Volatility. *Journal of Empirical Finance*, 15(4), 729–750. <https://doi.org/10.1016/j.jempfin.2007.12.001>
- Coombs, N., & Van Der Heide, A. (2020). Financialization as mathematization: The calculative and regulatory consequences of risk management. In P. Mader, D. Mertens, & N. Van Der Zwan (Eds.), *International Handbook of Financialization* (pp. 358–368). The Routledge.
- Corlu, C., Meterelliyo, M., & Tinicc, M. (2016). Empirical distributions of daily equity index returns: A comparison. *Expert Systems with Applications*, 54, 170–192. <https://doi.org/10.1016/j.eswa.2015.12.048>
- Da Silva, A., & De Mendes, B. (2003). Value-at-risk and extreme returns in asian stock markets. *International Journal of Business*, 8(1), 17–40.
- Dahlen, K., Solibakke, P., Westgaard, S., & Naess, A. (2015). On the estimation of extreme values for risk assessment and management: The ACER method. *International Journal of Business*, 20(1), 33–51.
- Danielsson, J., & De Vries, C. (2000). Value-at-risk and extreme returns. *Annals of Economics and Statistics*, 60, 239–270.
- Dimitrakopoulos, D. N., Kavussanos, M. G., & Spyrou, S. (2010). Value at risk models for volatile emerging markets equity portfolios. *The Quarterly Review of Economics and Finance*, 50(4), 515–526. <https://doi.org/10.1016/j.qref.2010.06.006>
- Dowd, K. (2005). *Measuring market risk*. Wiley.
- Ellis, C. (2017). Scenario-based stress tests: Are they painful enough? *Contemporary Economics*, 11(2), 219–233. <https://doi.org/10.5709/ce.1897-9254.238>
- Embrechts, P., Klüppelberg, C., & Mikosch, T. (1997). *Modelling Extremal Events for Insurance and Finance*. Springer.
- Fan, Y., Zhang, Y.-J., Tsai, H.-T., & Wei, Y.-M. (2008). Estimating ‘value at risk’ of crude oil price and its spillover effect using the GED-GARCH approach. *Energy Economics*, 30(6), 3156–3171. <https://doi.org/10.1016/j.eneco.2008.04.002>
- Favre, L., & Galeano, J. (2002). Mean-modified value-at-risk optimization with hedge. *Journal of Alternative Investment*, 5(2), 2–21. <https://doi.org/10.3905/jai.2002.319052>
- Fisher, R., & Tippett, L. (1928). Limiting forms of the frequency distribution of the largest or smallest member of a sample. *Proceedings of the Cambridge Philosophical Society*, 24(2), 180–190. <https://doi.org/10.1017/S0305004100015681>
- Fleming, J., & Kirby, C. (2003). A Closer Look at the Relation between GARCH and Stochastic Autoregressive Volatility. *Journal of Financial Econometrics*, 1(3), 365–419. <https://doi.org/10.1093/jjfinec/nbg016>
- Fuentes, F., Herrera, R., & Clements, A. (2018). Modelig extreme risks in commodities and commodity currencies. *Pacific-Basin Finance Journal*, 51(C), 106–120. <https://doi.org/10.1016/j.pacfin.2018.06.003>
- Fuss, R., Kaiser, D. G., & Adams, Z. (2007). Value at risk, GARCH modelling and the forecasting of hedge fund return volatility. *Journal of Derivatives & Hedge Funds*, 13(1), 2–25. <https://doi.org/10.1057/palgrave.jdhf.1850048>
- Gencay, R., & Selcuk, F. (2004). Extreme value theory and value-at-risk: Relative performance in emerging markets. *International Journal of Forecasting*, 20(2), 287–303.
- Gerlach, R.H., Chen, C.W.S., & Chan, N.Y.C. (2011). Bayesian Time-Varying Quantile Forecasting for Value-at-Risk in Financial Markets. *Journal of Business & Economic Statistics*, 29(4), 481–492. <https://doi.org/10.1198/jbes.2010.08203>
- Gettinby, G., Sinclair, C., Power, D., & Brown, R. (2006). An analysis of the distribution of extremes in indices of share returns in the US, UK and Japan from 1963 to 2000. *International Journal of Finance & Economics*, 11(2), 97–113.
- Gettinby, G., Sinclair, C., Power, D., & Brown, R. A. (2004). An analysis of the distribution of the extreme share returns in the UK from 1975 to 2000. *Journal of Business Finance & Accounting*, 31(5–6), 607–645. <https://doi.org/10.1111/j.0306-686X.2004.00551.x>
- Giamouridis, D., & Ntoula, I. (2009). A comparison of alternative approaches for determining the downside risk of hedge fund strategies. *The Journal of Futures Markets*, 29(3), 244–269. <https://doi.org/10.1002/fut.20358>
- Giot, P., & Laurent, S. (2003). Value-at-Risk for long and short trading positions. *Journal of Applied Econometrics*, 18(6), 641–664. <https://doi.org/10.1002/jae.710>
- Gkillas, T., & Katsiampa, P. (2018). An application of extreme value theory to cryptocurrencies. *Economics Letters*, 164(3), 109–111. <https://doi.org/10.1016/j.econlet.2018.01.020>
- Glasserman, P., Heidelberger, P., & Shahabuddin, P. (2000a). Importance sampling and stratification for value-at-risk. In Y. S. Abu-Mostafa, B. LeBaron, A. Lo, & A. Weigend (Eds.), *Computational finance 1999*

