# Measuring Option Implied Degree of Distress in the US Financial Sector Using the Entropy Principle[1]

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Abstract

We introduce a procedure to estimate time series of option implied Probabilities of Default (PoDs) for 19 major US financial institutions from 2002 to 2012. These PoDs are estimated as mass points of entropy based risk neutral densities and subsequently corrected for maturity dependence. The obtained time series are evaluated with regard to their consistency and predictive power and their properties are compared to Credit Default Swap Spreads (CDS). Moreover, we also derive an indicator for the systemic risk in the US financial sector. We find that the PoDs are superior to CDS in identifying the high risk banks prior to the Lehman crisis.

*Keywords:* Entropy Principle, Risk Neutral Density, Probability of Default, Financial Stability Indicator, Credit Default Swaps
*JEL classification:* C14, C32, G01, G21

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# 1 Introduction

Monitoring and assessing national and international financial system soundness in a timely manner is a wide and complex field of work. Vast research in finance has led to a great variety of non-mutually exclusive financial stability indicators based on different theoretical and empirical grounds (see e.g. IMF (2009)).

This paper derives a market based indicator by applying the so-called option implied Probability of Default (option iPoD) methodology to derive time series of option based financial stability measures together with the corresponding asset distributions. The approach was suggested in Capuano (2008) and numerically robustified as well as evaluated in Vilsmeier (2011). The framework uses the cross entropy function in order to estimate the option implied risk neutral densities (RNDs) and allows for a probability mass point in the RND at a value of zero for the underlying. This mass point can be interpreted as Probability of Default (PoD). As opposed to CDS- or bond based PoD estimation approaches, our methodology has the substantial advantage that it requires no assumptions for the recovery rate. Further, we do not need to assume any stochastic process for our risk neutral pricing model, which is the basis for approaches like Distance to Default and for the derivation of option based indicators like Implied Volatility. Using a non-parametric estimation procedure, our approach provides the entire option implied RND from the observed option prices and is highly flexible regarding the functional form of the implied distribution. Hence, unlike above mentioned approaches our procedure sets the stage for copula based-multivariate financial stability analyses with time varying RNDs and PoDs.

There exists a large literature on RND estimations, differing by the statistical methods applied to extract the RND from the observed option prices (for an extensive overview see Jackwerth (2004)). So far, though, RND estimates have not been applied to systematically evaluate a specific firm's soundness over a longer period of time; instead they were used for short term applications like evaluations of option pricing models (e.g. Figlewski (2008)) or testing market expectations around certain events (e.g. Capuano (2008); Melick and Thomas (1997)). Possible reasons are that RNDs do not provide a unique and easy to interpret stability measure and that their estimations are often plagued by limited sets of strikes, noisiness and maturity dependence. Moreover, one faces high computational efforts, and numerical instabilities of the statistical approach can make it difficult to obtain consistent RND estimates over long periods of time. However, our empirical implementation of the option iPoD framework has the great advantage that it overcomes these described problems.

We estimate RND- and, hence, PoD time series for 19 of the largest US banks and financial institutions. The considered sample spans over eleven years from February 2002 to February 2012, which leaves us with a unique opportunity to evaluate our indicator's properties and forecasting abilities in an environment of huge macroeconomic distress and to compare it with more resilient periods as from 2004 to 2007.

In order to obtain the RND/PoD estimates, we use alternately five-, six-, and seven month call option contracts. Subsequently, we remove the maturity dependence inherent in the original time series by applying a non-parametric quantile regression approach to the pooled PoDs. The time series of the maturity corrected PoDs are evaluated with regard to their consistency and predictive power and their properties are compared to Credit Default Swap Spreads (CDS). In this context, we derive an indicator for the systemic risk prevailing in the US financial sector by applying a Principal Component Analysis (PCA) to the firm specific PoDs. Thereby, we isolate the systematic components from the idiosyncratic risks of each bank. Further, for a more clear interpretation of the respective levels of CDS and PoDs, we check and compare the indicators' properties in relation to the systemic risk.

Our results give evidence for the predictive/signalling power of the option iPoD methodology with regard to crises periods and for its ability to identify financially vulnerable institutions in a timely manner. We find that CDS and the option implied PoDs exhibit very similar dynamics, but PoDs being superior to CDS in identifying the high risk banks prior to the Lehman crisis in September 2008.

