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Abstract

This paper addresses the impact of developments in the credit risk transfer market on the viability of a group of systemically important financial institutions. We propose a bank default risk model, in the vein of the classic Merton-type, which utilizes a multi-equation framework to model forward-looking measures of market and credit risk using the credit default swap (CDS) index market as a measure of the global credit environment. In the first step, we establish the existence of significant detrimental volatility spillovers from the CDS market to the banks' equity prices, suggesting a credit shock propagation channel which results in serious deterioration of the valuation of banks' assets. In the second step, we show that substantial capital injections are required to restore the stability of the banking system to an acceptable level after shocks to the CDX and iTraxx indices. Our empirical evidence thus informs the relevant regulatory authorities on the magnitude of banking systemic risk jointly posed by CDS markets.

JEL-Code: C320, G210, G330.

Keywords: distance of default, credit derivatives, credit default swap index, financial stability.

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1. Introduction

In 2007-2008 the global financial system has undergone a period of unprecedented instability. The difference, however, between past financial crises and that which appears to have begun in earnest in August 2007 is the presence of the credit derivatives (CDs) market. The transmission of credit risk via these types of instruments appears, according to international financial regulators, to have amplified the global financial crisis by offering a direct and unobstructed mechanism for channelling defaults among a variety of types of financial institutions. Whilst the causes of this crisis are fairly well recognized, the mechanism of transmission of shocks between CDs markets and the banking sector is not so well understood from an empirical perspective. In fact, the academic and practitioner literature have not yet reached firm conclusions on the financial stability implications of credit default swaps (CDSs) instruments.

The turbulences experienced during the crisis on OTC derivatives markets have prompted regulators to find solutions to enhance the smooth functioning of these markets. It is crystal clear that in a context of inadequate underwriting practices in the US subprime mortgage markets and excessive granting of loans by non regulated entities, financial innovation based on CDs was at the heart of the financial crisis.

The objective of this paper is to shed some light on the mechanisms involved in banking stability by studying the credit default swap (CDS) index market during the 2005-2010 period and exploring how negative shocks affected financial institutions as the subprime crisis of 2007 unfolded and then evolved into the global financial crisis of 2008. To explore this issue, we address empirically the relationship between CDS index markets and the viability of systemically important financial institutions.

We use a contingent claims approach, which explicitly integrates forward looking market information and recursive econometric techniques to track the evolution of default risk for

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a sample of 16 large complex financial institutions (LCFIs). We adopt the classic distance to default (henceforth D-to-D) to the pricing of corporate debt. The well known market based credit risk model is the Merton (1974) model, which views a firm's equity liability as a call option on asset with exercise price equals its total debt liability. By backing out asset values and volatilities from quoted stock prices and balance sheet information, the Merton (1974) model is able to generate updates of firms' default probabilities. Since one of the most important determinant of CDS prices is the likelihood of the reference entity involves in a credit event, and this likelihood is tightly linked to stock market valuation as indicated in the Merton (1974) theoretical framework, it is natural to investigate empirically the link between the stock market and CDS markets.

A priori, it is not clear whether and to what extent CDS indices and LCFIs equity values are related. We are not aware of any studies analyzing this relationship either theoretically or empirically. There is a considerable volume of literature that attempts to describe the effect of CDS on asset prices. Most of this literature relates to the co-movement of the CDS market, the bond market and the equity market. However, to our knowledge, the closest precursor to our analysis is the research by Bystrom (2005, 2006) and Longstaff (2010). Bystrom (2004) finds a linkage between equity prices, equity return volatilities and CDS spreads throughout studying a set of data from the European iTraxx CDS indices and stock indexes.

Longstaff (2010) finds that during the subprime crisis of 2007, the value of asset-backed collateralized debt obligations (CDOs) (using the ABX index as proxy) had a strong prediction power for stock market returns (using the S&P 500 and the S&P 500 financial subindex as proxies). He demonstrates empirically that the ABX indices were signalling critical information of market distress by as much as three weeks ahead and he finds strong evidence supporting a contagion mechanism - from the ABS subprime market to other financial markets - driven primarily by market premia and liquidity channels instead of the correlated-information channel. Although his data is limited to the period between 2006 and 2008 and the results focus only on the subprime crisis of 2007, the study is a highly valuable contribution as it sheds light on the potential correlation between the ABX index market and other financial markets (in primis, the equity market for financial institutions).

Our paper makes three distinctive contributions. The first contribution is a new approach to modelling banking fragility that explicitly incorporates the transmission of corporate credit risk from the CDS index market. Our model thus contributes to the existing literature on credit risk models and measures of systemic risk by exploring the intuition that CD premia are univariate timely indicators of information pertinent to systemic risks. To the best of our knowledge, this paper is the first to combine the D-to-D analytical prediction of individual banking fragility with measures of CD markets instability. While applications of the D-to-D methodology have so far mostly concentrated in the option pricing literature, we show that the Merton approach can be applied to the area of CRT. Hence, we provide a readable implementable empirical application to infer default probabilities and credit risk (or other tail behavior) on individual LCFIs.

To this purpose, we utilize a multivariate ARCH model to forecast the future volatility of banks assets conditioned on the co-evolution of banks equity and the CDs market. The incorporation of uncertainty and asset volatility are important elements in risk analysis since uncertain changes in future asset values relative to promised payments on debt obligations ultimately drive default risk and credit spreads - important elements of credit risk analysis and, further, systemic risk (IMF, 2009). The econometric framework allows testing for the predictive contribution of developments in the CD market on the stability of the banking sector as depicted by the D-to-D of major financial institutions.

The paper includes a section that sets out the possible links between the value of banks equity and the CDS market. The basic idea is that as banks deliberately undertake risky projects that embed counter party risk the value and volatility of the banks assets will co-evolve with developments in CDS markets.

In the same section we outline the econometric methodology we employ for the calculation of the probability of default for the 16 institutions in our sample. We have opted for a mixture of MV-GARCH model and Monte Carlo simulations instead of a multivariate stochastic volatility model. We believe that this is a rather robust approach as it allows us to obtain the empirical distribution of volatilities, based on the dynamic structure given by the MV-GARCH model, and subsequently compute the probability of default when the actual volatility is not known but its frequency distribution can be computed. A full account of the methodology is presented in the paper.

The impact of developments in the CD market on the asset volatility is captured by the evolution of the corporate investment-grade CDS indices (CDX and the iTraxx). CDX North-American is the brand-name for the family of CDS index products of a portfolio consisting of 5-year default swaps, covering equal principal amounts of debt of each of 125 named North American investment-grade issuers. The iTraxx Europe index is composed of the most liquid 125 CDSs' referencing European investment grade and high yield corporate credit instruments.

In addition, the study makes a second methodological contribution. Having established a relationship between CDS indices and our measure of fragility for LCFIs we turn the focus of our analysis to the problem of determining an institution's potential regulatory capital requirement. To this end, we again use the VAR framework to perform a forward-looking stress test exercise to estimate capital surcharges based on a variety of asset volatility scenarios. Essentially, we impute the required capital injections per institution, based on the distribution of the volatility of their own assets, given a-priori maximum probability of default that is set at 1%. We believe that this setting constitutes a useful predictive tool that financial regulators may wish to employ to gauge the implications for the stability of systemically important financial institutions given developments in CDs markets.

The analytical foundations of our stress test scenario exercise draw from the stress testing literature-thus allowing the model to focus on credit risk-and from the structured finance literature-thus enabling the model to consider the systemic effects of CDS shocks. By adopting a clear and thorough methodology based on severe scenarios, providing detailed bank-by-bank results and deploying, where necessary, remedial actions to strengthen the capital position of individual banks, the stress test exercise is an important contribution to strengthening the resilience and robustness of the global banking system.

In the past regulators have focused on traditional lending risks that form the basis of bank capital requirements. The stress test provides a more rounded assessment of the amount of equity a bank needs in order to be considered well capitalised relative to the risks it is running. Since the goal is to lessen the probability of tail-risk scenarios, following this approach, the regulator would be able to identify the highest default risk probability assigned to each institution over the cycle and base the capital surcharge on that asset volatility scenario.

The third contribution is an empirical test of this framework for an important category of financial institutions, the Large Complex Financial Institutions (LCFIs), which can be regarded as representative of the global banking system. The degree to which individual banking groups are large in the sense that they could be a source of systemic risk depends on the extent to which they can be a conduit for diffusing idiosyncratic and systemic shocks through a banking system. Broadly we can distinguish between two types of pure shocks to a banking system systemic and idiosyn1cratic. The focus of attention of the authorities, entrusted with the remit of financial stability, is the monitoring of the impact of shocks affecting simultaneously all the banks in the system.

A common finding in the empirical literature is that the level of banks' exposure to systemic shocks tends to determine the extent and severity of a systemic crisis. However, another source of systemic risk may originate from an individual bank through either its bankruptcy or an inability to operate. The transmission channel of the idiosyncratic shock can be direct, for example if the bank was to default on its interbank liabilities, or indirect, whereby a bank's default leads to serious liquidity problems in one or more of the financial markets where it was involved.

As far we are able to determine, this is the first investigation to establish a relationship between the CDX and the iTraxx CDS indices and the banking sector which supports the consideration of a transmission mechanism in order to account for the potential of default risk of several global LCFIs. We adopt a working definition of banking instability as an episode in which there is a significant increase in cross-market linkages after a shock occurs in the CDS market.

In early 2009, the US Fed conducted stress tests on its banking industry and found that 10 lenders needed nearly $75bn of additional capital between them. This managed to soothe the markets and helped US banking stocks rebound. The stress tests were designed to ensure the 19 leading US banks have enough capital in general, and equity in particular, comfortably to survive a deeper-than-expected recession. They were also intended to provide more standardized information about bank asset portfolios. Recently, the European Union has also conducted stress tests on banks accounting for about 65 per cent of the EU banking sector.

This application can be useful for supervisory scenario stress testing when complemented with models of the probability of default and loss given default. Scenarios stress tests involving both US and European LCFIs could help establish the level of impairment to assets and capital needs.

Our most important findings are threefold. First, we find that systemically important financial institutions are exposed simultaneously to systematic CDs shocks. In practice, we find that the sensitivity of default risk across the banking system is highly correlated with both the CDX and the iTraxx indices markets and that this relationship is of positive sign. Hence, direct links between financial institutions and the CDS index market matter. This is evidence of some spillover effects from the CDS market after the onset of the crisis. Second, our model allows us to quantify the required capital needs for each LCFI via the overall price-discovery process in the two CDS indices markets. The main insight from our estimates is that the US government re-capitalization programmes considerably underestimated the necessary capital injections for the US LCFIs. A plausible explanation for this result is that the specification of our model does do not reflect any explicit or implicit government guarantees on the total debt liabilities of the institutions. Third, XXXXXXXX

All our results have several important implications both for the financial stability literature and for global banking regulators. The study offers an insight on the intricate interrelationships between CDS markets developments and the individual and the systemic stability dimensions of the international banking system. It helps to quantify the transmission of shocks and their volatility to a specific metric of financial stability. Our model specification can help policymakers monitor default-risk and the distance to specific capital thresholds of individual financial institutions at a daily frequency by testing the extent of co-movements between North American and European CDS market conditions in normal as well as stressful periods.

This suggests that our approach can serve as an early warning system for supervisors to pursue closer scrutiny of a bank's risk profile, thereby prompting additional regulatory capital and enhanced supervision to discourage practices that increase systemic risk. The remainder of the paper is organized as follows. Section §(2) briefly reviews the related literature. Section §(3) outlines the theoretical foundations of our approach. Section 4 introduces the D-to-D approach and sketches in some detail our stress testing framework. Section §(4) describes the data. The results are presented in §(5) and Section §(6) concludes.

2. Related Literature

The recent and growing literature on financial innovation and financial stability is characterized by a lack of consensus on the net effect of CRT on the financial system. Duffie (2008) discusses the costs and benefits of CRT instruments for the efficiency and the stability of the financial system. The argument is that if CRT leads to a more efficient use of lender capital, then the cost of credit is lowered, presumably leading to general macroeconomic benefits such as greater long-run economic growth. CRT could also raise the total amount of credit risk in the financial system to inefficient levels, and this could lead to inefficient economic activities by borrowers. Allen and Gale (2006) develop a model of banking and insurance and show that, with complete markets and contracts, inter-sectoral transfers are desirable. However, with incomplete markets and contracts, CRT can occur as the result of regulatory arbitrage and this can increase systemic risk.

Using a model with banking and insurance sectors, Allen and Carletti (2006) document that the transfer between the banking sector and the insurance sector can lead to damaging contagion of systemic risk from the insurance to the banking sector as the CRT induces insurance companies to hold the same assets as banks. If there is a crisis in the insurance sector, insurance companies will have to sell these assets, forcing down the price, which implies the possibility of contagion of systemic risk to the banking sector since banks use these assets to hedge their idiosyncratic liquidity risk.