- (*Proceedings of the sixth international conference on computational finance*) (pp. 7–24). Massachusetts Institute of Technology (MIT) Press.
- Glasserman, P., Heidelberger, P., & Shahabuddin, P. (2001). Efficient Monte Carlo methods for value-at-risk. In C. Alexander (Ed.), *Mastering risk* (Vol. 2, pp. 7–20). Financial Times - Pearson Education.
- Glasserman, P., Heidelberger, P., & Shahabuddin, P. (2000b). Variance reduction techniques for estimating value-at-risk. *Management Science*, 46(10), 1349–1364. <https://doi.org/10.1287/mnsc.46.10.1349.12274>
- Glasserman, P., Heidelberger, P., & Shahabuddin, P. (2002). Portfolio value-at-risk with heavy-tailed risk factors. *Mathematical Finance*, 12(3), 239–269. <https://doi.org/10.1111/1467-9965.00141>
- Gonzalez-Rivera, G., Lee, T., Mishra, S. (2004). Forecasting Volatility: A Reality Check Based on Option Pricing, Utility Function, Value-at-Risk, and Predictive Likelihood. *International Journal of Forecasting*, 20, 629–645. <https://doi.org/10.1016/j.ijforecast.2003.10.003>
- Gottesman, A., & Leobrock, M. (2017). *Understanding systemic risk in global financial markets*. John Wiley & Sons.
- Gueyjié, J. P., & Amvella, S. P. (2006). Optimal portfolio allocation using funds of hedge funds. *The Journal of Wealth Management Fall*, 9(2), 85–95. <https://doi.org/10.3905/jwm.2006.644221>
- Guner, B., Mitov, I., & Racheva-Yotova, B. (2012). Fat-Tailed models for risk estimation. In F. J. Fabozzi (Ed.), *Encyclopedia of financial models* (Vol. ume II, pp. 731–755). John Wiley & Sons, Inc.
- Hansen, B. (1994). Autoregressive Conditional Density Estimation. *International Economic Review*, 35(3), 705–730. <https://doi.org/10.2307/2527081>
- Harris, R., Kucukozmen, C., & Yilmaz, F. (2004). Skewness in the conditional distribution of daily equity returns. *Applied Financial Economics*, 14(3), 195–202. <https://doi.org/10.1080/0960310042000187379>
- Hendricks, D. (1996). Evaluation of value-at-risk models using historical data. *Economic Policy Review*, 2(1), 39–69.
- Hill, B. M. (1975). A simple general approach to inference about the tail of a distribution. *Annals of Statistics*, 3(5), 331–341. <https://doi.org/10.1214/aos/1176343247>
- Hong, L. J., Hu, Z., & Liu, G. (2014). Monte Carlo Methods for value-at-risk and conditional value-at-risk: A review. *ACM Transactions on Modeling and Computer Simulation (TOMACS) - Special Issue on Emerging Methodologies and Applications*, 24(4), 22: 1–22:37.
- Huang, A., & Tseng, T. (2009). Forecast of value at risk for equity indices: An analysis from developed and emerging markets. *The Journal of Risk Finance*, 10(4), 393–409. <https://doi.org/10.1108/15265940910980687>
- Huang, A. Y. (2010). An optimization process in value-at-risk estimation. *Review of Financial Economics*, 19(3), 109–116. <https://doi.org/10.1016/j.rfe.2010.03.001>
- Huang, Y. C., Lin, C. H., Chien, C. C., & Lin, B. J. (2004). The tail fatness and value-at-risk analysis of TAIFEX and SGX-DT Taiwan stock index futures. *Asia Pacific Management Review*, 9(4), 729–750.
- Huisman, R., Koedijk, K., Kool, C., & Palm, F. (2001). Tail-Index estimates in small samples. *Journal of Business and Economic Statistics*, 19(2), 208–216.
- Hull, J., & White, A. (1998a). Value at risk: When daily changes in market variables are not normally distributed. *Journal of Derivatives*, 5(3), 9–19. <https://doi.org/10.3905/jod.1998.407998>
- Hull, J., & White, A. (1998b). Incorporating volatility updating into the historical simulation method for value-at-risk. *Journal of Risk*, 1(1), 5–19. <https://doi.org/10.21314/JOR.1998.001>