Our paper contributes to the literature in several ways. We are the very first to empirically apply the option iPoD framework to derive time series of RNDs/PoDs and, hence, are the first that give a comprehensive empirical evaluation of that methodology. It is demonstrated how the option iPoD methodology can be empirically implemented in order to get consistent, smooth and maturity corrected PoDs. This was achieved by the appropriate choice of liquidity weights and the use of a suitable maturity cycle of option contracts. With the estimated PoDs we provide firm individual financial risk indicators, and in addition we use them to derive an indicator for the systemic risk of the overall US financial sector. Moreover, we give empirical evidence for the high informational content of the option iPoD framework, which is shown to be superior to the informational content of CDS. We stress that this is due to the fact that for CDS differing and unknown recovery rates over firms and periods of time complicate the interpretation of the levels of CDS, while iPoDs can be interpreted directly as risk neutral default probabilities as they are equity based. This allows for a consistent comparison of our PoD levels irrespective of the considered financial institutions and time. Finally, our approach provides a sound basis for multivariate - copula based - financial risk analyses, as the framework provides time series for firm specific PoDs jointly with the entire corresponding asset distributions.

The remainder of the paper is structured as follows. Section 2 describes the underlying methodology of our empirical framework. This comprises mainly the entropy based estimation of the RND and the PoD. This is followed by the description of the data used in our analysis. Section 4 explains the empirical implementation of our approach on how to obtain a stable and smooth time series of PoD- and RND estimates. The estimation results as well as the comparisons with the CDS are presented in section 5. Finally, section 6 provides concluding remarks and offers prospects for further research.

# 2 Methodology

The statistical framework used in this paper was originally suggested by Capuano (2008). In Vilsmeier (2011) a more stable objective function for the RND estimation and an alternative PoD determination procedure were proposed. In this paper, we apply this version.

The idea of the framework is to allow for a probability mass point for a value of zero of the stock $S$ in the estimation of a stock option implied RND. A RND is a density function $f(S_T)$ that describes the investors' expectations regarding the value of the underlying at time to maturity $T$, implied by the observed option prices for different strikes. In order to obtain a RND one uses the continuous risk neutral pricing formula for a call option

$$C_0^{K_i} = e^{-rT} \int_{S_T=K_i}^{\infty} (S_T - K_i) f(S_T) dS_T, \quad i = 1 \ldots B. \tag{1}$$

The formula should be solved with respect to the unknown density $f(S_T)$ for given option prices $C_0^{K_i}$ at different strikes $K_i$. Equation (1) states that the today's observed option prices must be equal to the discounted expectation of the inner values under risk neutral probability measure (risk neutral pricing), where $r$ denotes the annualized risk free rate and $T$ the time to maturity of the option (measured in years). The number of observable option prices for different strikes $K$ is denoted by $B$ whereat the current stock price $S_0$ is included as an option with strike $K_1 = 0$. One faces an underdetermined estimation problem, as we do not have an infinite set of strikes (Breeden and Litzenberger (1978)). There are different statistical approaches to determine a unique density $f^*(S_T)$ out of the infinite many that are compatible with the observed prices (see e.g. Jackwerth (2004)). The approach chosen in this paper is to minimize the so-called cross entropy function

$$CE[f(S_T), f^0(S_T)] = \int_0^\infty f(S_T) \log \frac{f(S_T)}{f^0(S_T)} dS_T, \tag{2}$$

under restrictions imposed on the moments of $f(S_T)$ given by the system of equations (1) and where $f^0(S_T)$ denotes some prior distribution.[4] Thereby, the so-called entropic distance of $f(S_T)$ to some prior density $f^0(S_T)$ is minimized (see e.g. Cover and Thomas (2006)). We use the cross entropy concept since the prior density, $f^0(S_T)$, is necessary for the determination of the PoD.