Morrison (2005) shows that a market for CDs can destroy the signalling role of bank debt and lead to an overall reduction in welfare as a result. He suggests that disclosure requirements for CDs can help offset this effect. Bystrom (2005) investigates the relationship between the European iTraxx index market and the stock market. CDS spreads have a strong tendency to widen when stock prices fall and vice versa. Stock price volatility is also found to be significantly correlated with CDS spreads and the spreads are found to increase (decrease) with increasing (decreasing) stock price volatilities. The other interesting finding in this paper is the significant positive autocorrelation present in all the studied iTraxx indices. Building upon a structural credit risk model (CreditGrades), Bystrom (2006) reinforces this argument through a comparative evaluation of the theoretical and the observed market prices of eight iTraxx sub-indices. The paper's main insight is the significant autocorrelation between theoretical and empirical CDS spreads changes. Hence, this finding proves to be consistent with the hypothesis that the CDS market and the stock market are closely interrelated.

Baur and Joossens (2006) demonstrate under which conditions loan securitization can increase the systemic risks in the banking sector. They use a simple model to show how securitization can reduce the individual banks' economic capital requirements by transferring risk to other market participants and demonstrate that stability risks do not decrease due to asset securitization. As a result, systemic risk can increase and impact on the financial system in two ways. First, if the risks are transferred to unregulated market participants where there is less capital in the economy to cover these risks and second if the risks are transferred to other banks, interbank linkages increase and therefore augment systemic risk. A recent study by Hu and Black (2008) concludes that, thanks to the explosive growth in CDs, debt-holders such as banks and hedge funds have often more to gain if companies fail than if they survive. The study warns that the breakdown in the relationship between creditors and debtors, which traditionally worked together to keep solvent companies out of bankruptcy, lowers the system's ability to deal with a significant downwar shift in the availability of credit.

There is also little consensus on the relative importance of CDS and bond markets, and even less consensus on the CDS-equity markets relation. At least part of the difficulty has to do with measurement.

Zhu (2003) discusses the role of the CDS market in price discovery. Using a vector autoregression (VAR) framework, he finds that in the short run the results are slightly in favour of the hypothesis that the CDS market moves ahead of the bond market, thus contributing more to price discovery. Similar to Zhu approach, Longstaff, Mithal and Neis (2005) use a VAR model to examine the lead-lag relationship between CDS, equity and bond markets. They find that both changes in CDS premiums and stock returns often lead changes in corporate bond yields. In Jorion and Zhang (2006) investigation of the intra-industry credit contagion effect in the CDS market and the stock market, the CDS market is found to lead the stock market in capturing the contagion effect.

The traditional literature on the empirical applications of the Merton Model has long recognized that the D-to-D measure can be an efficient analytical predictor of individual firm fragility. A vast number of contributions have been developed, particularly in the banking literature. Chan-Lau et al (2004) measure bank vulnerability in emerging markets using the D-to-D. The indicator is estimated using equity prices and balance-sheet data for 38 banks in 14 emerging market countries. They find that the D-to-D can predict a bank's credit deterioration up to nine months in advance and it may prove useful for supervisory core purposes.

Berndt, Douglas, Duffie, Ferguson and Schronz (2004) examine the relationship between CDS premiums and EDFs. Moodys KMV EDFs are conditional probabilities of default, which are fitted non-parametrically from the historical default frequencies of other firms that had the same estimated D-to-D as the targeted firm. The D-to-D is the number of standard deviations of annual asset growth by which its current assets exceed a measure of book liabilities. They found that there is a positive link between 5-year EDFs and 5-year CDS premiums. However, the sample only includes North American companies from three industries. The result therefore might not be representative of the whole market.

Gropp et al (2006) show that the D-to-D may be a particularly suitable way to measure bank risk, avoiding problems of other measures, such as subordinated debt spreads. The authors employ the Merton's model of credit risk to derive equity-based indicators for banking soundness for a sample of European banks. They find that the Merton style equity-based indicator is efficient and unbiased as monitoring device. Furthermore, the equity-based indicator is forward looking and can pre-warn of a crisis 12 to 18 months ahead of time. The D-to-D is able to predict banks' downgrades in developed and emerging market countries.

Lehar (2005) proposes a new method to measure and monitor banking systemic risk. This author proposes an index, based on the Merton model, which tracks the probability of observing a systemic crisis - defined as a given number of simultaneous bank defaults - in the banking sector at a given point in time. The method proposed allows regulators to keep track of the systemic risk within their banking sector on an ongoing basis. It allows comparing the risk over time as well as between countries. For a sample of North American and Japanese banks (at the time of the Asian crisis in 1997/98) the author finds evidence of a dramatic increase in the probability of a simultaneous default of the Japanese banks whilst this decreases over time for the North American banks.

3. Methodology

We divide our empirical analysis into three sections. In the first section §§(3.1), we develop a theoretical framework for objective levels of default risk. In the second section of our investigation, §§(3.2), we outline a generalized stochastic volatility model of bank assets with multiple volatility instruments. Finally in the third section §§(3.3), we define an econometric model using a vector autoregressive model with multivariate autoregressive conditionally heteroskedastic disturbances (VAR-MV-GARCH) to determine the time evolution of the joint volatilities of the equity and our benchamrk CDS indices. We also extend this model to infer forward looking simulations of the joint evolution of the asset value process and hence determine the additional contingent capital requirements for each individual LCFI.

3.1. Objective Levels of Default Risk

Consider a policy objective setting the default risk probability, over some relative time horizon $T-t$, defined as p^*, such that for any systemically important institution, $p_{i,t} > p^*$, imposed by a regulator. The probability of default at time t, for the i^{th} institution, will be conditioned on the imputed conditional annualized volatility, $\hat{\sigma}_{A,t}$, and value of assets, $\hat{V}_{A,t}$. For any given systemically important financial institution suffering from some form of financial distress, with probability of default, $p_{i,t}$, the difference in probability $p^* - p_{i,t}$, under the assumption of conditional normality, will correspond to the difference between the minimum D-to-D set by the regulators and the current imputed distance

$$\delta_{i,t} = \eta\left(p^*\right) - \eta\left(p_{i,t}\right) \tag{1}$$

If $\delta_{i,t} < 0$, then we define $\delta_{i,t}$ as the *distance to distress*, if $\delta_{i,t} > 0$, then we define $\delta_{i,t}$ as the *distance to capital adequacy.* Given $\delta_{i,t} > 0$, the required capital injection to boost the value of assets to a point whereby $\eta\left(p^*\right) = \eta\left(p_{i,t}\right)$, i.e. $\gamma_{i,t} = V_A\left(p^*\right) - V_A\left(p_{i,t}\right)$, is defined as the *capital shortfall.*

Assuming that V_E is the observed value of equity and V_L is the observed value of liabilities at time t, we can treat the capital requirement problem as a typical option pricing problem. We first take the standard assumption that V_E is equivalent to a European call option on assets at time T, which we impose exogenously. Furthermore we treat the liabilities as being fixed. The value of this call option will be dependent on the properties of the underlying stochastic process driving the value of assets, with structural parameters θ_A and the current value of these assets $V_{A,t}$, with strike price $V_{L,t}$.

$$V_{E,t} = C\left(t, T, V_{A,t}, V_{L,t}, \theta_A\right) \tag{2}$$

The value of the call option will be proportional to the probability of default

$$p \propto C\left(t, T, V_{A,t}, V_{L,t}\theta_A\right) \tag{3}$$

furthermore assuming that for a given stochastic process the terminal distribution of asset values at T is given by,

$$\mathcal{P}\left(V_{A,T}\right) = \Gamma\left(V_{A,T}; t, T, V_{A,t}, \theta_A\right) \tag{4}$$

for a regulator the objective is to assess whether the probability that the value of assets at T will be less than the policy objective, i.e.

$$\int_0^{V_{L,T}} \Gamma\left(V_{A,T}; t, T, V_{A,t}, \theta_A\right) ds > p^* \tag{5}$$

this terminal distribution will depend on the choice of stochastic process driving $V_{A,t}$.

3.2. A Stochastic Volatility Model of Bank Assets

We motivate our proposed relationship between the fluctuations of the banks' assets and developments in the market for CDS by considering the development of the value of the assets V_A of a typical bank with assets and liabilities V_L.

Liabilities are fixed and are of known value and liquidity. Assets are chosen from a portfolio V_A of risky underlying assets and hedging instruments such that $V_A(t) = \alpha' S(t) + \beta' H(t)$, where $S(t)$ and $H(t)$ are vectors of risky and hedging instruments, respectively. The appropriate length vectors of dynamically re-balanced weights that ensure the hedging ratio maintains a target level of volatility are denoted by α and β . We define two risk vectors. The first vector is the chosen level of risk σ^{V_A} to which a bank exposes itself in order to generate potential excess return. The second risk vector is the level of *completeness* of the hedging instruments. We consider this risk vector to be driven by $k-1$ risk instruments $x_i \in \{x_1, \ldots, x_{k-1}\}$ which can be regarded as representing counterparty risk embedded into the hedging contracts used to control the banks exposure to risky assets and may or may not be observed. Combining the assets and the instruments in the second risk vector, we define the k length vector $y(t) = \left[V_A(t), x^1(t), \ldots, x^k(t)\right]'$ and the multivariate stochastic differential equation that denotes its time evolution as follows

$$dy(t) = \mu\left(y(t) \,|\theta\right) dt + \sigma\left(y(t) \,|\theta\right) dW(t) \tag{6}$$

where μ is a vector/matrix function of drifts, σ is a vector/matrix function driving volatility and $W(t)$ is a k dimensional Weiner process, i.e. $W^i(t+h) - W^i(t) \sim \mathcal{N}(0,h)$. Regarding the the nature of $\mu(\cdot)$ and $\sigma(\dot{})$, we proceed following the approach suggested by Williams and Ioannidis (2010) and adopt a stochastic covariance model of the form

$$
\begin{aligned}
dy(t) &= r(y(t))\,dt + \Sigma^{\frac{1}{2}}(t)\,(idiag\,(y(t))\,dW(t)) & (7)\\
\Sigma_A(t) &= A(t)\,A'(t) & (8)\\
A(t) &= ivech\,(\log a(t)) & (9)\\
da(t) &= \lambda(a(t))\,dt + \xi(a(t))\,dW(t)^{\sigma} & (10)
\end{aligned}
$$

where $r(y(t)) = \left[rV_A(t), \mu^1 x^1(t), \dots, \mu^{k-1}x^{k-1}(t)\right]'$ The first term indicates that the evolution asset growth is based on the instantaneous risk free rate r and $\{\mu^1, \dots, \mu^{k-1}\}$ are the independent drifts of the instruments. The stochastic covariance matrix $\Sigma_A(t)$ consists of a $\frac{1}{2}k(k+1)$ vector stochastic process $a(t)$. For simplicity, we set λ, for the covariance process to zero and the volatility of volatility function, $\xi(\cdot)$, is considered time invariant $a_i(t) \in \mathbb{R}$. Williams and Ioannidis (2010) derive the optimal number of hedging instruments for a simple stochastic covariance model to be $\frac{1}{2}k(k+1)+1$, given k diagonal and $\frac{1}{2}k(k-1)$ off-diagonal processes driving the volatility component. The attractive feature of this model is that it enables to derive an analytic specification of a single quantity that combines all the relevant variance and covariance terms as $\Sigma_A(t)$ is guaranteed to be PSD. The evolution of $y(t)$ from time t to $t+h$ can be represented by an instantaneous multivariate Brownian motion with covariance matrix

$$
\Sigma_A(t, t+h) = \int_{t}^{t+h} f\,(dW(t)^{\sigma})ds \qquad (11)
$$

where f is a function that aggregates the steps in the volatility equation in 7. The use of the *ivech* transformation ensures positive semi-definiteness (PSD) on any instantaneous realization of Σ_t that allows for its factorization. Now, we denote $\Sigma^{\frac{1}{2}}(t)$ as the matrix square-root of the instantaneous covariance matrix $\Sigma(t)$. Depending upon the complexity of the assumed processes driving a we can find either an analytic solution to the variance of volatility density or use Monte Carlo simulations. Here, we implement a Monte Carlo estimation procedure. A European call option on the bank's assets would therefore be priced over the integral of the possible volatilities

$$C\left(t, T, V_S, K \left| \theta \right.\right) = \int_0^\infty \Phi\left(\sigma_s\right) \tilde{C}\left(t, T, V_s, K, \sigma_s\right) ds \tag{12}$$

where K is the strike price, T is the maturity of the call, under the assumption of an equivalent time horizon $T - t = h$. Next we assign the $\tilde{C}$ to denote the individual Black and Scholes price of a call option with volatility σ_s, over an experiment space with respect to s. Note that we are unable to observe the continuous time asset process. However, the specification of our model can predict values of the call option, i.e. the value of equity, that exhibit some form of stochastic covariation with the evolution of the chosen volatility instruments. Therefore, we incorporate this property into an econometric specification of equity. Consequently, the actual realisation of the volatility of equity results from the matrix squareroot of the instantaneous covariance between equity and CDS indices and not merely from the squareroot of the realisation of its variance. In practice this means simulating across the parameter space of $\Sigma(t)$, to generate draws of the volatility process.