- Jackson, P., Maude, D. J., & Perraudin, W. (1997). Bank capital and value at risk. *Journal of Derivatives*, 4(3), 73–89. <https://doi.org/10.3905/jod.1997.407972>
- Jaschke, S. (2002). The Cornish-Fisher expansion in the context of Delta-Gamma-normal approximations. *Journal of Risk*, 4(4), 33–52. <https://doi.org/10.21314/JOR.2002.068>
- Jin, X., & Zhang, A. X. (2006). Reclaiming Quasi-Monte Carlo efficiency in portfolio value-at-risk simulation through Fourier transform. *Management Science*, 52(6), 925–938. <https://doi.org/10.1287/mnsc.1060.0505>
- Jondeau, E., & Rockinger, M. (1999). The tail behavior of stock returns: Emerging versus mature markets. Bank of France, Study and Research Notes - 66.
- Jorion, P. (2010). Risk management. *Annual Review of Financial Economics*, 2(1), 347–365. <https://doi.org/10.1146/annurev-financial-073009-104045>
- Karmakar, M. (2013). Estimation of tail-related risk measures in the Indian stock market: An extreme value approach. *Review of Financial Economics*, 22(3), 79–85. <https://doi.org/10.1016/j.rfe.2013.05.001>
- Karwowski, E., Shabani, M., & Stockhammer, E. (2017). Financialization: Dimensions and determinants. A Cross-Country Study. Economics Discussion Papers 2017-1, School of Economics, Kingston University London.
- Kellner, R., & Rösch, D. (2016). Quantifying market risk with value-at-risk or expected shortfall? - Consequences for capital requirements and model risk. *Journal of Economic Dynamics and Control*, 68(3), 45–63. <https://doi.org/10.1016/j.jedc.2016.05.002>
- Kemp, M. (2011). *Extreme events - robust portfolio construction in the presence of fat tails*. John Wiley & Sons.
- Koedijk, K., Schafgans, M., & De Vries, C. (1990). The tail index of exchange rate returns. *Journal of International Economics*, 29(1–2), 93–108. [https://doi.org/10.1016/0022-1996\(90\)90065-T](https://doi.org/10.1016/0022-1996(90)90065-T)
- Kou, S., & Peng, X. (2014). Expected shortfall or median shortfall, *Journal of Financial Engineering (JFE)*, 1(01), 1–6. <https://doi.org/10.1142/S234576861450007X>
- Kourouma, L., Dupre, D., Sanfilippo, G., & Taramasco, O. (2011). Extreme value at risk and expected shortfall during financial crisis. *Hyper Articles en Ligne - Humanity Society and Sciences (HAL)* 00658495.
- Kuester, K., Mittnik, S., & Paolletta, M. (2006). Value-at-risk prediction: A comparison of alternative strategies. *Journal of Financial Econometrics*, 4(1), 53–89. <https://doi.org/10.1093/jjfinec/nbj002>
- Lee, M., Su, J., & Liu, H. (2008). Value-at-risk in US stock indices with Skewed generalized error distribution. *Applied Financial Economics Letters*, 4(6), 425–431. <https://doi.org/10.1080/17446540701765274>
- Lee, S., & Lee, T. (2011). Value-at-risk forecasting based on Gaussian mixture ARMA-GARCH model. *Journal of Statistical Computation and Simulation*, 81(9), 1131–1144. <https://doi.org/10.1080/00949651003752320>
- Lehar, A., Scheicher, M., & Schittenkopf, C. (2002). GARCH vs. stochastic volatility: Option pricing and risk management. *Journal of Banking & Finance*, 26(2–3), 323–345. [https://doi.org/10.1016/S0378-4266\(01\)00225-4](https://doi.org/10.1016/S0378-4266(01)00225-4)
- Lian, C., Ma, Y., & Wang, C. (2019). Low interest rates and risk taking: Evidence from individual investment decision. *Review of Financial Studies*, 32(6), 2107–2148.
- Liang, B., & Park, H. (2010). Predicting hedge fund failure: A comparison of risk measures. *Journal of Financial*

