Institution: London School of Economics and Political Science		
Unit of Assessment: 10 - Mathematical Sciences		
Title of case study: Counterparty credit risk management at Barclays: estimating extreme quantiles		
Period when the underpinning research was undertaken: 2012-2014		
Details of staff conducting the underpinning research from the submitting unit:		
Name(s):	**Role(s) (e.g. job title):**	**Period(s) employed by submitting HEI:**
Qiwei Yao	Professor of Statistics	2000 to present
Period when the claimed impact occurred: 2013-2020		
Is this case study continued from a case study submitted in 2014? No		

1. Summary of the impact (indicative maximum 100 words)

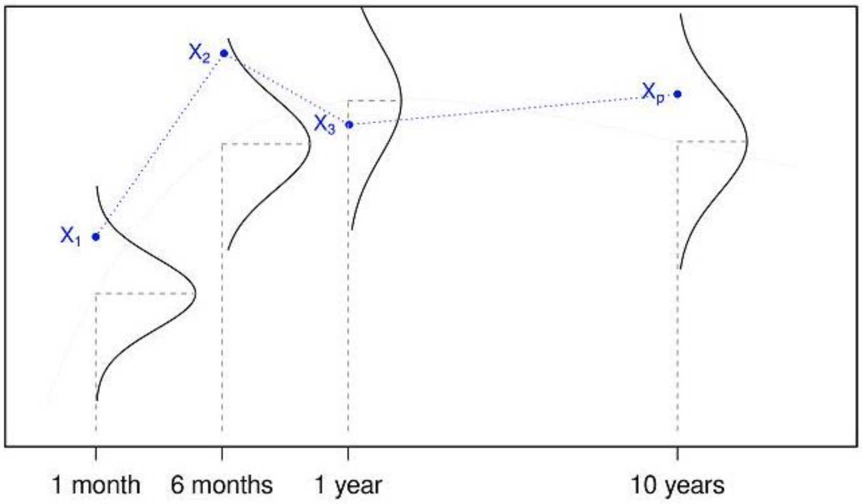
An innovative method for estimating extreme quantiles of multiple random variables was developed at the LSE in collaboration with investment bank Barclays. Its application to the management of the tens of billions of US-dollars' worth of counterparty risk-weighted assets (RWA) held by Barclays has helped the bank meet the requirements of Basel III. Specifically, a new methodology for future counterparty RWA evaluation, in which the extreme quantile estimation method plays a key role, has enabled the bank to calculate an appropriate capital reserve to protect customers' interests as well as its own business in an effective and efficient manner, avoiding holding excessively large additional capital. This reduces the cost of borrowing and contributes positively to investment and economic growth. Barclays' new methodology for future counterpart RWA evaluation has withstood backtesting under the Basel III framework since its inception in November 2013.

2. Underpinning research (indicative maximum 500 words)

The research underpinning impacts described here arose in the context of an ongoing research programme within LSE's Department of Statistics on statistical inference for time series and complex dependent data. The specific underpinning research (published in **[1]**) was directly motivated by a backtesting problem in financial risk management. Between January 2012 and January 2014, Professor Qiwei Yao (with Dr Jinguo Gong, at that time a visiting scholar at LSE) worked with the then-Director of Quantitative Exposure at Barclays to develop an improved backtesting methodology for the bank. They particularly sought to establish a more reliable and robust method to estimate potential future exposure to counterparty credit risk. Yao was invited to join the project on the basis of his established expertise in relevant areas of statistical analysis, especially in time series and dependent data (see, for example, **[2]**).

Backtesting is a primary analytical tool used by banks and their regulators to monitor the performance of risk factor valuation methods adopted by banks. It uses historical data showing realised prices to (back)test the efficacy of existing risk factor models. This is often facilitated by testing whether the extreme quantiles of potential future exposure (PFE) under those models are correctly quantified. PFE refers to the maximum expected credit exposure during the lifetime of transactions with a prespecified probability. It is a key metric to measure counterparty credit risk (CCR) - the risk of suffering a loss because another party to a contract fails to meet its side of the deal.

The figure below provides a simple illustration of the backtesting setup for a price model of a term structure asset; that is, an asset which can be traded with different time maturities at different prices. Herein, a realised price path (i.e. the actually traded prices at different maturities) is represented by $X_1, X_2, \ldots, X_p$ and the solid curves represent the price distributions at different time maturities determined by a price model.



Backtesting is a method for assessing whether the realised price path is an extreme event with very small probability, say, 0.01%, under those price distributions. If so, this would strongly suggest a mis-specified price model and a “red light” would be designated. Two complicating factors make backtesting difficult:

(i) the interdependency of prices at different time horizons; and

(ii) the explicit unavailability of price distributions.