3.3. Econometric Specification

Under the framework illustrated above, we use a vector autoregression (VAR) model, $y_t = Zy_{t-1} + \mu + u_t$, with BEKK type multivariate autoregressive conditionally heteroskedastic disturbances to define the discrete time dynamics of the mean and variance systems. Z is the 3×3 matrix of lagged coefficients, μ is a vector of intercepts and u_t is a disturbance process with conditional covariance matrix $\mathbb{E}_t u_t u_t' = \Sigma_t$. The vector of interest is the VAR of the equity returns and log differences of the CDX and iTraxx CDS indices, $y_t = \left[\Delta \log\left(V_{E,t}\right), \Delta \log\left(CDX_t\right), \Delta \log\left(iTraxx_t\right)\right]'$. The VAR model disturbances are driven by a BEKK conditional covariance model

$$\Sigma_t = KK' + A\Sigma_{t-1}A' + Bu_{t-1}u_{t-1}B' \tag{13}$$

We impose a lag order of one on both the mean and variance covariance equations. KK' is the intercept in the variance equation and A and B are the 3×3 ARCH and GARCH autoregression coefficients, respectively. The long run covariance matrix of the VAR system disturbances takes the following form

$$vec\Sigma = (I - A \otimes A - B \otimes B)^{-1} vec(KK') \tag{14}$$

The structural disturbances ε_t are computed from $\Sigma_t^{\frac{1}{2}} u_t = \varepsilon_t$, where $\Sigma_t^{\frac{1}{2}}$ is the matrix square root of Σ_t. Note that the mean and variance models are jointly estimated with maximum likelihood estimation (MLE). Setting the parameter vector θ as $\theta = [vecZ', \mu', vechK', vecA', vecB']'$, the MLE objective function is given by

$$\mathfrak{L}\left(\hat{\theta}\right) \triangleq \max\left(-\tfrac{1}{2}3T\log(2\pi) + \sum_{t=1}^{T} \ell_t \,|\theta\right) \tag{15}$$

where the recursion of the likelihood function is

$$\begin{aligned} \ell_t \,|\theta \quad = \quad & \det\log KK' + A'\Sigma_{t-1}A + B'(y_{t-1} - Zy_{t-2} - \mu)(y_{t-1} - Zy_{t-2} - \mu)' B \\ & + (y_t - Zy_{t-1} - \mu)' \ldots \\ & \times \left(KK' + A\Sigma_{t-1}A' + B(y_{t-1} - Zy_{t-2} - \mu)(y_{t-1} - Zy_{t-2} - \mu)' B'\right)^{-1} \ldots \\ & \times (y_t - Zy_{t-1} - \mu) \end{aligned} \tag{16}$$

Using the estimated VAR and MV-GARCH parameters, we generate a set of Monte Carlo pathways to simulate a set of possible future asset volatilities and then stratify these into a set of future volatility scenarios.

3.4. Forward Looking Simulations

Specifically, we draw N one year (252 days) pathways of the 3×1 column vector ε_t, i.e. for the s

$$\left(\tilde{y}_{t+s}, \tilde{\Sigma}_{t+s}\right) \left|\tilde{\varepsilon}_{t+(s-1)}, \ldots, \tilde{\varepsilon}_t; \hat{\theta}\right. \tag{17}$$

For each pathway, we compute the annualized average volatility[2]. We use to represent the draw and evolution from one sample path. Following Hwertz (2005) who demonstrated that BEKK type processes exhibit time varying multivariate fourth moments, we conduct our simulation study across these time paths to capture this effect. We then sum over one forward looking year $\tilde{\Sigma} = \sum_{s=1}^{252} \tilde{\Sigma}_{t+s} \left|\tilde{\varepsilon}_{t+(s-1)}, \ldots, \tilde{\varepsilon}_t; \hat{\theta}\right.$. Using the methodology of Merton, we then compute for each pathway the value of assets, the volatility of assets, the distance to default and the average probability of default. $\left(\tilde{V}_A, \tilde{\sigma}_A, \tilde{\eta}, \tilde{p}\right)$, **??** outlines our approach to computing the Merton model for a deterministic volatility. We then weight each of these pathways by $\frac{1}{N}$ and sort them via the pathway average asset volatility. We exclude the top and bottom 2.5% of the simulated asset volatilities and stratify the rest into ten quantiles, ordered from low to high volatility levels. For each of these volatility quantiles, $\sigma_A^{i \in 1,\ldots,10}$, we then derive the asset volatilities and compute the D-to-D for a variety of asset levels starting with the current implied asset value $\hat{V}_{A,t}$. To obtain the current asset value we take a mean of the asset values computed over the three trading months (66 days) prior to April 29, 2009. To further implement our test, we then construct an upward sloping curve relating the extra required assets ΔV_A against the D-to-D, for the i^{th} volatility quantile, $\eta^* \left|\hat{V}_A + \Delta V_A; \sigma_A^i\right.$. For a particular objective D-to-D we can then compute the increase in assets required to reestablish adequate capital buffers for each bank.

4. Data Sample

The group of LCFIs consist of eight US based institutions, three UK banks, two French banks, two Swiss and one German banks. The Bank of England Financial Stability Review

[2]The variance-covariance matrices over all the paths will be centred around $\hat{\Sigma}$

(2001) [?] sets out classification criteria for LCFIs. Marsh, Stevens and Hawkesby (2003) [?] provide substantial empirical evidence for this classification. To join the group of LCFIs studied, a financial institution must feature in at least two of six global rankings on a variety of operational activities (these are set out in table 1). We base our classification on the 2003 rankings so that all the systemically important financial institutions prior to the recent financial crisis are included. These institutions are systemically important as the fallout from a bank failure can cause destabilizing effects for the world financial system. It is not only an institution's size that matters for its systemic importance - its interconnectedness and the vulnerability of its business models to excess leverage or a risky funding structure matter as well. These financial institutions are ABN Amro/Royal Bank of Scotland, Bank of America, Barclays, BNP Paribas, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC Holdings, JP Morgan, Lehman Brothers, Merrill Lynch, Morgan Stanley, Société Générale and UBS. In addition, we consider Bear Stearns, given its crucial role as market-maker in the global CDs market.

The CDX and iTraxx CDS indices are broad investment-grade barometers of investment grade risk and preliminary studies suggest that these offer a reasonable benchmark of the corporate credit environment. The data used in this paper is presented in Table **??**. The sample period extends from October 20, 2003 to April 29, 2009 for a total of 1462 trading days. All data is obtained from Thomson Reuters, Datastream. Liabilities are reported on a quarterly basis and are interpolated to daily frequency using piecewise cubic splines. The equity value of the LCFIs utilized in the VAR-MV-GARCH model are dividend adjusted. The market capitalization values are computed from the product of the number of shares (NOSH), the closing equity price (PC) and the index adjustment factor (AF), (Datastream series types in parentheses).

Appendix **??** presents our methods of analysis of the indices available to measure credit risk. Figures **??** to **??** illustrate the evolution of the variables used in the econometric model over the sample period, in addition to several other CDS benchmarks that we have examined in the data analysis stage of this research.

Table 1: LCFI Inclusion Criteria, Source: Marsh, Stephens and Hawkesby (2003), page 94

1. Ten largest equity bookrunners world-wide
2. Ten largest bond bookrunners world-wide
3. Ten largest syndicated loans bookrunners world-wide
4. Ten largest interest rate derivatives outstanding world-wide
5. Ten highest FX revenues world-wide
6. Ten largest holders of custody assets world-wide.

Table 2: Data Information

Short Name	Full Name	DataStream Mnemonic	Thomson-Reuters Code
BOA	Bank of America	U:BAC	923937
BS	Bear Stearns	U:BSC	936911
CITI	Citigroup	U: C	741344
GS	Goldman Sachs	U: GS	696738
JPM	JP Morgan	U: JPM	902242
LB	Lehman Brothers	U: LEH	131508
ML	Merrill Lynch	U: MER	922060
MS	Morgan Stanley	U: MWD	327998
SG	Societe Generale	F: SGE	755457
BNP	BNP Paripas	F: BNP	309449
DB	Deutsche Bank	D: DBK	905076
CS	Credit Suisse	S: CSGN	950701
UBS	UBS	S: UBSN	936458
BARC	Barclays	BARC	901443
HSBC	HSBC	HSBA	507534
RBS	Royal Bank of Scotland	RBS	901450

4.1. Causation in Mean and Variance

We set up two restriction tests for our econometric methodology. The first is a conventional directional block exogeneity test to test for directional effects on bank equity returns. We define $Z = [z_i]$ where z_i is the i^{th} row of the mean equation coefficients, $z_i = [z_{i,1}, z_{i,2}, z_{i,3}]$. The system consistent restriction allows for correlation in the structural disturbances u_t, but not in the autoregressive terms, Therefore, the restricted regression is of the form $y_t = (I \circ Z)\, y_{t-1} + \mu + u_t$, where I is a 3×3 identity matrix and $\circ$ is the Hadamard or element by element product. Setting the evaluated log likelihood of the restricted regression to $\mathfrak{L}^* \left(\hat{\theta}^1\right)$ versus the unrestricted regression $\mathfrak{L}^* \left(\hat{\theta}\right)$, the standard likelihood ratio test of the in mean restriction is $\Lambda^1 = 2\left(\mathfrak{L}^* \left(\hat{\theta}\right) - \mathfrak{L}^* \left(\hat{\theta}^1\right)\right)$, where $\Lambda^1 \sim \chi^2(6)$, for each of the block restrictions.

The variance test is slightly more complex, since the restrictions are block cross products. Again setting $y_t = Zy_{t-1} + \mu + u_t$, the BEKK restriction is of the form

$$\Sigma_t = \tfrac{1}{2}\left(\tilde{K}\tilde{K}' + \tilde{A}\Sigma_{t-1}\tilde{A}' + \tilde{B}u_{t-1}u_{t-1}\tilde{B}'\right) \tag{18}$$

where $\tilde{A} = \Psi \circ A$, $\tilde{B} = \Psi \circ B$, $\tilde{K} = \Psi \circ K$, with block restriction

$$\Psi = \begin{bmatrix} \sqrt{2} & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix} \tag{19}$$

setting the restricted likelihood to be $\mathfrak{L}^* \left(\hat{\theta}^2\right)$ versus the unrestricted regression $\mathfrak{L}^* \left(\hat{\theta}\right)$. The likelihood test statistic is $\Lambda^2 = 2\left(\mathfrak{L}^* \left(\hat{\theta}\right) - \mathfrak{L}^* \left(\hat{\theta}^2\right)\right)$. In total 12 parameters are restricted. Therefore, $\Lambda^2 \sim \chi^2(12)$, under the assumption of asymptotic normality[3].

[3]To see how the covariance restriction works note that $\frac{1}{2}\Psi\Psi' = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix}$

4.2. Parameter Stability Tests

Out data sample covers the period October 20, 2003 to April 29, 2009 and hence fully covers the financial crisis that began in August 2007. An important consideration in the parameter estimation and inference testing for this type of model is the issue of structural breaks and substantial time variation in the underlying true parameters. To account for this, we utilize a rolling versus static parameter estimation, which is an adaptation of the modified KLIC forecast breakdown approach suggested in Giacomini and Rossi (2010). We specify a minimum rolling window size of 20% of the complete sample, which is $l = 292$ days. We estimate the model using a rolling window starting at $t - l, t$, i.e. taking $t = 292$ as the starting date (November 30, 2004). We now consider two models: the model estimated ex-post over the whole sample, denoted with superscript W and the rolling model denoted with the superscript R. Consequently, the rolling sample comparative log likelihoods are

$$\mathfrak{L}_t^R\left(\hat{\theta}_t^R\right) \triangleq \max\left(-\tfrac{1}{2}3T\log(2\pi) + \sum_{t-l}^{t} \ell_t \left|\theta_t^R\right.\right) \tag{20}$$

$$\mathfrak{L}_t^W\left(\hat{\theta}^W\right) \triangleq -\tfrac{1}{2}3T\log(2\pi) + \sum_{t-l}^{t} \ell_t \left|\theta^W\right. \tag{21}$$

The rolling Kullback-Leibler statistic is defined as $\tilde{\kappa}_t = \mathfrak{L}_t^R\left(\hat{\theta}_t^R\right) - \mathfrak{L}_t^W\left(\hat{\theta}^W\right)$. Setting $\tilde{\varsigma}$ to be the heteroskedasticity and autocorrelation consistent estimate of the standard deviation of $\tilde{\kappa}_t$, we construct the rolling sum $\tilde{\lambda}_t = \sum_{t=1}^{t} \tilde{\varsigma}^{-1}\tilde{\kappa}_t$, for $t \in \{1, ..., T\}$. Diebold and Mariano (1996) derive the limit theorem for this type of comparative forecast statistic under relatively mild distributional assumptions, suggesting that $\tilde{\lambda}_t \sim \mathcal{N}(0,1)$, as $T \to \infty$. As a robustness check, we construct a Monte Carlo simulation with random and persistent jumps. These jumps are both positive and negative in magnitude. From the simulation we generate draws of $\tilde{\lambda}_t$. The Kolomogorov-Smirnoff test failed to reject the null of equality for 10,000 draws versus 10,000 draws from a $\mathcal{N}(0,1)$ distribution.