- and *Quantitative Analysis*, 45(1), 199–222. <https://doi.org/10.1017/S0022109009990482>
- Lin, C., Changchien, C., Kao, T., & Kao, W. (2014). High-order moments and extreme value approach for value-at-risk. *Journal of Empirical Finance*, 29, 1–448. <https://doi.org/10.1016/j.jempfin.2014.10.001>
- Lin, C., & Shen, S. (2006). Can the student-t distribution provide accurate value at risk? *The Journal of Risk Finance*, 7(3), 292–300. <https://doi.org/10.1108/15265940610664960>
- Liu, G., Wei, Y., Chen, Y., Yu, J., & Hua, Y. (2018). Forecasting the value-at-risk of Chinese stock market using the HARQ model and extreme value theory. *Physica A*, 499(3), 288–297. <https://doi.org/10.1016/j.physa.2018.02.033>
- Longin, F. (1996). The asymptotic distribution of extreme stock market returns. *Journal of Business*, 69(3), 383–408. <https://doi.org/10.1086/209695>
- Longin, F. (2000). From Value-at-Risk to stress testing: The extreme value approach. *Journal of Banking and Finance*, 24(7), 1097–1130. [https://doi.org/10.1016/S0378-4266\(99\)00077-1](https://doi.org/10.1016/S0378-4266(99)00077-1)
- Maghyereh, A., & Awartani, B. (2012). Modeling and forecasting value-at-risk in the UAE stock markets: The role of long memory, fat tails and asymmetries in return innovations. *Review of Middle East Economics and Finance*, 8(1), 1–22. <https://doi.org/10.1515/1475-3693.1402>
- Maillard, D. (2012, January). A user's guide to the Cornish fisher expansion. Working paper. SSRN. Retrieved July 3, 2019, from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1997178
- Marimoutou, V., Raggad, B., & Trabelsi, A. (2009). Extreme value theory and value at risk: Application to oil market. *Energy Economics*, 31(4), 519–530. <https://doi.org/10.1016/j.eneco.2009.02.005>
- McDonald, J. B., & Newey, W. K. (1988). Partially adaptive estimation of regression models via the generalized T distribution. *Econometric Theory*, 4(3), 428–457. <https://doi.org/10.1017/S0266466600013384>
- McNeil, A., Frey, R., & Embrechts, P. (2005). *Quantitative risk management*. Princeton University Press.
- Miftahurrohman, B., Iriawan, N., & Fithriyanti, K. (2017). On the value at risk using bayesian mixture Laplace autoregressive approach for modelling the Islamic Stock risk investment. *Journal of Physics: Conference Series*, 855(1), 01–10.
- Mina, J., & Ulmer, A. (1999). Delta-Gamma Four Ways (J.P. Morgan/Reuters Working Paper). RiskMetrics Group, J.P. Morgan. <http://www.riskmetrics.com/research/working>
- Mishkin, F. (2009). Is monetary policy effective during financial crises? *American Economic Review*, 99(2), 573–577. <https://doi.org/10.1257/aer.99.2.573>
- Muela, S., Martín, C., & Sanz, R. (2017). An application of extreme value theory in estimating liquidity risk. *European Research on Management and Business Economics*, 23(3), 157–164. <https://doi.org/10.1016/j.iedeen.2017.05.001>
- Nageswaran, V., & Natarajan, G. (2019). *The rise of finance: Causes, consequences and cures*. Cambridge University Press.
- Navaro, G., & Olmeda, I. (2009). Computational aspects of value at risk. In G. Gregoriou (Ed.), *The VaR Implementation Handbook* (pp. 167–183). Mc-Graw Hill.
- Nikolaev, N., Boshnakov, G., & Zimmer, R. (2013). Heavy-tailed mixture GARCH volatility modeling and value-at-risk estimation. *Expert Systems with Applications*, 40(6), 2233–2243. <https://doi.org/10.1016/j.eswa.2012.10.038>