If one assumes that a stock price of zero implies default, then a probability mass point for $S_T = 0$ in the RND could be interpreted as the investors' expectation regarding a firm's default between now and time to maturity $T$ of the option. Given our continuous estimation framework, such a mass point cannot be estimated as a 'jump' in the density at $S_T = 0$. Instead, we extend the domain of the RND for $S_T$ such that all realisations within this additional interval of values imply a future stock price of zero. In this way the PoD is not estimated as a mass point but as the integral over the density assigned to a certain sub-domain of the RND. The additional interval of values is obtained by shifting the domain for the future stock value $S_T$ upwards by some constant $D$, and estimating $f(V_T)$, with $V_T = S_T + D$. For the payoff of the option in $T$ (the inner value) now holds: $C_T = \max(V_T - D - K; 0)$, and any value $V_T \leq D$ will imply an inner value of zero for arbitrary $K$.[5] The integral of $f(V_T)$ over the interval $[0; D]$ will yield our PoD estimate.

A theoretical interpretation to the described PoD estimation procedure is possible, if one assumes that the so-called structural approach of Merton (1974) applies to a firm's balance sheet. In the structural approach a firm's value of assets is given by the value of its debt plus the value of its equity. The firm defaults if the value of assets does not cover the value of debt. Hence, in the PoD mechanism $V_T$ can be interpreted as value of assets, $S_T$ as the value of equity and $D$ as the value of debt.[6]

Using numerical experiments, in Vilsmeier (2011) it was found that for arbitrary reasonable RND forms and PoD levels the procedure can perfectly estimate a probability mass point for $S_T = 0$ given that the constant $D$ lies within the interval $[0; 20]$. As an exact rule for the

[4]The cross entropy function is based on the entropy concept. For a more thorough discussion about that concept see Shannon (1948) and Jaynes (1957).

[5]Note that before extending the domain of $S_T$ only $S_T = 0$ implied an inner value of zero for arbitrary $K$.

[6]Note that the assumptions of the structural approach have no implications for the PoD estimation. Any event that will lead in the investors' expectation to $S_T = 0$ will increase the PoD.

determination of the optimal $D$ has not yet been detected, we average the PoDs obtained for RND estimates with $D$s ranging from 0 to 20. The optimal RND is then identified as the one that provides the PoD closest to the average PoD ('averaging approach'). Despite its quite ad hoc nature, in numerical experiments this procedure yielded highly accurate estimates covering a great number of RND/PoD specifications. As will be seen in section 5 the procedure produces also highly plausible results if applied to real option data.[7]. For the RND estimation we use the following system of equations, which we express in terms of $V_T$ and $D$:

$$CE[f(V_T), f^0(V_T)] = \int_0^\infty f(V_T) \log \frac{f(V_T)}{f^0(V_T)} dV_T \tag{3}$$

$$C_0^{K_i} = e^{-rT} \int_{V_T=D+K_i}^\infty (V_T - D - K_i) f(V_T) dV_T, \quad i = 1 \dots B \tag{4}$$

$$\int_{V_T=0}^\infty f(V_T) dV_T = 1. \tag{5}$$

(3) is the cross entropy function for $f(V_T)$ with regard to some prior distribution $f^0(V_T)$. (4) denotes the continuous risk neutral pricing formula and (5) is an additional moment condition that ensures that the density integrates up to one.

Combining (3) to (5), the estimation setup can be written using the Lagrange multiplier approach:

$$\begin{aligned} L = & \int_{V_T=0}^\infty f(V_T) \left[ \log \frac{f(V_T)}{f^0(V_T)} \right] dV_T + \lambda_0 \left[ 1 - \int_{V_T=0}^\infty f(V_T) dV_T \right] \\ & + \sum_{i=1}^B \lambda_i \left[ C_0^{K_i} - e^{-rT} \int_{V_T=D+K_i}^\infty (V_T - D - K_i) f(V_T) dV_T \right]. \end{aligned} \tag{6}$$

Optimizing (6) with respect to $f(V_T)$ yields (see e.g. Cover and Thomas (2006)):

$$f^*(V_T) = \frac{1}{\mu(\lambda)} f^0(V_T) \exp \left[ \sum_{i=1}^B \lambda_i e^{-rT} \mathbf{1}_{V_T > D+K_i} (V_T - D - K_i) \right], \tag{7}$$

[7] The intuition behind the ad hoc procedure is explained in Vilsmeier (2011)

with

$$\mu(\lambda) = \exp(1-\lambda_0) = \exp(-\lambda_0') = \int_{V_T=0}^{\infty} f^0(V_T) \exp\left[\sum_{i=1}^{B} \lambda_i e^{-rT} \mathbf{1}_{V_T > D+K_i}(V_T - D - K_i)\right] dV_T. \quad (8)$$