4.3. Estimating The Forward Looking Recapitalization Requirements

We establish a policy forecast period of one year, beginning on April 29, 2009. To compute the simulations suggested in §§(3.4), we need to discriminate between the parameter vectors $\bar{\theta} \in \{\hat{\theta}_T^R, \hat{\theta}^W\}$, i.e. the whole period vector and the last 292 day estimated rolling window parameter vector. We use the whole sample model parameters $\hat{\theta}^W$ as the benchmark and only choose $\hat{\theta}_T^R$ if the rolling window coefficients pertain to a better fit over the majority of the preceding 292 days. For instance, under the normality assumption this means that $\tilde{\lambda}_t < 1.96$ for more than 147 days out of 292, from $t = T - 292$ to $t = T$, where T is April 29, 2009. We repeat this exercise for each bank. We report the optimal forward looking model in Tables .4 and .5. In practice, the rolling window is preferred in the case of all 16 banks in the sample[4].

For each set of optimal forward looking parameters, we compute the restriction tests, described in §§(4.1). The results are presented in Table 3. Again, we can observe that for every bank in the analysis we reject the inclusion of the block exogeniety restrictions in mean and variance.

4.4. Understanding the Results: A Comparative Example of RBS and Bear Stearns

To provide a more comprehensive understanding of our methodology, we now present an illustrative example from our sample of 16 banks. Specifically, here we focus on two institutions adversely affected by the subprime mortgage crisi, namely RBS and Bear Stearns. Table **??** outlines the performance of these institutions after the onset of the crisis. We can see that both RBS and Bear Stearns suffered severe losses, which resulted in changes in the ownership structure from the pre to post crisis periods. RBS was partly nationalized by the UK government and Bear Stearns was rescued by the Federal Reserve and then sold to J. P. Morgan. The subplots in Figures 1 and 2 outline, respectively for RBS and Bear Stearns, the market capitalization (top left), total liabilities (top right), historical volatility from the rolling VAR-MV-GARCH models (bottom left) and the historical D-to-Ds (bottom right). Bear Stearns was rescued by the Federal Reserve on March 14, 2008. As such, the

[4]The full set of recursive coefficients is available on the authors website.

Table 3: The block exogeniety/causation tests in mean, Λ^1, and variance Λ^2 for each bank in the sample.

	Λ^1	$p-value$	Λ^2	$p-value$
BOA	186.3036	0.0000	4,210.4354	0.0000
BS	5,000.4120	0.0000	12,936.3721	0.0000
CITI	173.4772	0.0000	4,078.8147	0.0000
GS	131.8649	0.0000	2,299.6358	0.0000
JPM	216.0993	0.0000	3,110.2434	0.0000
LB	133.2388	0.0000	5,205.7893	0.0000
ML	1,410.7806	0.0000	4,754.0902	0.0000
MS	213.7156	0.0000	3,130.9067	0.0000
SG	156.1321	0.0000	2,328.5144	0.0000
BNP	188.3487	0.0000	2,362.9616	0.0000
DB	200.1796	0.0000	2,524.7460	0.0000
CS	206.2118	0.0000	2,354.1980	0.0000
UBS	190.0040	0.0000	2,567.1817	0.0000
BARC	129.5412	0.0000	3,069.9669	0.0000
HSBC	171.0778	0.0000	2,892.7295	0.0000
RBS	121.8059	0.0000	3,794.0576	0.0000

we truncate the rolling analysis at this point. Consequently, we run the forward looking recapitalization requirement from this date. Note that RBS stock was still traded until the end of the sample window. Therefore, we carry the analysis forward to the truncation date, that is April 29, 2009. Note also that, in addition to Bear Stearns, Merrill Lynch (acquired by Bank of America) and Lehman Brothers (filed for bankruptcy on September 15, 2008) are no longer traded as a separate entity within the sample.

We next compute the rolling parameter estimates for each model versus the whole sample parameter estimates. We present four examples for each bank over the sample period. These are plotted in Figures 3 and 4. We can observe the first order vector autoregressive coefficient, $z_{1,1}$ on equity (top left), the variance equation intercept coefficient on the equity, $k_{1,1}$, (top right), the lagged coefficient transmitting the lag of the CDX to equity, $z_{1,2}$, (bottom left), and finally the variance equation intercept cross product $k_{1,2}$ for the variance of equity from the lagged squared disturbance in the CDS index (top right).

Using the time varying parameters, we can compute the rolling comparative test statistic and infer the correct forward looking model specification. Figures 5 and 6 present the rolling

Figure 1: RBS Data

Figure 2: Bear Stearns Data

comparative loss statistics and their respective Monte Carlo significant bounds. For both banks the test estimates are below the lower significance threshold (indicating the rolling window is the optimal model) for the final part of the sample. As a result, we choose the model estimated over the 20% of the sample preceding April 29, 2009 for RBS and March 14, 2008 for Bear Stearns.

For each bank we then run the simulation outlined in §§(3.4). We report the results in the following format. Rows represent different tolerated risk stratifications, from one standard deviation to default, $\nu = 1$, to four standard deviations from default, $\nu = 4$. In the second column we also report the conditional log-normal probability of default. The columns represent the 90% mass of expected (unhedged, see §(3)) asset volatilities partitioned by 15-percentiles, ranging from the lowest (5%) to the highest (95%) expected asset volatility. The second row reports the asset volatility associated with the relative 15-percentiles. The interior of the grid reports the extra required assets for each risk tolerance - asset volatility 15-percentiles, in billions of US Dollars. For instance, in the event that Bear Stearns was subjected to an unhedged asset and volatility of 1%, which is in the first 15-percentiles below the median expected volatility, the bank would require US$ 8.0377 billion to contain the one-year insolvency risk at below 0.5%.

By contrast, RBS for the same level of unhedged asset volatility and risk tolerance would incur in an asset shortfall of US$81.1805 billion. For comparison, we also report in Table **??** the raised private and public support received by each troubled LCFI.

Figure 3: RBS Parameters

Figure 4: Bear Stearns Parameters

Figure 5: RBS Comparative Loss Statistic

5. Results and Analysis

5.1. Analysis of Dynamic Correlations

The objective of our analysis is to forecast the volatility of assets and its conditional quadratic covariation with the benchmark CDS indices. The VAR-MV-GARCH model captures time varying dependency in both direction and variation of the dynamic equations of interest (in our case equity, CDX and iTraxx). The employment of the VAR-MV-GARCH model allows for the estimation and testing of volatility transmission between the elements entering the VAR. The results from VAR-MV-GARCH models are presented in Appendix B. The vast majority of the estimated coefficients are statistically significant and there is no evidence of statistical misspecification. The results indicate a strong negative correlation between both indices and institutional equity and more importantly when the correlation of returns between the indices increases there is a marked rise in the negative correlation between equity returns of banks and the indices. Exclusion restrictions to establish the linear independence of equity returns and the evolution of the indices were decisively rejected in all cases establishing thus the empirical validity of the estimated model.

From the estimated coefficients we calculate the time evolution of the conditional volatilities and associated correlation coefficients. On the basis of these estimates, we also compute the value of the assets (Figure E.13), the imputed volatility (Figure E.17), the D-to-D (figure E.15) and the subsequent probability of default (figure E.16) for the sixteen LCFIs. For ease of presentation, the results are disaggregated based primarily on geography. As such, we follow a nationality grouping classification criteria as indicated by obvious divisions between US, UK, Swiss/German and French LCFIs. It can be seen that the time evolution of equity volatility exhibits common characteristics across LCFI's and, as expected, the conditional

Figure 6: Bear Stearns Comparative Loss Statistic

correlation with equity is consistently negative with both indices. However, there are subtle differences in these patterns both in terms of magnitude and more importantly in terms of the timing that changes in direction and intensity occur.

Beginning the discussion of the results with the group of US-based LCFIs, the path of the conditional equity volatility displays a modest upward movement since August 2007, following a very flat trajectory in the sub-period sample preceding the crisis. We can also see that asset volatility peaks up very rapidly by the last quarter of 2008. For pure investment banks such as Goldman Sachs, Merrill Lynch and Morgan Stanley, the peaked values range between .1 and .2 and they subsequently decline to lower levels, albeit still-elevated compared to their pre-crisis peak values. Unsurprisingly, for Lehman Brothers the increase is of exceptional magnitude as it is equal to 1.1, a five-fold increase compared to its peers. At the same time the conditional correlations of the equity value for the three survived investment banks with both the CDX and the iTraxx are negative throughout the entire sample period and show an accelerating negative trend in early 2008. Such trend does not dissipate even in early 2009 and demonstrates that there is a very clear pattern of feedback effects between the CDS index market and the equity market value of these institutions. In particular, such relationship becomes more pronounced over the financial crisis period with an average correlation value rising almost continuously from the beginning of 2005 through the first quarter of 2009, by which time correlation levels have increased from -.25 to -.6. The estimated conditional correlation from the model also shows that for Lehman Brothers correlations are relatively steady over the period starting from a substantially higher value of approximately -.4. The Lehman collapse causes the largest increase of co-movements between these variables.

It is important to note that at the beginning of the sample the correlation between the equity and the CDX index tends to exceed that with the iTraxx but then this relationship encounters a potential break during the onset of the subprime crisis, then the relative dominance of the CDX almost disappears and the relative weight of the two indices becomes virtually indistinguishable. Citigroup follows approximately the same pattern but with a higher intensity as the maximum equity volatility reaches .35 and the correlation with both indices reaches -.8. The findings also suggest that Bear Stearns equity volatility sharply explodes in the first quarter of 2008 picking up to around 0.6, with negative conditional correlations sharply reversing their downward trend during 2007.

Within the group of UK LCFIs, noticeably RBS exhibits the highest equity volatility, with a value of .35, compared to relatively contained levels for HSBC (.1) and for Barclays (.2). Thus, the equity volatility of RBS spikes dramatically during 2008, but then essentially, following the UK Government's financial support for RBS, returns to its pre-crisis pattern. Note also that there are no major changes in the conditional correlations although quite remarkably the average correlation of equity for the UK banks with the iTraxx index precipitously jumps at an elevated level.

Our estimates of the conditional equity volatility of continental European banks are substantially lower with the maximum values not exceeding .1. The volatility paths followed by BNP Paribas, Societe Generale and UBS display a very modest upward trend and do show abrupt upwards movements, whilst the volatility patterns observed for Deutsche Bank and Credit Suisse track closely the levels experienced by the US and the UK institutions. With the exception of UBS, the average correlation across the indices is of the same magnitude and is in line with the evolution of the other two banks. Remarkably, in the case of UBS the conditional correlation remains negative throughout the whole period and starting from a relatively important level (-.4) declines steadily after August 2007 end ends the sample period at just above zero.

Overall, the average correlation between the indices increases from approximately .4 (its average pre-crisis value) to a value in excess of .6, whilst the correlation between the indices and equity returns becomes more pronounced with an average value of -.6 compared to -.25. Such patterns are observed uniformly across all the banks and constitute strong evidence of detrimental volatility transmission between the evolution of the indices and the equity of all the banks included in this study. It is the uniformity of reaction, both in terms of size and direction to the same shock that constitutes a severe threat to the stability of the banking system.

For all sixteen LCFIs the resulting CDPs increase very sharply during 2008. These indicators therefore show that when the subprime crisis begins to evolve into a global financial crisis the average dependence among the global sample of banks equity and CDS indices enters an accelerating phase that reaches a peak towards the end of 2008. This finding is consistent with the evidence presented in a recent study by Longstaff (2010) who finds a rapid increase in cross-financial markets linkages as the subprime crisis developed.

From a visual inspection, the banks included in this study, in principle, clearly divide into two groups: the US and UK LCFIs AND the continental European LCFIs, the difference being the height of the jump of the default probability at the peak of the crisis in the wake of the Lehman Brothers bankruptcy. For several US banks the CDP rises to 35% whilst for the European block the CDP are generally not greater than 25%. In the UK for HSBC the relevant probability is just above 5% (on an annual basis) whilst, not surprisingly, whilst Barclays and RBS are subject to substantial increases to default probability. More specifically, this value for RBS far exceeds 35%, rendering the bank totally dependent on government support to ensure its survival. After the announcement of in-all-but-name nationalization of the bank, the associated probability of default reverts sharply to safe levels. The results also show significant dissimilarities in the probability of default between the US institutions as some of them show distinct reductions, whilst for others the probability of default increases over the latest part of the period under consideration. More specifically, the distress indicators clearly shows that for Citigroup, Bank of America and Morgan Stanley default risk continue to increase much above the historical trend, in the aftermath of Lehman Brothers' default. At the other hand of the spectrum, LCFIs, such as Goldman Sachs and J. P. Morgan, are about equally less vulnerable to pullover effects from the CDS market and hence more resilient to the liquidity crisis. Overall, the results indicate that systemic bank risks and CD market shocks appear to be highly dependent. These results are also consistent with those found in other studies (see, the IMF (2009, a, b)).