- Odening, M., & Hinrichs, J. (2003). Using extreme value theory to estimate value-at-risk. *Agricultural Finance Review*, 63(1), 55–73. <https://doi.org/10.1108/00215000380001141>
- Orlowski, L. (2012). Financial crisis and extreme market risks: Evidence from Europe. *Review of Financial Economics*, 21(3), 120–130. <https://doi.org/10.1016/j.rfe.2012.06.006>
- Ozun, A., Cifter, A., & Yilmazer, S. (2010). Filtered extreme-value theory for value-at-risk estimation: Evidence from Turkey. *Journal of Risk Finance*, 11(2), 164–179. <https://doi.org/10.1108/15265941011025189>
- Paul, S., & Sharma, P. (2017). Improved VaR forecasts using extreme value theory with the realized GARCH model. *Studies in Economics and Finance*, 34(2), 238–269. <https://doi.org/10.1108/SEF-05-2015-0139>
- Pichler, S., & Selitsch, K. (1999). A Comparison of Analytical VaR Methodologies for Portfolios That Include Options (TU Wien Working Paper). Vienna University of Technology (TU Wien). <http://www.gloriamundi.org>
- Pickands, J., III. (1975). Statistical inference using extreme order statistics. *Annals of Statistics*, 3(1), 119–131.
- Polanski, A., & Stoja, E. (2010). Incorporating higher moments into value-at-risk forecasting. *Journal of Forecasting*, 29(6), 523–535. <https://doi.org/10.1002/for.1155>
- Ponwall, R., & Koedijk, K. G. (1999). Capturing downside risk in financial markets: The case of the Asian crisis. *Journal of International Money and Finance*, 18(6), 853–870. [https://doi.org/10.1016/S0261-5606\(99\)00040-6](https://doi.org/10.1016/S0261-5606(99)00040-6)
- Pritsker, M. (1997). Evaluating value at risk methodologies: Accuracy versus computational time. *Journal of Financial Services Research*, 12(2/3), 201–242. <https://doi.org/10.1023/A:1007978820465>
- Ren, F., & Giles, D. (2010). Extreme value analysis of daily Canadian crude oil prices. *Applied Financial Economics*, 20(12), 941–954. <https://doi.org/10.1080/09603101003724323>
- Roy, I. (2011). Estimating Value at Risk (VaR) using filtered historical simulation in the Indian capital market. *Reserve Bank of India Occasional Papers*, 32(2), 81–98.
- Samuel, Y. (2008). Value at risk and conditional extreme value theory via Markov switching models. *The Journal of Futures Markets*, 28(2), 155–181. <https://doi.org/10.1002/fut.20293>
- Schoroek, G. (2002). *Risk management and value creation in financial institutions*. John Wiley & Sons.
- Sener, E., Baronyan, S., & Menguturk, L. (2012). Ranking the Predictive Performances of Value at Risk estimation methods. *International Journal of Forecasting*, 28(4), 849–873. <https://doi.org/10.1016/j.ijforecast.2011.10.002>
- Siegl, T., & West, A. (2001). Statistical bootstrapping methods in VaR calculation. *Applied Mathematical Finance*, 8(3), 167–181. <https://doi.org/10.1080/13504860110093504>
- Smith, R. (1987). Estimating tails of probability distributions. *Annals of Statistics*, 15(3), 1174–1207.
- Straetmans, S., Verschoor, W., & Wolff, C. (2008). Extreme US stock market fluctuations in the wake of 9/11. *Journal of Applied Econometrics*, 23(1), 17–42. <https://doi.org/10.1002/jae.973>
- Su, E., & Knowles, T. W. (2006). Asian Pacific stock market volatility modeling and value at risk analysis. *Emerging Markets Finance and Trade*, 42(2), 18–62. <https://doi.org/10.2753/REE1540-496X420202>