We see from (7) that the optimal solution will be in the family of exponential distributions. Hence, the estimation procedure is highly flexible regarding the underlying shape of the RNDs and is able to approximate almost arbitrary functional forms if we have enough option prices. Further, the estimated PoD will be equal to $\int_0^D \frac{f^0(V_T)}{\mu(\lambda)}$ as the expression in the exponential function will be equal to $0$ for all $V_T \leq D$. That means that the estimated PoD and the shape of the RND interact, as the Lagrange multipliers also determine the shape of the RND.

If we assume some value for $D$, we obtain our RND and PoD if we are able to determine the $\lambda_i$ in (7). This could be achieved if one replaces $f(V_T)$ in the Lagrangian by (7), and optimizes regarding the $\lambda_i$. The resulting system of equations could be solved using e.g. a multivariate Newton-Raphson algorithm. The search for the roots, though, is numerically very unstable due to near singularities of the involved Jacobian for large domains of the $\lambda_i$. Hence, in Vilsmeier (2011), following the suggestions in Alhassid et al. (1978) and Agmon et al. (1979), an objective function for the $\lambda_i$ was derived that yields efficient and numerically stable optimizations. The derivation is based on the finding that a function can be defined such that for any trial set of parameters $\lambda^{Tr}$ it provides a theoretical lower bound to the value of the cross entropy of the optimal density. This function has its minimum for the optimal set of $\lambda$s.

If one assumes some finite maximum and minimum value, $V_{max}$ and $V_{min}$, for the value of assets (per share) in the RND domain[8] and a uniform prior, one can solve the integrals

[8]The value of $V_{max}$ should be large (e.g. ten times the current stock price) but can be arbitrarily chosen as it does not significantly influence the estimates. $V_{min}$ denotes the minimal possible realisation for $V_T$ and is set equal to zero in our applications.

involved in the objective function analytically and obtains:

$$
\begin{aligned}
F = {} & \log\left(\frac{1}{V_{max}-V_{min}}\right) + \log\Bigg\{\exp\left(-\sum_{i=1}^{B} w_i\lambda_i C_0^{K_i}\right)(D-V_{min}) \\
& -\sum_{i=1}^{B-1}\left[\frac{\exp\left(\sum_{j=1}^{i} w_j\lambda_j(e^{-rT}(K_i-K_j)-C_0^{K_j})-\sum_{k=i+1}^{B} w_k\lambda_k C_0^{K_k}\right)}{e^{-rT}(\sum_{j=1}^{i} w_j\lambda_j)}\right. \\
& \qquad \left. -\frac{\exp\left(\sum_{j=1}^{i} w_j\lambda_j(e^{-rT}(K_{i+1}-K_j)-C_0^{K_j})-\sum_{k=i+1}^{B} w_k\lambda_k C_0^{K_k}\right)}{e^{-rT}(\sum_{j=1}^{i} w_j\lambda_j)}\right] \\
& -\left[\frac{\exp\left(\sum_{j=1}^{B} w_j\lambda_j(e^{-rT}(K_B-K_j)-C_0^{K_j})\right)-\exp\left(\sum_{j=1}^{B} w_j\lambda_j(e^{-rT}(V_{max}-D-K_j)-C_0^{K_j})\right)}{e^{-rT}(\sum_{j=1}^{B} w_j\lambda_j)}\right]\Bigg\},
\end{aligned} \tag{9}
$$

where $w_i$ denotes weights that are pre-multiplied to the Lagrange multiplier. The weights will ensure that more liquid option contracts (measured in our approach in terms of open interest) have to be met more closely by the estimated RND. The assignment of the liquidity weights is very important in order to obtain timely consistent and smooth PoD estimates. This issue will be addressed in section 4. The minimization of (9) is numerically highly stable and can be computed in a fast manner, which is prerequisite for our applications as we had to estimate in total about one million RNDs based on options that provide up to 40 strikes a day.