Stress testing involves hypothesizing changes in the aggregate volatility of the banks' assets and gives a simple measure of potential risk vectors in their aggregate form. These types of measures should prevent banks from leveraging themselves to a point whereby they are extremely vulnerable to changes in asset volatility, which would then require costly readjustments, possibly forcing a bank below some critical solvency thresholds

5.2. Analysis of D-2-D Injections (Stress Testing)

In view of the econometric evidence, we proceed by conducting a bank stress-testing exercise for a given value of the liabilities to evaluate the imputed adequate bank capital requirements to ensure the soundness of each institution. Such a strong assumption is justified in the current circumstances because their valuation is more accurate when compared to the valuation of assets. A stress test exercise involves hypothesizing changes in the aggregate volatility of the banks' assets and gives a simple measure of potential risk vectors in their aggregate form. These types of measures should prevent banks from leveraging themselves to a point whereby they are extremely vulnerable to changes in asset volatility, which would then require costly readjustments, possibly forcing a bank below some critical solvency thresholds.

5.3. Asset Volatility and Required Capital Injections

The results are presented in figures D.8-D.10. The limiting D-to-D is denoted by the horizontal line that marks the associated D-to-D for each bank given the imposed 1% probability to default as the maximum tolerated stay requirement before a regulator could decide to impose a contingent capital surcharge following a distress event. These figures associate the required increase in the value of equity for any realised value of asset volatility conditional on a fixed value of liabilities. The analysis is necessarily aggregate and stylized, and is not intended to substitute for detailed analysis of the needs of specific institutions' business activities or portfolios.

The required capital injections estimates, computed using the D-to-D methodology, need the following qualification. The assets are assumed to be drawn from a pool that preserves the overall level of volatility and capital injections by governments are considered almost risk-less and therefore will reduce the accumulation of balance sheet risks. Whether the re-payment level on these assets is recognized as a liability is a current point of debate in policy circles, particularly in the US and the UK.

A key aspect of the study is that stress-test indicators can show moves to medium- and high-volatility states and hence can be used to assess the degree of current banking fragility and uncertainty. Such indicators may also be useful in establishing whether and when a systemic crisis is subsiding, particularly if the low-volatility state persists, and thus when the withdrawal supportive crisis measures can be safely considered.

The volatility estimates are obtained from Monte-Carlo simulations using the estimated coefficients from the multivariate GARCH model. They are sorted in deciles with the exclusion of the tails immediately above the 2.5% cut-off. A close inspection of the range of the projected asset volatility values reveals substantial differences across financial institutions. Of those US LCFIs able to survive the crisis, Bank of America exhibits the largest degree of variability of asset volatility, ranging from .019 to 0.15, whilst unsurprisingly the institution with the narrowest dispersion is Goldman Sachs whose upper deciles remain below 0.079. The estimated asset volatilities for Citigroup, J.P. Morgan and Morgan Stanley are shown here to range between 0.018 and .11. By contrast, the asset volatility range for European LCFIs is rather narrow, with the exception of RBS whose volatility range reaches 0.077 exceeding by far the upper limit of the other European institutions. Such wide variations clearly underscore substantial differences in the resilience of LCFI to withstand identical adverse-case scenarios. A slight increase in volatility from a given overall safe level results in differing additional capital requirements for the sixteen institutions included in our sample. Overall, the main takeaway from our simulations is that the 'average' asset volatility of US-based LCFIs is substantially higher compared to non-US institutions. With such system-wide heterogeneity across institutions the development of common prudential regulatory standards aimed at protecting banks solvency may prove somewhat problematic and thus the implementation of reliable tools for this task should proceed expeditiously.

The magnitudes of the effects are nontrivial. Indeed, with respect to the US institutions, we find that for only a rather narrow range of asset volatilities they are able to comply with the imposed safety requirement. Morgan Stanley, Citigroup, J.P. Morgan and Goldman Sachs require no further capital injections provided that asset volatility does not exceed 0.002. This finding is noteworthy as this value represents the lowest of deciles in the empirical volatility distribution derived from our simulations. The results indicate that a severe deterioration of market conditions resulting in higher asset volatility will augment aggregate banking system capital needs. Assuming that all the US LCFIs were to experience the same level of asset volatility of 0.04, a value consistent with the mid-decile of the empirical distribution, the needed funds for a complete bank recapitalization will be roughly \$300bn. Interestingly, the most vulnerable institutions appear to be Bank of America and J.P. Morgan requiring \$150bn each whereas the individual capital injections for bank holding companies such as Goldman Sachs and Morgan Stanley stand at \$40bn and \$50bn, respectively. Furthermore, if each individual institution were subject to the 'mode' of the empirical asset volatility distribution, which corresponds to the fourth decile, then the required capital adequacy, surcharges are statistically and economically significant. Specifically, we project such injections ranging from \$250bn required for Bank of America to \$40bn for Goldman Sachs.

In striking contrast, BNP Paribas and Societe Generale, the two French LCFIs in the sample, appear to be relatively safe within the limits of their volatility distributions as no capital injections are required for asset volatility levels not exceeding the fourth decile. Even in presence of rather adverse volatility regimes the size of capital cushions does not exceed \$200bn. The Swiss and German banks appear somewhat more vulnerable to realisations of volatility in excess of the third decile, although conditions have to substantially deteriorate to absorb extra capital in the case of Deutsche Bank. This finding indicates that for realised asset volatility at the 'mode' these banking institutions will face a capital shortfall of \$160bn. As such, this should be viewed as indicative of the recapitalization needs by these banks to stabilize this segment of the European banking system.

Focusing next on the UK based-LFCIs, the results show a mixed pattern. Interestingly, HSBC appears to be the most resilient institution. For the first two deciles of volatility no further equity is needed to meet the policy objective, whilst at 'mode' \$100bn will be required. In contrast, Royal Bank of Scotland seems to be one of the more vulnerable LCFIs as reflected in its higher capital requirements. Our calculations suggest that if asset volatility reaches the specific threshold requirement, capital injections would need to be some

$200bn whilst a more demanding level of volatility - standing at a 'mode' intensity -raises the amount of capital to be injected to around $260bn. Barclays experiences a wide range within its volatility distribution suggesting no call for extra capital. However, a higher volatility scenario for the bank - asset volatility at mode value of 0.017- will push up considerably the recapitalization needs, possibly totalling $100bn.

Overall, our stress-testing results clearly highlight the dangers of significant losses, as a relatively large number of LCFIs are not adequately capitalized and individually capable of surviving reasonable stress events. The deterioration of the quality of assets signalled by conditions in the CDS index market points to comparatively substantial capital injections required to restore banks' balance sheets to health. Notably for most European banks there is a reasonably wide range of asset volatilities for which additional equity is not needed to cushion potential writedowns. In contrast, for the US banks the 'safe range' of volatilities is somewhat narrow. Not surprisingly, given the common heavy exposure of these institutions to subprime-mortgage related securities, what emerges from this exercise is that in absence of rigorous policy measures to address troubled assets, the banks included in this study (with the notable exception of HSBC) enter the 'insolvency state'. However, in some cases this distress proves to be relatively short-lived. Thus, the empirical evidence underscore that capital adequacy for systemically important financial institutions remains fractured in response to CDS index market shocks.

Remaining in a high-volatility regime for long could indicate a serious threat to the stability of the banking system. Consequently, there is clear evidence that the resilience of the banking sector is conditional upon a sustained improvement to the banks' balance sheets. As a result, there remains considerable scope for further fresh capital infusions for LCFIs.

Thus, these results are consistent with the emerging consensus that the long-term viability of institutions needs to be revaluated to assess both prospects for further write downs and potential capital needs. Without a thorough cleansing of banks' balance sheets of impaired assets, accompanied by restructuring and, where needed, recapitalization, risks remain that banks' problems will continue to exert upward pressure on systemic risk. Without making a judgment about the appropriateness of our asset volatility scenarios, it is important to note that these amounts are 'inflated' to the degree that governments have guaranteed banks against further losses of some of the bad assets on their balance sheets.

Furthermore, if we consider a more conservative regulatory approach establishing the maximum tolerated default probability below 1% almost all of the institutions included in this study will be in need of substantial additional equity injections from governments. For any given safety limit the key information provided by developments in the CRT market provide a valuable signal to the authorities about the additional capital requirements for each financial institution and more importantly about the overall fragility of the banking system.

In summary, these results do provide evidence that observing shifts in asset volatility regimes using the CDX and iTraxx indices as aggregating measures of corporate default risk can be helpful in detecting the degree to which the financial system is suffering a systemic event.

6. Concluding Remarks

Bank default risk is currently the predominant issue of concern to academic, financial practitioners and policymakers across the world. The recent failure of several LCFIs illustrates that the *too big to fail* paradigm predominant in the analysis of financial stability of large mainstream commercial and investment banks is no longer valid. We approach the issue of the stability of the banking sector by studying the potential effects of CDs on the statistical moments of the equity of LFCIs.

This paper offers a concrete illustration of the direct links between the global banking system and the CDs index market. We propose a set of models and empirical tests for predicting the current and future linkages between various CD markets and financial institutions. Specifically, we jointly model the evolution of equity returns and asset return volatility of 16 systemically important LCFIs, using a VAR-MV-GARCH model, with the evolution of the two standardized CDS indices. The conditional equity volatilities are used to impute the value and volatility of assets using a Merton type model.

The impact of developments in the CD market on asset volatility is captured by the evolution of the investment-grade CDX North-American and the iTraxx Europe indices. We estimate a multivariate GARCH model to forecast the future volatility conditioned on the co-evolution of the equity returns and the CDs market. The econometric framework allows for testing of the predictive contribution of developments in the CD market on the stability of the banking sector as depicted by the D-to-D of major financial institutions.

The evidence in the paper suggests that the presence of a market for CDs would tend to increase the propagation of shocks and not act as a dilution mechanism. We have produced strong econometric evidence of a substantial detrimental volatility pullover from the CDs market to bank equity, which affects negatively the stability of the banking system in both the USA and Europe.

In view of this evidence, we conclude that banks' equity volatility associated with significant stress in the CD market matters for systemic distress. In the presence of increasing asset volatility, financial institutions require fresh capital injections. Our calculations are based on the assumption that the value of liabilities is know. Therefore, the safety and soundness of each particular institution is a function of the market value of the assets. We view these results as encouraging, and we hope that the approach we take will be useful in future explorations.

Future research should relax this assumption and allow for the stochastic fluctuation of the value of the liabilities and its possible relationship with the value of assets. An additional innovation could be the adoption of pareto-stable distributions in place of the normal distribution that is commonly believed to underestimate the true frequency of *extreme* observations. This study helps to shed more light on the CDS index market and its interaction with other markets and inform on regulatory implications. Authorities are currently implementing a diverse set of regulatory regimes to ensure an effective regulation of CD markets through enhanced transparency and disclosure of the sector. The on-going debate on CD markets regulation calls for further investigation - both theoretical and empirical - to assist policymakers and regulators to identify the most effective regulatory response.

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	CDX	ITRAXX	BOA	BS	CITI	GS	JPM	LB	ML
Mean	0.000972	0.000774	-0.00085	-0.002352	-0.002232	0.000286	0.000203	-0.006172	-0.001591
Median	0.000486	0.000387	-0.000425	-0.001176	-0.001222	0.000143	0.0001015	-0.0036855	-0.0007955
Maximum	0.241033	0.224172	0.302096	0.63531	0.45633	0.23478	0.223917	1.423721	0.323885
Minimum	-0.199979	-0.205834	-0.34206	-1.830511	-0.494711	-0.210267	-0.232279	-2.856085	-0.299991
Std. Dev.	0.032431	0.036858	0.049537	0.066094	0.05356	0.033091	0.037112	0.132692	0.03937
Skewness	0.104544	0.246816	-0.190345	-20.2718	-0.310815	0.442909	0.346184	-8.167383	-0.076155
Kurtosis	9.479919	6.904945	15.61117	578.6376	22.08125	13.57165	12.14105	227.402	23.93058

	MS	SG	BNP	DB	CS	UBS	BARC	HSBC	RBS
Mean	-0.000293	-0.000248	0.000227	-0.000127	0.000181	-0.000846	-0.000505	4.87E-05	-0.00238
Median	-0.0001465	-0.000124	0.0001665	0.00006	0.0000905	-0.000423	-0.00026585	0.0000049	-0.0014655
Maximum	0.625849	0.184003	0.197465	0.248307	0.238393	0.267469	0.569044	0.151596	0.314772
Minimum	-0.299652	-0.191911	-0.16141	-0.191298	-0.168571	-0.190279	-0.274752	-0.225545	-1.117126
Std. Dev.	0.048167	0.032701	0.031167	0.033041	0.031937	0.034999	0.046209	0.025223	0.058302
Skewness	1.638006	-0.278676	0.42114	0.341736	0.527172	0.339538	1.492062	-0.265961	-7.096391
Kurtosis	38.48999	8.646752	10.69132	12.74992	11.5025	11.26325	30.73276	16.57982	137.3987