- Tarullo, D. K. (2014, May 8). Rethinking the aims of prudential regulation. Federal Reserve. Retrieved July 03, 2019, from <http://www.federalreserve.gov/newsevents/speech/tarullo20140508a.htm>
- Tesfalidet, A., Desmond, A. F., Hailu, G., & Singh, R. (2014). Statistical evaluation of value at risk models for estimating agricultural risk. *Journal of Statistical and Econometric Methods*, 3(1), 1–2.
- Theodossiou, P. (2000). Skewed Generalized Error Distribution of Financial Assets and Option Pricing. Working Paper No. 219679, School of Business, Rutgers University.
- Tian, M. Z., & Chan, N. H. (2010). Saddle point approximation and volatility estimation of value-at-risk. *Statistica Sinica*, 20(3), 1239–1256.
- Tolikas, K. (2008). Value-at-risk and extreme value distributions for financial returns. *Journal of Risk*, 10(3), 31–77. <https://doi.org/10.21314/JOR.2008.174>
- Tolikas, K. (2014). Unexpected tails in risk measurement: Some international evidence. *Journal of Banking and Finance*, 40(3), 476–493.
- Tolikas, K., & Fifield, S. G. M. (2011). Rare event risk in African emerging markets. *Managerial Finance*, 37(3), 275–294. <https://doi.org/10.1108/03074351111113324>
- Tolikas, K., & Gettinby, G. (2009). Modeling the distribution of the extreme share returns in Singapore. *Journal of Empirical Finance*, 16(2), 254–263. <https://doi.org/10.1016/j.jempfin.2008.06.006>
- Tolikas, K., Koulakiotis, A., & Brown, R. (2007). Extreme risk and value-at-risk in the German stock market. *The European Journal of Finance*, 13(4), 373–395. <https://doi.org/10.1080/13518470600763737>
- Tomaskov-Devey, D., & Lin, K. (2011). Income dynamics, economic rents and the ‘financialization’ of the US economy. *American Sociological Review*, 76(4), 538–559.
- Venkataraman, S. (1997). Value at risk for a mixture of normal distributions: The use of Quasi-Bayesian estimation techniques. *Economic Perspectives*, 21(2), 2–13.
- Vlaar, P. J. (2000). Value at risk models for Dutch bond portfolios. *Journal of Banking and Finance*, 24(7), 1131–1154. [https://doi.org/10.1016/S0378-4266\(99\)00068-0](https://doi.org/10.1016/S0378-4266(99)00068-0)
- Walls, W., & Zhang, W. (2006). Using extreme value theory to model electricity price risk with an application to the Alberta power market. *Energy Exploration & Exploitation*, 23(5), 375–403. <https://doi.org/10.1260/014459805775992690>
- Wijeyakulasuriya, D., & Wickremasinghe, W. (2015). Measuring extreme market risk: The Sri Lankan context. *Asia Pacific Journal of Risk and Insurance*, 9(2), 185–201. <https://doi.org/10.1515/apjri-2014-0026>
- Wójcik, D., & Ioannou, S. (2020). COVID-19 and Finance: Market Developments So Far and Potential Impacts on the Financial Sector and Centres. *Journal of Economic and Human Geographic History*, 111(3), 387–400.
- Wong, C. S., & Li, W. K. (2001). On a mixture autoregressive conditional heteroscedastic model. *Journal of the American Statistical Association*, 96(455), 982–995. <http://www.jstor.org/stable/2670244>
- Wong, M. (2013). *Bubble value at risk: A cuntercyclical risk measurement approach*. John Wiley & Sons.
- Xu, D., & Wirjanto, T. (2010). An empirical characteristic function approach to VaR under a mixture of normal distribution with time-varying volatility. *Journal of Derivatives*, 18(2), 39–58. <https://doi.org/10.3905/jod.2010.18.1.039>
- Youssef, M., Belkacem, L., & Mokni, K. (2015). Value-at-Risk estimation of energy commodities: A long-memory GARCH-EVT approach. *Energy Economics*, 51(3), 99–110. <https://doi.org/10.1016/j.eneco.2015.06.010>
- Yu, P., Li, W.K., & Jin, S. (2010). On Some Models for Value-At-Risk. *Econometric Reviews*, 29 (5–6), 622–641. <https://doi.org/10.1080/07474938.2010>
- Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 36. <https://doi.org/10.1016/j.frl.2020.101528>
- Zhou, J., & Anderson, R. (2012). Extreme risk measures for international REIT markets. *The Journal of Real Estate Finance and Economics*, 45(1), 152–170. <https://doi.org/10.1007/s11146-010-9252-5>
- Zikovic, S., & Filer, R. (2013). Ranking of VaR and ES models: Performance in developed and emerging markets. *Czech Journal of Economics and Finance*, 63(4), 327–359.
- Şener, E., Baronyan, S. and Ali Mengütürk, L. (2012). Ranking the predictive performances of value-at-risk estimation methods. *International Journal of Forecasting*, 28(4), 849–873. <https://doi.org/10.1016/j.ijforecast.2011.10.002>