# 3 Data

Our option and stock data sample comprises 19 US banks and financial institutions and ranges from February 6, 2002 to February 24, 2012. Hence, the late consequences of the early 2000s recession, the first financial turmoils in mid-2007, the world financial crisis of 2008/2009 as well as the repercussions of the European sovereign debt crisis of 2011/2012 are included in our data set. Regarding the level and variance in the degree of financial distress, this data sample provides us with a unique opportunity to evaluate our indicator's properties over a highly diversified period of time.

Among the 19 covered financial institutions there are 14 banks, namely: Goldman Sachs (GS), Wells Fargo (WFC), Citigroup (C), Bank of America (BAC), JPMorgan Chase (JPM), Morgan Stanley (MS), PNC Bank (PNC), State Street (STT), Bank of New York Mellon (BK), Lehman Brothers (LEH), Bear Stearns (BSC), Wachovia (WB), Merill Lynch (MER) and Washington Mutual (WM).[9] This data set comprises the past and present largest US banks. In addition to the mentioned 14 banks, our sample includes 5 non-banking financial entities with great relevance for the overall US financial sector: The American International Group (AIG), Countrywide (CFC), MBIA (MBI), Blackstone (BX) and Blackrock (BLK).

Our data set covers not only a varied time period but also includes a quite heterogeneous sample of financial institutions. Some have performed quite well during the recent financial crisis, some others depended on governmental financial aid during the turmoils and still others went bankrupt or were taken over. Thus, our sample can be viewed as an appropriate proxy for the US financial sector and leaves us with a substantial informational input for our empirical analysis.

The daily equity option, stock and their related data of the above mentioned financial institutions were obtained from the New York Stock Exchange (NYSE) via the data provider Stricknet. The extraction of the relevant information from our vast data set is a quite challenging and complex task, due to option market inherent complexities, major shortcomings of the old stock option symbology (before February 2010) and due to changes in the option symbolic system in February 2010.[10]

As a risk free interest rate we used the 3-month Treasury Bill secondary market rate obtained from the FRED data base. The CDS spread data were obtained from Markit Group and range from February 6, 2002 to January 18, 2012. The sample covers the same institutions as the stock and option data, except for BK, BX and BLK. Due to enhanced data availability, we extracted 5-year CDS under the credit event of modified restructuring[11].

# 4 Empirical Implementation

There are important issues that have to be taken into account in order to be able to estimate smooth and timely consistent RND time series. Some of these will be briefly sketched in this section.

[9] We are well aware of the fact that a distinctive classification of the the financial entities is subjected to certain inaccuracies due to the complexity of the underlying business portfolios.

[10] For the sake of brevity we do not address this issue further. However, explanations concerning our data filtering procedure are available upon request.

[11] Under this contract clause, restructuring of debt is still defined as a credit event but deliverable obligations are limited to bonds with maturity of less than 30 months after a restructuring.

The first issue concerns the so-called maturity dependence of RND estimates. That is, when estimating RNDs for subsequent days using option contracts with the same expiry date, RNDs closer to the expiry date will exhibit ceteris paribus less uncertainty regarding the future value of the underlying. The problem arises because traded option contracts exist only for a few expiry dates within a year, such that one cannot extract time series of RNDs with constant time to maturity. To solve this problem we introduce in the following a regression based procedure to remove the maturity effects from the moments and PoDs of the estimated RNDs. For our procedure to work, though, we need to keep the maturity effect between the estimated RNDs as small as possible. Very similar time to maturity would be obtained if one constantly uses option contracts that expire in the subsequent month (as such a contract always exists). However, this approach has the serious drawback that the derived PoDs would indicate the probability of a firm's default within the next few weeks only, and the obtained results would be very erratic as only very imminent risks significantly change investors' expectations. Consequently, one wishes for a risk evaluation over a longer time period. Option contracts with longer time to maturity (e.g. 6 month) are not newly initiated at each month, though. Instead, different firms have different cycles within they initiate contracts with longer time to maturity than one month.

Taking into account the trade-off between maturity dependence and long term risk evaluation, we identified and applied three different 'maturity cycles' for our examined companies and allocated institutions with the same maturity scheme into one group. Hence, in our estimation implementation we considered three sub-samples of financial institutions. The first group consists of GS, WFC, MS, BLK, BK, LEH, BSC, WB, MER, CFC and WM with, starting in January, a cycle of six-, five- and seven month maturity (i.e. seven month contracts are initiated in March, June, September and December), alternating throughout the years. The second group uses a five-, seven- and six month maturity scheme and covers C, JPM and BX. Finally, the third group comprises BAC, AIG, MBI, PNC and STT and follows a seven-, six- and five month time to maturity cycle. Thereby, over the entire considered time period of 2583 days for which we estimated the RNDs, we obtain repeatedly RNDs with the same time to maturity. This is the prerequisite for our maturity dependence adjustment procedure to work.