	Market Capitalisation				Total Liabilities			
	July 1, 2007	September 1, 2008	January 1, 2009	April 1, 2009	July 1, 2007	September 1, 2008	January 1, 2009	April 1, 2009
Bank of America	210419.3	134751.2	42062.96	45129.77	1568943000	1640891000	1991855000	1991855000
Bear Stearns	14076.55	1359.36	1359.36	1359.36	382105100	382105100	382105100	382105100
Citigroup	231664.8	85764.81	19345.86	14774.29	2074033000	1796840000	1701673000	1701673000
Goldman Sachs	76401	52379.97	37279.84	50930.15	1065554000	810176000	769330900	769330900
J.P. Morgan	148925.2	140024.8	95212.38	105747.8	1438926000	2008168000	1866624000	1866624000
Lehman Brothers	32908.72	206.7	28.59	28.94	666264100	666264100	666264100	666264100
Merrill Lynch	63759.15	33929.93	18620.86	18620.86	988118000	647540000	647540000	647540000
Morgan Stanley	67226.06	31828.69	21737.09	25497.83	1014140000	607981100	718682100	718682100
Societe Generale	81340.44	46690.38	24520.58	22893.34	1420025000	1584635000	1351058000	1288492000
BNP Paribas	104797.3	74794.88	35075.99	39696.98	2235935000	2936181000	2734727000	2608083000
Deutsche Bank	72912.44	39019.4	14996.36	25658.12	2706447000	3154254000	2023336000	1929637000
Credit Suisse	80794.25	48859.86	29155.99	37946.85	1076156000	1008724000	915058400	853122000
UBS	118213.9	43472.52	36988.34	28549.78	1850614000	1782076000	1205441000	1123850000
Barclays	92987.25	44507.66	12809.89	18928.16	2425092000	3609186000	1895167000	1963579000
HSBC	218271	179570.4	95115.31	101632	2267030000	2984609000	1977778000	2049171000
RBS	113854.5	55514.96	12514.69	20347.09	3670184000	4162320000	2292946000	2375717000

	CDX	ITRAXX	BOA	BS	CITI	GS	JPM	LB	ML	MS	SG	BNP	DB	CS	UBS	BARC	HSBC
CDX	1.0000																
ITRAXX	0.5198	1.0000															
	[19.6436]																
BOA	-0.3294	-0.2562	1.0000														
	[-11.2621]	[-8.5564]															
BS	-0.0213	-0.0595	0.0525	1.0000													
	[-0.6900]	[-1.9265]	[1.6983]														
CITI	-0.3165	-0.2928	0.8031	0.0987	1.0000												
	[-10.7739]	[-9.8856]	[43.5134]	[3.2047]													
GS	-0.3278	-0.3085	0.6727	0.1488	0.6334	1.0000											
	[-11.2024]	[-10.4715]	[29.3505]	[4.8595]	[26.4227]												
JPM	-0.2939	-0.2385	0.8125	0.0192	0.7124	0.7258	1.0000										
	[-9.9259]	[-7.9305]	[44.9933]	[0.6203]	[32.7780]	[34.0666]											
LB	-0.2436	-0.2798	0.3013	0.0897	0.2706	0.3589	0.2808	1.0000									
	[-8.1107]	[-9.4102]	[10.2003]	[2.9080]	[9.0741]	[12.4147]	[9.4450]										
ML	-0.2557	-0.2287	0.5414	0.1597	0.5438	0.5869	0.5824	0.2846	1.0000								
	[-8.5394]	[-7.5844]	[20.7895]	[5.2250]	[20.9210]	[23.3989]	[23.1279]	[9.5866]									
MS	-0.3235	-0.3026	0.6383	0.1294	0.6104	0.8203	0.6385	0.2974	0.5768	1.0000							
	[-11.0362]	[-10.2488]	[26.7694]	[4.2127]	[24.8811]	[46.3082]	[26.7850]	[10.0580]	[22.7969]								
SG	-0.2978	-0.4236	0.3527	0.1102	0.3920	0.4258	0.3463	0.2478	0.2190	0.3675	1.0000						
	[-10.0715]	[-15.0988]	[12.1681]	[3.5798]	[13.7562]	[15.1929]	[11.9191]	[8.2584]	[7.2453]	[12.7570]							
BNP	-0.2758	-0.4174	0.4102	0.0790	0.4029	0.4214	0.3722	0.2183	0.2094	0.3878	0.7684	1.0000					
	[-9.2638]	[-14.8273]	[14.5207]	[2.5596]	[14.2138]	[15.0009]	[12.9457]	[7.2219]	[6.9145]	[13.5811]	[38.7616]						
DB	-0.3386	-0.3929	0.5249	0.0770	0.5184	0.5871	0.4907	0.2149	0.3741	0.5760	0.7199	0.7317	1.0000				
	[-11.6162]	[-13.7939]	[19.9066]	[2.4945]	[19.5712]	[23.4152]	[18.1825]	[7.1062]	[13.0236]	[22.7497]	[33.4860]	[34.6610]					
CS	-0.3450	-0.4364	0.3583	0.0991	0.3974	0.5287	0.3479	0.1949	0.3155	0.5279	0.6670	0.6806	0.7155	1.0000			
	[-11.8687]	[-15.6607]	[12.3907]	[3.2169]	[13.9806]	[20.1064]	[11.9794]	[6.4156]	[10.7342]	[20.0654]	[28.8990]	[29.9903]	[33.0607]				
UBS	-0.3508	-0.4641	0.4004	0.1591	0.4569	0.4826	0.3652	0.2968	0.3478	0.4626	0.6915	0.6988	0.6771	0.7610	1.0000		
	[-12.0930]	[-16.9166]	[14.1086]	[5.2046]	[16.5834]	[17.7883]	[12.6634]	[10.0349]	[11.9774]	[16.8445]	[30.9039]	[31.5406]	[29.7014]	[37.8683]			
BARC	-0.2698	-0.3732	0.3695	0.1048	0.3426	0.3532	0.2720	0.2179	0.2482	0.3319	0.6345	0.6837	0.5959	0.5547	0.5887	1.0000	
	[-9.0479]	[-12.9859]	[12.8385]	[3.4022]	[11.7749]	[12.1902]	[9.1275]	[7.2083]	[8.2736]	[11.3588]	[26.5025]	[30.2430]	[23.9585]	[21.5253]	[23.5128]		
HSBC	-0.2982	-0.4075	0.4313	0.0776	0.4620	0.4439	0.3881	0.2069	0.2574	0.4321	0.6704	0.7340	0.6731	0.6440	0.6513	0.6613	1.0000
	[-10.0859]	[-14.4050]	[15.4343]	[2.5157]	[16.8179]	[15.9919]	[13.5942]	[6.8294]	[8.6015]	[15.4670]	[29.1653]	[34.8900]	[29.3866]	[27.1755]	[27.7076]	[28.4653]	
RBS	-0.1913	-0.2694	0.3253	0.0783	0.2856	0.3219	0.2423	0.1730	0.2026	0.3129	0.5416	0.5247	0.5296	0.4672	0.5430	0.5993	0.5404
	[-6.2921]	[-9.0328]	[11.1051]	[2.5364]	[9.6220]	[10.9785]	[8.0629]	[5.6709]	[6.6811]	[10.6348]	[20.7982]	[19.8969]	[20.1556]	[17.0600]	[20.8780]	[24.1701]	[20.7330]

Table .4:

	BOA	BS	CITI	GS	JPM	LB	ML	MS	SG	BNP	DB	CS	UBS	BARC	HSBC	RBS
$z_{1,1}$	-0.0113	-0.0318	0.0375	-0.0244	-0.0626	-0.0657	0.0016	0.0342	0.1017	-0.0138	0.0305	0.0891	0.0862	0.0048	-0.0269	-0.0349
	[-0.4236]	[-0.8225]	[1.2636]	[-0.8893]	[-2.4093]	[-2.2901]	[0.0528]	[1.1777]	[3.1936]	[-0.4429]	[1.0491]	[2.8896]	[2.9669]	[0.1765]	[-0.8874]	[-1.1621]
$z_{1,2}$	-0.0254	-0.0000	-0.0318	-0.0643	-0.0466	-0.0938	0.0000	-0.0185	-0.0642	-0.0716	-0.0576	-0.0628	-0.0550	-0.0590	-0.0178	-0.0760
	[-1.8007]	[-0.0009]	[-2.4855]	[-3.4293]	[-2.8785]	[-2.9560]	[0.0192]	[-0.8380]	[-3.5811]	[-3.7117]	[-3.4689]	[-3.7513]	[-3.1389]	[-3.1565]	[-2.2219]	[-4.8168]
$z_{1,3}$	-0.0041	0.0000	-0.0076	-0.0464	-0.0094	0.0743	-0.0000	-0.0120	-0.0080	0.0063	-0.0088	-0.0104	-0.0234	-0.0241	-0.0152	0.0292
	[-0.2872]	[0.0020]	[-0.4409]	[-2.4724]	[-0.5516]	[1.8530]	[-0.0136]	[-0.5116]	[-0.3921]	[0.2852]	[-0.4586]	[-0.5841]	[-1.1877]	[-1.0576]	[-1.4858]	[1.4673]
μ_1	0.0002	-0.0000	0.0004	0.0006	0.0007	0.0002	-0.0000	0.0010	0.0003	0.0008	0.0005	0.0005	0.0002	0.0005	0.0004	0.0009
	[0.6588]	[-0.0392]	[1.0349]	[1.4241]	[1.5715]	[0.2585]	[-0.0104]	[1.8848]	[0.6782]	[1.5088]	[1.0748]	[0.9706]	[0.4751]	[1.0103]	[1.2968]	[1.6641]
$z_{2,1}$	-0.0531	-0.0212	-0.0777	-0.1242	-0.1627	0.0254	-0.1728	-0.1090	-0.0166	-0.0482	-0.0560	-0.0695	-0.0563	0.0024	-0.0360	-0.0002
	[-2.2633]	[-0.9547]	[-3.6325]	[-4.4690]	[-6.1065]	[5.4799]	[-7.9026]	[-4.6862]	[-0.5052]	[-1.3278]	[-1.6155]	[-2.0789]	[-1.9555]	[0.1182]	[-0.7244]	[-0.0096]
$z_{2,2}$	0.0017	0.0338	0.0058	0.0414	0.0018	0.0119	0.0105	-0.0130	0.0304	0.0259	0.0232	0.0340	0.0113	0.0487	0.0202	0.0136
	[0.0576]	[0.9596]	[0.1761]	[1.3895]	[0.0631]	[0.3737]	[0.3240]	[-0.3920]	[0.9312]	[0.8035]	[0.7442]	[1.0402]	[0.3431]	[1.4997]	[0.6178]	[0.4211]
$z_{2,3}$	0.3044	0.3002	0.2871	0.2794	0.2797	0.3213	0.2717	0.2744	0.2620	0.2639	0.2729	0.2667	0.2497	0.2779	0.2950	0.2683
	[9.4887]	[8.2391]	[8.8378]	[10.3164]	[9.0040]	[10.4926]	[8.6611]	[9.3460]	[8.2768]	[8.4261]	[8.9700]	[8.5673]	[8.0932]	[8.6123]	[9.5219]	[8.3167]
μ_2	-0.0004	0.0003	-0.0007	-0.0001	-0.0003	-0.0009	0.0010	-0.0002	-0.0003	-0.0000	-0.0003	-0.0002	-0.0005	-0.0004	-0.0002	-0.0007
	[-0.5762]	[0.3858]	[-0.9015]	[-0.2899]	[-0.4453]	[-1.1401]	[1.2882]	[-0.3598]	[-0.4751]	[-0.0012]	[-0.4669]	[-0.3456]	[-0.6571]	[-0.5610]	[-0.2381]	[-0.8107]
$z_{3,1}$	-0.0227	-0.0656	-0.0310	-0.1158	-0.0935	0.0251	-0.2067	-0.0849	-0.0492	-0.0558	-0.0674	-0.1078	-0.0563	-0.0195	-0.0551	0.0001
	[-1.3274]	[-3.8388]	[-1.8029]	[-2.7896]	[-4.2327]	[5.9592]	[-11.0947]	[-4.1392]	[-1.6915]	[-1.9543]	[-2.4214]	[-3.6780]	[-2.1120]	[-0.9659]	[-1.4221]	[0.0099]
$z_{3,2}$	0.1699	0.2249	0.1806	0.1625	0.1897	0.1777	0.1960	0.1772	0.1910	0.1959	0.1895	0.1806	0.1877	0.2061	0.1892	0.1939
	[8.1896]	[8.3999]	[7.8573]	[5.0805]	[9.1551]	[8.7253]	[7.7854]	[8.0724]	[8.1770]	[8.7984]	[9.1738]	[8.1333]	[8.3862]	[9.0631]	[7.9232]	[8.5376]
$z_{3,3}$	0.0207	0.0868	-0.0080	0.0592	-0.0101	0.0158	-0.0516	0.0246	-0.0187	-0.0087	-0.0243	-0.0240	-0.0202	-0.0161	-0.0021	-0.0001
	[0.7001]	[2.7802]	[-0.2678]	[1.1994]	[-0.3585]	[0.5181]	[-1.5831]	[0.8470]	[-0.6191]	[-0.2927]	[-0.8235]	[-0.8244]	[-0.6684]	[-0.5277]	[-0.0657]	[-0.0061]
μ_3	-0.0003	0.0001	-0.0006	0.0001	-0.0005	-0.0009	0.0011	-0.0000	-0.0000	-0.0000	-0.0003	-0.0001	-0.0003	-0.0003	-0.0001	-0.0003
	[-0.4649]	[0.1077]	[-0.8248]	[0.0977]	[-0.7388]	[-1.3049]	[1.2223]	[-0.1055]	[-0.1289]	[-0.1046]	[-0.5257]	[-0.1985]	[-0.4215]	[-0.4229]	[-0.1319]	[-0.3982]