Although the distributions are not available, banks store 1,000 *simulated* price paths as a proxy for them, allowing backtesting based on a comparison of these with a realised price path. (Note that due to various constraints most banks, including Barclays, can *only* store 1,000 simulated price paths.) Typically, banks take *ad hoc* approaches to calculating extreme PFE quantiles. Usually this involves raising the PFE profile according to the number of prices exceeding, say, the 98% PFE at each time horizon; raising the PFE at different time horizons together in order to offset the correlations/associations among the prices at different time horizons; and using simulation models which impose various unrealistic conditions. Those *ad hoc* approaches cannot be justified theoretically, leading to incorrect and sometimes excessively conservative estimation.

A sensible approach to mitigating the difficulties caused by the multiple distributions along different time horizons is to use some appropriate risk metrics which are function of $X_1, X_2, \ldots, X_p$. The challenge, then, is accurately finding the extreme quantiles of those risk metrics with only 1,000 observations, because those quantiles have to be so extreme that they can only occur with probability between 0.05% and 0.01%. The standard approach to achieving this is to appeal to extreme value theory (EVT). Unfortunately, this involves the selection of tuning parameters such as the proportion of extreme-valued data points to be used in estimation. While the asymptotic properties of the tuning parameters are well understood, the methods to choose them in practice are *ad hoc*; leading to estimates which are too unreliable to be used in evaluating extreme PFE.

In late 2013, in collaboration with Barclays QA Exposure Analytics team, Yao began to tackle the challenge of estimating extreme PFE quantiles based on the small available samples of just 1,000 simulated price paths. The new method developed takes advantage of the fact that the extreme quantiles required are determined by multiple random variables (i.e. $X_1, X_2, \ldots, X_p$). The key idea here is that it is not necessary to go to extremes along any component variable in order to observe the joint extreme events. A risk metric can therefore fall into the region of extreme values without any of $X_1, X_2, \ldots, X_p$ actually taking extreme values. This seemingly counter-intuitive observation is central to the success of the new approach which, despite being readily demonstrable, had never previously been explored in either extreme value inference literature or in practice.

The resulting method, described in **[1]**, provides a satisfactory solution to quantify the extreme quantiles of PFE accurately and reliably. The method is conceptually simple, easy to implement, and involves no tuning parameters. It provides robust performance in practice. Based on the key observation above, the new method fits a joint distribution of multiple random variables $X_1, X_2, \ldots,$ X_p within their observed range based on a vine-copula structure which captures the term structure in the data. It then draws a large bootstrap sample from the fitted joint distribution and uses the sample (extreme) quantiles as the estimates for the required quantiles. (Note that the bootstrap sample space from a sample of size n of p-variables is in the order of n to the p-th power). This new method is backed up by appropriate asymptotic theory (see **[1]**).

Yao was the main creator of the new methodology. Gong conducted the numerical experiments. Their partner at Barclays provided the background, contributed to the development of the methodology, and was responsible for the case study reported in **[1]**. Liang Peng (Professor of Risk Management and Insurance at Georgia State University) was brought in at a later stage to provide the expertise on EVT required for establishing the asymptotic theory for publication **[1]**.

3. References to the research (indicative maximum of six references)

[1] Gong, J., Li, Y., Peng, L., and Yao, Q. (2015). Estimation of extreme quantiles for functions of dependent random variables. *Journal of the Royal Statistical Society*, *Series* B, 77(5), pp. 1001-1024. DOI: 10.1111/rssb.12103.

[2] Fan, J. and Yao, Q. (2003). *Nonlinear Time Series: Nonparametric and Parametric Methods*. Springer. ISBN: 9780387693958.

4. Details of the impact (indicative maximum 750 words)

The Basel III framework is an internationally agreed set of measures intended to strengthen the regulation, supervision, and risk management of banks, in response to weaknesses exposed by the financial crisis of 2007-2009. It requires banks and other financial institutions to apply a backtesting procedure to various market risk factors, trade, and portfolio prices.

The challenges of managing counterparty credit risk: one of the requirements of Basel III is enhanced management of counterparty credit risk (CCR) **[A]**. This makes CCR backtesting a mandatory requirement for all banks with advanced model approval for CCR, including Barclays. Basel III also requires investment banks to hold adequate capital and liquidity to cover the CCR, which is the potential loss in derivative positions due to the default of trading counterparties. The reason for this strong emphasis on banks' proper management of CCR is that it is important to the stability not only of individual banks but also, in light of the interconnections between them, to the financial system as a whole. The failures of Lehman Brothers and MF Global, and their impacts on the global financial system, illustrate the disruptive potential of instability in any part of the system.

However, CCR is a complex risk to assess; as a hybrid of credit and market risk, it is contingent both on changes in the counterparty's creditworthiness and on movements in underlying market risk factors. The first step in computing CCR capital is typically to jointly simulate various future market risk factors such as interest rates, equities, and foreign exchange rates. Next, all the derivative positions of the bank are computed at each time horizon of each of these simulated market scenarios, to determine the bank's potential future exposure (PFE) to counterparty default. The amount of holding capital required to cover CCR is then calculated, based on PFE and according to the relevant regulation.