The basic idea of our regression based maturity correction approach is quite simple. We start by pooling our PoDs over periods of time and firms, and assign to each PoD estimate the time to maturity of the options that was used to estimate the RND. Then we regress the PoDs on the respective time to maturity. As all times to maturity run repeatedly from 130 days to 220 days, we have for each of the time to maturities several PoD estimates such that the regression based approach should yield rough approximations of the true maturity effects. In order to admit for non-linear maturity effects as well as for different effects for different quantiles of the PoD distribution we apply a non-parametric quantile regression approach. More precisely, we use the methodology of additive quantile regressions (Hastie and Tibshirani (1986); Hastie and Tibshirani (1990)) in which the usual predictor of the quantile regression is augmented with additive non-parametric terms, and smoothing restrictions are imposed onto the fitted function. As smoothing restriction we apply the method of total variation regularization as suggested in Koenker et al. (1994).[12] Further, we restrict our fitted function to have a positive slope, as we expect that a higher time to maturity leads on average to a higher PoD. Figure 7 (Appendix) exemplarily depicts for each time to maturity the 40%- and 90%-PoD quantiles, as well as the respective fitted functions for each quantile. In order to carry out the maturity correction, we obtain the fitted PoDs for each time to maturity and different quantiles (in 5% steps), and calculate the difference between the fitted values of the highest time to maturity and the respective lower time to maturities for each quantile. The obtained differences are our correction factors for the estimated PoDs. The size of the correction factor applied to a specific PoD depends on how large the assigned time to maturity is and to which quantile the respective PoD belongs. After the correction all PoDs have a theoretical time to maturity of 220 days that is the maximum possible time to maturity that we have in our sample.[13] Figure 8 (Appendix) shows examplary the effects of our maturity correction procedure on the original PoD time series of Lehman Brothers. We can state that the maturity correction changes nothing regarding the dynamics of the time series. PoDs are only systematically higher, which is what we expect if time to maturity increases.

A further important issue that we detected in the estimation of our RND time series is the use of adequate liquidity weights in the optimization procedure as shown in our objective function (9). These weights ensure that more liquid option contracts, which presumably exhibit more information about the future value of the underlying (prices with less noise), are met more closely by our estimated RNDs than illiquid contracts. The weights are calculated by dividing open interest (contracts traded in the past and not exercised or evened up yet) for a specific strike by the sum of open interest over all available strikes for a firm's stock option. We found that the use of liquidity weights based on open interest leads to much smoother and more consistent time series than the use of trading volume, as often suggested in the literature. One reason might be that crucial market information are discarded if the

[12]The methodology is available in the statistical software R using the 'quanteg' package.

[13]The correction process could also be applied to different moments of the RNDs in order to obtain maturity corrected densities.

sample is weighted by trading volume. As the currently observed price arises as a result of current and past trading, a contemporaneous trading volume of zero does not necessarily imply such a contract is illiquid and has no information about the investors' expectations. Quite the contrary, if there is no trading today but there was high trading in the past (measured in open interest), this means the contract is liquid but the investors' expectations did not change with respect to the previous day(s).

Finally, we have to set some model parameters before we can carry out the RND estimations. The framework described in section 2 is designed such that we can set global parameters which are used for the RND estimations for all institutions and all periods in order to be able to estimate such a large number of RNDs. As pointed out in Vilsmeier (2011) the level of $D$, i.e. our debt value, does not influence our estimation results but only the length of the interval $[V_{min}; D]$. This implies that no matter how large we set $D$, if $V_{min}$ is always $D$ minus some constant (e.g. 10), the obtained results are exactly the same. Knowing this, we set our $V_{min} = 0$ and $D$ takes integer values 0 to 20 in the averaging approach. For $V_{max}$, we choose $V_{max} = 850$ that will be large enough for the asset value domain of all banks and for all time periods.