Table .5:

	BOA	BS	CITI	GS	JPM	LB	ML	MS	SG	BNP	DB	CS	UBS	BARC	HSBC	RBS
$k_{1,1}$	0.0015	-0.0000	0.0023	0.0014	0.0014	0.0002	0.0000	0.0021	0.0027	0.0025	0.0020	0.0025	0.0017	0.0020	-0.0001	0.0030
	[8.7168]	[-0.5360]	[13.7300]	[5.9156]	[6.7041]	[0.0298]	[0.5820]	[7.6889]	[7.7069]	[7.1997]	[8.6885]	[7.5796]	[6.7697]	[6.7754]	[-0.1188]	[11.7987]
$k_{1,2}$	-0.0002	0.0026	-0.0001	0.0033	-0.0005	0.0030	-0.0035	-0.0004	-0.0011	-0.0011	-0.0009	-0.0015	-0.0009	-0.0008	0.0026	-0.0015
	[-0.3719]	[0.0895]	[-0.1828]	[7.1179]	[-0.7325]	[0.0292]	[-0.1332]	[-0.7655]	[-2.1564]	[-2.4321]	[-1.6446]	[-3.0490]	[-1.3696]	[-1.6578]	[0.1171]	[-2.5886]
$k_{1,3}$	0.0000	0.0003	0.0003	0.0026	-0.0000	0.0039	-0.0013	0.0004	-0.0009	-0.0008	-0.0004	-0.0004	-0.0005	-0.0005	0.0050	-0.0013
	[0.0605]	[0.0024]	[0.7257]	[1.6912]	[-0.0958]	[0.0300]	[-0.0176]	[0.8850]	[-1.7587]	[-1.6363]	[-0.9367]	[-0.8357]	[-1.0657]	[-0.8424]	[0.1207]	[-1.9268]
$k_{2,2}$	0.0043	0.0019	0.0042	0.0007	0.0041	0.0028	0.0004	0.0043	0.0041	0.0040	0.0042	0.0041	0.0042	0.0042	-0.0037	0.0038
	[11.8982]	[0.0510]	[12.0833]	[0.4224]	[11.7785]	[0.0261]	[0.0019]	[11.6282]	[10.5663]	[11.2480]	[11.2697]	[10.4623]	[11.7192]	[11.6208]	[-0.2266]	[11.0338]
$k_{2,3}$	0.0020	0.0014	0.0024	0.0089	0.0020	-0.0012	0.0041	0.0022	0.0016	0.0016	0.0017	0.0018	0.0017	0.0020	0.0002	0.0015
	[5.8932]	[0.0076]	[8.3134]	[0.4646]	[5.4553]	[-0.0039]	[0.0028]	[5.7262]	[4.9476]	[4.9615]	[5.0011]	[5.3294]	[4.9811]	[5.8228]	[0.0039]	[3.8540]
$k_{3,3}$	0.0035	0.0008	-0.0035	-0.0000	-0.0034	0.0000	0.0011	-0.0037	0.0033	0.0033	0.0036	0.0034	0.0034	0.0035	-0.0000	0.0033
	[12.5825]	[0.0032]	[-12.9494]	[-0.0000]	[-11.7893]	[0.0000]	[0.0002]	[-11.8544]	[12.3801]	[12.2436]	[12.3460]	[11.8341]	[12.5018]	[12.7701]	[-0.0000]	[12.1015]
A_1	0.3500	0.8178	0.4219	0.2584	0.2729	0.4538	0.7077	0.2849	0.3504	0.2747	0.2911	0.3340	0.2643	0.3206	0.3359	0.5181
	[22.5452]	[81.1842]	[20.8889]	[19.8571]	[20.4104]	[30.8470]	[61.9968]	[21.8299]	[19.9274]	[14.7010]	[21.5320]	[18.7879]	[16.9423]	[24.3199]	[22.9355]	[46.2015]
A_2	0.2603	0.1882	0.2529	0.3318	0.2494	0.2912	0.2590	0.2605	0.2642	0.2525	0.2767	0.2623	0.2704	0.2549	0.2465	0.2528
	[16.7437]	[16.6667]	[17.4033]	[19.2090]	[16.6432]	[15.5988]	[14.8741]	[17.1981]	[15.8140]	[15.6025]	[17.4513]	[15.8295]	[15.7396]	[14.6751]	[15.1470]	[16.9238]
A_3	0.3152	0.0844	0.2526	0.4145	0.3356	0.3033	0.2829	0.3399	0.2956	0.3034	0.3158	0.2929	0.3111	0.2938	0.3405	0.2706
	[19.7256]	[10.4001]	[17.7373]	[10.1469]	[21.9345]	[15.8910]	[14.2168]	[19.6893]	[18.4202]	[18.1029]	[18.6393]	[17.0637]	[18.0399]	[17.3355]	[16.7938]	[17.4146]
$B_{1,1}$	0.9427	0.7934	0.9150	0.9657	0.9634	0.9474	0.8076	0.9603	0.9391	0.9594	0.9568	0.9425	0.9656	0.9515	0.9533	0.8903
	[210.1620]	[3498.8957]	[137.5982]	[348.5225]	[311.4317]	[392.6591]	[1942.0523]	[287.4377]	[183.1192]	[175.9423]	[259.8678]	[157.8795]	[251.3334]	[281.5061]	[240.4076]	[145.0429]
$B_{2,2}$	0.9608	0.9817	0.9631	0.9449	0.9630	0.9558	0.9663	0.9606	0.9591	0.9616	0.9559	0.9584	0.9571	0.9613	0.9633	0.9630
	[236.0391]	[578.0862]	[261.2307]	[198.0115]	[249.8207]	[196.1223]	[259.3536]	[241.2347]	[212.5441]	[223.8041]	[208.2144]	[207.0664]	[203.9593]	[215.0648]	[234.2748]	[267.6662]
$B_{3,3}$	0.9452	0.9968	0.9599	0.9190	0.9401	0.9481	0.9583	0.9373	0.9520	0.9494	0.9450	0.9519	0.9469	0.9510	0.9376	0.9580
	[165.8104]	[1671.9791]	[236.6457]	[65.0249]	[160.0957]	[151.3784]	[168.1619]	[145.9701]	[184.9690]	[171.0815]	[159.9146]	[174.2307]	[162.6896]	[171.8329]	[126.8111]	[217.2194]

Table .6: BOA

η	$p(\eta)$	$\sigma_{\alpha=0.05}$ 0.0207	$\sigma_{\alpha=0.20}$ 0.0222	$\sigma_{\alpha=0.35}$ 0.0247	$\sigma_{\alpha=0.50}$ 0.0280	$\sigma_{\alpha=0.65}$ 0.0346	$\sigma_{\alpha=0.80}$ 0.0454	$\sigma_{\alpha=0.95}$ 0.0860
1	0.1586	32.7031	35.8843	41.1420	47.8915	61.9483	85.0088	176.8674
1.5	0.0668	53.7815	58.5676	66.5171	76.6619	97.8949	132.7219	272.1701
2	0.0227	75.0791	81.5019	92.2014	105.8278	134.4558	181.5152	371.6495
2.5	0.0062	96.5982	104.7021	118.1940	135.4323	171.6410	231.4129	475.5413
3	0.0013	118.3411	128.1710	144.4985	165.4201	209.4755	282.4841	583.9765
3.5	0.0002	140.3100	151.8998	171.1570	195.8639	248.0005	334.7287	697.1529
4	0.0000	162.5074	175.8915	198.1491	226.7212	287.1836	388.1560	815.3456

Table .7: BS

η	$p(\eta)$	$\sigma_{\alpha=0.05}$ 0.0063	$\sigma_{\alpha=0.20}$ 0.0084	$\sigma_{\alpha=0.35}$ 0.0100	$\sigma_{\alpha=0.50}$ 0.0118	$\sigma_{\alpha=0.65}$ 0.0147	$\sigma_{\alpha=0.80}$ 0.0183	$\sigma_{\alpha=0.95}$ 0.0268
1	0.1586	0.5451	1.2165	1.7333	2.3088	3.2758	4.4347	7.2574
1.5	0.0668	1.5587	2.5634	3.3388	4.2075	5.6633	7.4031	11.6547
2	0.0227	2.5723	3.9186	4.9579	6.1140	8.0682	10.3985	16.1075
2.5	0.0062	3.5910	5.2790	6.5796	8.0377	10.4888	13.4213	20.6272
3	0.0013	4.6147	6.6428	8.2149	9.9673	12.9252	16.4716	25.2049
3.5	0.0002	5.6385	8.0168	9.8530	11.9123	15.3853	19.5498	29.8403
4	0.0000	6.6659	9.3909	11.5047	13.8673	17.8621	22.6588	34.5463

Table .8: CITI

η	$p(\eta)$	$\sigma_{\alpha=0.05}$ 0.0210	$\sigma_{\alpha=0.20}$ 0.0225	$\sigma_{\alpha=0.35}$ 0.0237	$\sigma_{\alpha=0.50}$ 0.0255	$\sigma_{\alpha=0.65}$ 0.0287	$\sigma_{\alpha=0.80}$ 0.0357	$\sigma_{\alpha=0.95}$ 0.0498
1	0.1586	28.5317	31.1782	33.2771	36.4709	42.1788	54.9721	80.8747
1.5	0.0668	46.8404	50.8381	54.0027	58.8028	67.3807	86.6883	125.8568
2	0.0227	65.3423	70.7240	74.9698	81.4080	92.9847	118.9856	171.9671
2.5	0.0062	84.0396	90.8326	96.1809	104.3079	118.9247	151.8802	219.2463
3	0.0013	102.9386	111.1664	117.6389	127.5201	145.2678	185.3608	267.7146
3.5	0.0002	122.0423	131.7278	139.3508	151.0164	171.9740	219.4377	317.4082
4	0.0000	141.3477	152.5194	161.3459	174.8003	199.0710	254.1213	368.3549

Table .9: GS

η	$p(\eta)$	$\sigma_{\alpha=0.05}$ 0.0181	$\sigma_{\alpha=0.20}$ 0.0199	$\sigma_{\alpha=0.35}$ 0.0220	$\sigma_{\alpha=0.50}$ 0.0283	$\sigma_{\alpha=0.65}$ 0.0341	$\sigma_{\alpha=0.80}$ 0.0422	$\sigma_{\alpha=0.95}$ 0.0571
1	0.1586	0.0000	11.9832	13.6585	18.7479	23.5148	30.1794	42.7638
1.5	0.0668	17.7163	19.8001	22.3209	29.9997	37.1748	47.2416	66.2968
2	0.0227	24.9007	27.6952	31.0783	41.4002	51.0639	64.6668	90.5099
2.5	0.0062	32.1501	35.6693	39.9318	52.9674	65.2087	82.4629	115.4228
3	0.0013	39.4650	43.7231	48.8824	64.7012	79.5902	100.6376	141.0556
3.5	0.0002	46.8459	51.8575	57.9312	76.5926	94.2122	119.1990	167.4291
4	0.0000	54.2936	60.0733	67.0792	88.6696	109.0939	138.1627	194.5646

Table .10: JPM

		$\sigma_{\alpha=0.05}$	$\sigma_{\alpha=0.20}$	$\sigma_{\alpha=0.35}$	$\sigma_{\alpha=0.50}$	$\sigma_{\alpha=0.65}$	$\sigma_{\alpha=0.80}$	$\sigma_{\alpha=0.95}$
η	$p(\eta)$	0.0183	0.0205	0.0238	0.0282	0.0348	0.0458	0.0762
1	0.1586	26.1236	30.3231	36.8266	45.4195	58.3192	80.6012	144.3920
1.5	0.0668	43.5918	49.9137	59.6957	72.6650	92.1297	125.8037	222.5284
2	0.0227	61.2198	69.7066	82.8598	100.2713	126.5207	172.0378	303.7204
2.5	0.0062	79.0199	89.7037	106.3054	128.3126	161.5018	219.3269	388.0738
3	0.0013	96.9883	109.9071	130.0253	156.7189	197.1164	267.7376	475.6975
3.5	0.0002	115.1212	130.3191	154.0228	185.5510	233.3628	317.2729	566.7180
4	0.0000	133.4204	150.9416	178.3009	214.7870	270.2313	367.9385	661.2665