The role of backtesting: backtesting is a critical component of the Basel III regulation, particularly as a means of assessing the extreme PFE quantiles used by banks and financial institutions to validate price models and to calculate their credit holding. The *ad hoc* approaches typically taken to calculating these extreme quantiles are inaccurate. Underestimating the extreme quantiles leads to the exposure of both banks and their customers to potential uncovered financial losses. Conservative estimation leads to additional unnecessary overheads and, consequently, to increases in the costs of borrowing and decreases in investment.

Implementing the new backtesting method at Barclays: Barclays work with Yao on the development of the new method for estimating extreme quantiles published in **[1]** has changed and improved important aspects of their approach to backtesting. Specifically, the new method has helped Barclays to:

"overcome the difficult technical challenges associated with backtesting uncollateralised portfolio…This allows Barclays to backtest the potential future exposure to counterparty default based on a theoretically sound method for the very first time." **[B]**

That new method "*has been used as the official production method to backtest Barclays' CCR exposure RWA* [risk weighted assets] *since November 2013"* **[B**, further confirmed in **C]**. As a result, it is now "*one of the key components for backtesting our large CCR RWA for uncollateralised portfolio day-to-day"* **[B**, further confirmed in **C]**.

Reducing the cost of borrowing by more accurately calculating an appropriate capital buffer: Barclays holds CCR RWA worth tens of billions of US dollars (commercial sensitivity prevents Barclays from releasing the exact figure). The new methodology is applied across that portfolio, allowing the bank to calculate an adequate capital buffer to protect both its own and its customers' interests by avoiding the need to hold excessively large additional capital. The direct saving from this new scientifically calculated buffer is substantial. This, in turn, also reduces the cost of borrowing, and potentially increases investment and economic growth, with substantial indirect benefits to society.

Helping Barclays to meet regulatory requirements and improve its CCR management: since its first use by Barclays in late 2013, the new method has withstood rigorous backtesting under the Basel III framework. The Managing Director and Head of Cross Product Modelling of Barclays explains:

"The new methodology has helped Barclays to meet [the] regulator's requirements and better manage and control our counterparty risk…[because it] has helped Barclays to demonstrate quantitatively that we hold an adequate amount of capital to manage our counterparty credit risk." **[B]**

This has helped to ensure that both Barclays and its customers have avoided exposure to highly risky positions. Had its backtesting failed, the bank would have been required to re-adjust its CCR RWA evaluation by increasing its estimates of CCR exposure. That increase would, in turn, demand that they hold additional capital add-ons, a requirement that would be extremely costly given the large size of the bank's counterparty RWA. Commercial confidentiality also prevents Barclays from releasing its backtesting methodology documentation or related quantitative backtesting results. However, the bank's Head of Cross Product Modelling writes:

"I am happy to provide this letter to recognise Professor Yao's contribution to our CCR backtesting methodology, which has helped Barclays to improve our Counterparty Credit Risk management." **[B]**.

Wider benefits of improved CCR management: the proper management of exposure to CCR based on the new method underpinned by **[1]** delivers several important benefits.

(i) First, it improves the overall stability of Barclays in the sense that both its customers' and the bank's own interests are protected by alleviating exposure to uncovered high risky positions within a small probability (such as 0.05% or 0.01%).

(ii) Secondly, it contributes to the stability of the global financial system as a whole by mitigating the potential impact of the failure of one bank on others. The collapse of Lehman Brothers in 2008 underscored the need for better protections of this sort within a highly interconnected global financial system.

(iii) Thirdly, it increases the bank's confidence in lending via a reduction of the cost of borrowing. This results from the fact that calculating the extreme PFE based on the new method helps the bank more accurately estimate an adequate capital buffer. In other words, the method allows banks to cover a given degree of risk with a smaller capital requirement. Given that Barclays holds CCR RWA worth tens of billions of US dollars, the direct saving from this new and scientifically calculated buffer is substantial. This substantial saving improves the bank's business and operations and encourages more investment.

Yao's innovative contribution in estimating extreme PFE quantiles is an indispensable part of the new backtesting method directly supporting these benefits. As such, the research has contributed indirectly to assuring greater financial system security at lower cost, with wider economic benefits.

5. Sources to corroborate the impact (indicative maximum of 10 references)

[A] Basel III: A global regulatory framework for more resilient banks and banking systems, Basel Committee on Banking Supervision. Revised version June 2011. See particularly Part D, Section II.

[B] Supporting statement from the Managing Director and Head of Cross-Product Modelling at Barclays, 10 July 2019.

[C] Supporting statement from the Director and Head of the Risk Models Group (Risk Management) and the Director and Head of Counterparty Credit Risk (Quantitative Analytics) at Barclays, 9 July 2019.