Appendix

Table A1. A non-exhaustive chronology of few extreme market events

Timeline	Extreme Market Event	Source/Classification	Markets
1636	Dutch Tulip Crisis	Asset (Price) Bubbles	Europe
1720	South Street Sea Bubble	Speculation	Europe
1763	End of Seven Years War	Asset Bubbles	Amsterdam
1825	Crisis of 1825–1826	Sovereign Bond Default	Europe, Latin America
1837	Crisis of 1836–1839	Cotton Prices	England, United States
1857	Hamburg Crisis of 1857	Credit Expansion	Hamburg, Sweden
1873	Panic of 1873	International Contagion	U.S., Austria, Germany
1907	Panic of 1907	Banking Crisis	across assets/markets
1929	Great Depression	Banking Crisis	U.S., Europe
1977	“Big Five” Crisis	Real Estate Bubble, Banking Crisis	Spain
1980’s	Debt Crisis of the 1980’s	Sovereign Bond Default, Currency Crash	US
1987	“Big Five” Crisis	Real Estate Bubble/ Banking Crisis	Norway
1990’s	“Big Five” Crisis	Real Estate Bubble/ Banking Crisis	Finland, Sweden, Japan
1994	Mexican Debt Crisis	Currency/Banking Crisis	Mexico
1997	East Asian Financial Crisis	Currency Crash	Asia
1998	Long-Term Capital Mgt.	Ruble, Money Market	US
1990’s	Latin American Crisis	Sovereign Bond Default	Latin America
2000	Dot-Com Tech Bubble	Asset Bubble	US, World Wide
2008	Global Financial Crisis (GFC)	Asset Bubble, Credit Expansion	US, World Wide
2009	Dubai’s “Debt Standstill”	GFC, Real Estate Bubble Burst, Credit Expansion	US, most currencies other than US\$/¥,
2010	European Debt Crisis (EDC)	Real Estate Bubble, Banking Crises, Sovereign Debt	European bond markets
2011	“August 2011 Stock markets fall”	EDC of 2010	US, Europe, Middle East, rest of Asia
2015–16	Chinese Equity Market Crash	Asset Bubbles	China, US
2018	Global Equity Market Downturn	Asset Bubbles	US
2020	March 2020 Crash	Zoonotic	Multiple

Source: Cieslak et al. (2019), Nageswaran and Natarajan (2019), and Coombs and Van Der Heide (2020).



© 2021 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license.

You are free to:

Share — copy and redistribute the material in any medium or format.

Adapt — remix, transform, and build upon the material for any purpose, even commercially.

The licensor cannot revoke these freedoms as long as you follow the license terms.

Under the following terms:

Attribution — You must give appropriate credit, provide a link to the license, and indicate if changes were made.

You may do so in any reasonable manner, but not in any way that suggests the licensor endorses you or your use.

No additional restrictions

You may not apply legal terms or technological measures that legally restrict others from doing anything the license permits.



***Cogent Economics & Finance* (ISSN: 2332-2039) is published by Cogent OA, part of Taylor & Francis Group.**

Publishing with Cogent OA ensures:

- Immediate, universal access to your article on publication
- High visibility and discoverability via the Cogent OA website as well as Taylor & Francis Online
- Download and citation statistics for your article
- Rapid online publication
- Input from, and dialog with, expert editors and editorial boards
- Retention of full copyright of your article
- Guaranteed legacy preservation of your article
- Discounts and waivers for authors in developing regions

Submit your manuscript to a Cogent OA journal at www.CogentOA.com