Table .11: LB

		$\sigma_{\alpha=0.05}$	$\sigma_{\alpha=0.20}$	$\sigma_{\alpha=0.35}$	$\sigma_{\alpha=0.50}$	$\sigma_{\alpha=0.65}$	$\sigma_{\alpha=0.80}$	$\sigma_{\alpha=0.95}$
η	$p(\eta)$	0.0153	0.0170	0.0200	0.0231	0.0303	0.0368	0.0553
1	0.1586	5.2570	6.0564	7.5798	9.1133	12.7370	16.0775	25.8031
1.5	0.0668	9.0150	10.2197	12.5136	14.8206	20.2872	25.3228	40.0313
2	0.0227	12.7993	14.4174	17.4972	20.5930	27.9442	34.7385	54.6557
2.5	0.0062	16.6179	18.6499	22.5310	26.4314	35.7260	44.3279	69.6887
3	0.0013	20.4671	22.9174	27.6157	32.3364	43.6193	54.0940	85.1518
3.5	0.0002	24.3435	27.2224	32.7516	38.3145	51.6397	64.0433	101.0455
4	0.0000	28.2470	31.5684	37.9393	44.3633	59.7768	74.1816	117.3818

Table .12: ML

		$\sigma_{\alpha=0.05}$	$\sigma_{\alpha=0.20}$	$\sigma_{\alpha=0.35}$	$\sigma_{\alpha=0.50}$	$\sigma_{\alpha=0.65}$	$\sigma_{\alpha=0.80}$	$\sigma_{\alpha=0.95}$
η	$p(\eta)$	0.0144	0.0164	0.0190	0.0221	0.0268	0.0373	0.0750
1	0.1586	7.3927	8.9716	10.9363	13.3747	17.0634	25.3325	56.7147
1.5	0.0668	12.8496	15.2093	18.1686	21.8381	27.3993	39.8679	87.4239
2	0.0227	18.3400	21.5090	25.4698	30.3949	37.8659	54.6757	119.3178
2.5	0.0062	23.8641	27.8591	32.8405	39.0532	48.4871	69.7669	152.4325
3	0.0013	29.4331	34.2592	40.2815	47.8086	59.2476	85.1460	186.8083
3.5	0.0002	35.0470	40.7098	47.7933	56.6605	70.1441	100.8134	222.4931
4	0.0000	40.6953	47.2112	55.3767	65.6102	81.2044	116.7745	259.5530

Table .13: MS

		$\sigma_{\alpha=0.05}$	$\sigma_{\alpha=0.20}$	$\sigma_{\alpha=0.35}$	$\sigma_{\alpha=0.50}$	$\sigma_{\alpha=0.65}$	$\sigma_{\alpha=0.80}$	$\sigma_{\alpha=0.95}$
η	$p(\eta)$	0.0163	0.0177	0.0198	0.0247	0.0318	0.0402	0.0540
1	0.1586	8.5237	9.6156	11.1593	14.8421	20.1939	26.6820	37.5091
1.5	0.0668	14.4819	16.1242	18.4424	23.9815	32.0469	41.8492	58.2318
2	0.0227	20.4865	22.6919	25.7982	33.2468	44.1041	57.3250	79.5154
2.5	0.0062	26.5377	29.3175	33.2273	42.6249	56.3466	73.1157	101.3837
3	0.0013	32.6358	36.0013	40.7306	52.1156	68.7854	89.2277	123.8596
3.5	0.0002	38.7849	42.7439	48.3088	61.7202	81.4300	105.6676	146.9439
4	0.0000	44.9922	49.5459	55.9626	71.4537	94.2642	122.4419	170.6528

Table .14: SG

		$\sigma_{\alpha=0.05}$	$\sigma_{\alpha=0.20}$	$\sigma_{\alpha=0.35}$	$\sigma_{\alpha=0.50}$	$\sigma_{\alpha=0.65}$	$\sigma_{\alpha=0.80}$	$\sigma_{\alpha=0.95}$
η	$p(\eta)$	0.0108	0.0119	0.0131	0.0145	0.0163	0.0189	0.0260
1	0.1586	8.6896	10.1533	11.9094	13.8448	16.3846	20.1114	30.2907
1.5	0.0668	16.2458	18.4330	21.0822	24.0012	27.8296	33.4280	48.7578
2	0.0227	23.8554	26.7955	30.3211	34.2211	39.3638	46.8709	67.4766
2.5	0.0062	31.4875	35.1850	39.6307	44.5266	50.9878	60.4473	86.4274
3	0.0013	39.1860	43.6320	48.9852	54.9138	62.7022	74.1543	105.6207
3.5	0.0002	46.8967	52.1330	58.4107	65.3660	74.5175	87.9914	125.0894
4	0.0000	54.6830	60.6649	67.9046	75.8836	86.4417	101.9600	144.7996

Table .15: BNP

		$\sigma_{\alpha=0.05}$	$\sigma_{\alpha=0.20}$	$\sigma_{\alpha=0.35}$	$\sigma_{\alpha=0.50}$	$\sigma_{\alpha=0.65}$	$\sigma_{\alpha=0.80}$	$\sigma_{\alpha=0.95}$
η	$p(\eta)$	0.0099	0.0106	0.0112	0.0119	0.0130	0.0148	0.0187
1	0.1586	15.0177	17.0099	18.7971	20.5850	23.9050	28.9842	40.0749
1.5	0.0668	29.0291	32.0073	34.6783	37.3668	42.3761	50.0361	66.7070
2	0.0227	43.1146	47.1186	50.7093	54.3001	60.9655	71.2264	93.5886
2.5	0.0062	57.2668	62.2666	66.7770	71.3055	79.7105	92.5578	120.7319
3	0.0013	71.4929	77.5488	82.9791	88.4091	98.5443	114.1015	148.1380
3.5	0.0002	85.7873	92.8501	99.2457	105.6408	117.5091	135.7871	175.8009
4	0.0000	100.1554	108.3042	115.6106	122.9282	136.6222	157.6152	203.7230

Table .16: DB

		$\sigma_{\alpha=0.05}$	$\sigma_{\alpha=0.20}$	$\sigma_{\alpha=0.35}$	$\sigma_{\alpha=0.50}$	$\sigma_{\alpha=0.65}$	$\sigma_{\alpha=0.80}$	$\sigma_{\alpha=0.95}$
η	$p(\eta)$	0.0070	0.0075	0.0082	0.0090	0.0098	0.0110	0.0134
1	0.1586	0.0000	0.0000	0.0000	0.0000	0.0000	13.4019	18.5260
1.5	0.0668	12.2912	13.9666	16.0248	18.5710	21.1919	24.9386	32.6015
2	0.0227	19.6373	21.8685	24.6092	27.9993	31.4884	36.5221	46.8105
2.5	0.0062	26.9835	29.7704	33.2075	37.4840	41.8851	48.1747	61.1013
3	0.0013	34.3549	37.7312	41.8782	47.0070	52.2850	59.8972	75.4661
3.5	0.0002	41.7749	45.7125	50.5488	56.5667	62.7834	71.6669	89.9622
4	0.0000	49.1949	53.7020	59.2832	66.1854	73.2879	83.5298	104.5467

Table .17: CS

		$\sigma_{\alpha=0.05}$	$\sigma_{\alpha=0.20}$	$\sigma_{\alpha=0.35}$	$\sigma_{\alpha=0.50}$	$\sigma_{\alpha=0.65}$	$\sigma_{\alpha=0.80}$	$\sigma_{\alpha=0.95}$
η	$p(\eta)$	0.0136	0.0150	0.0172	0.0195	0.0229	0.0269	0.0389
1	0.1586	8.2749	9.6197	11.6540	13.8389	17.0513	20.8538	32.4276
1.5	0.0668	14.5341	16.5615	19.6273	22.9176	27.7525	33.4689	50.9450
2	0.0227	20.8557	23.5532	27.6677	32.0855	38.5752	46.2745	69.8259
2.5	0.0062	27.2110	30.6119	35.7759	41.3435	49.5207	59.2422	89.0773
3	0.0013	33.6001	37.7182	43.9523	50.6924	60.5903	72.3801	108.7066
3.5	0.0002	40.0499	44.8723	52.1987	60.1330	71.7857	85.7124	128.7212
4	0.0000	46.5374	52.0769	60.5268	69.6664	83.1225	99.2134	149.1286

Table .18: UBS

η	$p(\eta)$	$\sigma_{\alpha=0.05}$ 0.0124	$\sigma_{\alpha=0.20}$ 0.0134	$\sigma_{\alpha=0.35}$ 0.0149	$\sigma_{\alpha=0.50}$ 0.0163	$\sigma_{\alpha=0.65}$ 0.0192	$\sigma_{\alpha=0.80}$ 0.0230	$\sigma_{\alpha=0.95}$ 0.0294
1	0.1586	9.5325	10.6766	12.5763	14.3341	17.8662	22.5342	30.5955
1.5	0.0668	17.0898	18.8120	21.6768	24.3264	29.6405	36.6636	48.8271
2	0.0227	24.7193	27.0157	30.8379	34.3969	41.5326	50.9536	67.3029
2.5	0.0062	32.3794	35.2750	40.0795	44.5463	53.5396	65.4060	86.0823
3	0.0013	40.0894	43.5764	49.3943	54.7751	65.6627	80.0245	105.1112
3.5	0.0002	47.8573	51.9459	58.7712	65.1041	77.9030	94.8266	124.4492
4	0.0000	55.6561	60.3736	68.2104	75.5167	90.2615	109.7971	144.0499

Table .19: BARC

η	$p(\eta)$	$\sigma_{\alpha=0.05}$ 0.0088	$\sigma_{\alpha=0.20}$ 0.0094	$\sigma_{\alpha=0.35}$ 0.0103	$\sigma_{\alpha=0.50}$ 0.0114	$\sigma_{\alpha=0.65}$ 0.0132	$\sigma_{\alpha=0.80}$ 0.0152	$\sigma_{\alpha=0.95}$ 0.0186
1	0.1586	9.0793	10.3792	12.3784	14.8478	18.6943	23.1703	30.7423
1.5	0.0668	18.6081	20.5521	23.5605	27.2884	33.0925	39.8189	51.1909
2	0.0227	28.2026	30.8166	34.8354	39.7971	47.5611	56.5984	71.8303
2.5	0.0062	37.8272	41.0917	46.1373	52.3948	62.1336	73.4941	92.6622
3	0.0013	47.4922	51.4466	57.5255	65.0292	76.8190	90.5065	113.6884
3.5	0.0002	57.2135	61.8250	68.9483	77.7860	91.5762	107.6621	134.9108
4	0.0000	66.9496	72.2711	80.4510	90.5755	106.4430	124.9643	156.3312

Table .20: HSBC

η	$p(\eta)$	$\sigma_{\alpha=0.05}$ 0.0136	$\sigma_{\alpha=0.20}$ 0.0150	$\sigma_{\alpha=0.35}$ 0.0179	$\sigma_{\alpha=0.50}$ 0.0203	$\sigma_{\alpha=0.65}$ 0.0227	$\sigma_{\alpha=0.80}$ 0.0278	$\sigma_{\alpha=0.95}$ 0.0466
1	0.1586	20.5801	23.7576	30.4072	36.0103	41.6315	53.4408	98.6934
1.5	0.0668	36.1350	40.8833	50.9033	59.3394	67.8220	85.5670	153.9037
2	0.0227	51.8031	58.1764	71.5818	82.9071	94.3082	118.1886	210.4330
2.5	0.0062	67.5560	75.5911	92.4443	106.7159	121.0933	151.2409	268.3055
3	0.0013	83.4250	93.1234	113.4922	130.7684	148.1806	184.7499	327.5148
3.5	0.0002	99.4222	110.7739	134.7272	155.0669	175.5736	218.7548	388.1364
4	0.0000	115.5058	128.5936	156.1646	179.6141	203.2757	253.1980	450.2007

Table .21: RBS

η	$p(\eta)$	$\sigma_{\alpha=0.05}$ 0.0111	$\sigma_{\alpha=0.20}$ 0.0122	$\sigma_{\alpha=0.35}$ 0.0130	$\sigma_{\alpha=0.50}$ 0.0141	$\sigma_{\alpha=0.65}$ 0.0156	$\sigma_{\alpha=0.80}$ 0.0176	$\sigma_{\alpha=0.95}$ 0.0219
1	0.1586	17.0341	20.0380	22.2071	24.9972	29.1690	34.3792	46.0806
1.5	0.0668	31.5986	36.1323	39.4049	43.6132	49.8983	57.6948	75.3085
2	0.0227	46.2820	52.3152	56.6834	62.3382	70.7817	81.2206	104.8566
2.5	0.0062	61.0223	68.6308	74.1215	81.1805	91.8171	104.9751	134.7283
3	0.0013	75.8533	85.0064	91.6559	100.2041	113.0055	128.9362	164.9395
3.5	0.0002	90.7716	101.5162	109.2725	119.3392	134.3661	153.1056	195.4966
4	0.0000	105.7516	118.1173	127.0630	138.5860	155.9230	177.4850	226.3885