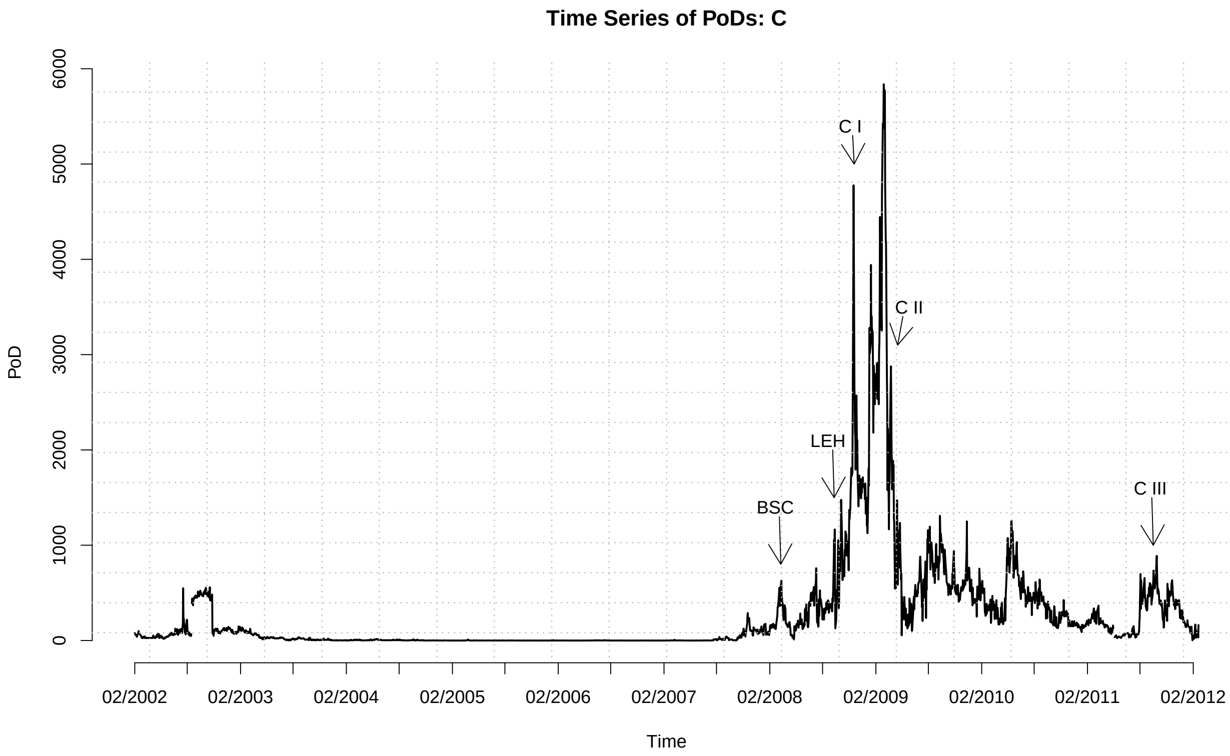
# 5 Results

This section will show that the empirical implementation of our estimation approach yields consistent and plausible PoD estimates. We compare their performance to established indicators like CDS and show that our iPoDs are better than CDS in identifying high risk institutions prior to incisive events.

## 5.1 Time Series of option iPoDs

In Figure 1 we see an example for an estimated time series of maturity corrected PoDs, namely for Citigroup. The time series covers the whole sample size running from February 2002 to February 2012 and displays some typical dynamics that one can find in the PoD time series of all institutes in our sample (see Figure 9 (Appendix) for a complete overview of PoDs for all institutions). PoD levels are elevated in the aftermath of the 2001 recession, followed by a very calm period with low PoDs until mid-2007. Starting with July 2007, PoDs increase continuously until mid-2009 in the course of the US subprime crisis. The bankruptcies of Bear Stearns (BSC) and Lehman Brothers (LEH) led to sharp inclines (see highlights in Figure 1) but strongly elevated risk is already displayed in advance of these events. In mid-

**Figure 1:** Time Series of maturity corrected PoDs in basis points for Citigroup from February 2002 to February 2012




*Note*: C I indicates the governmental rescue of Citigroup on November 23, 2008, C II denotes Citigroup's large restructuring measures on April 22, 2009 and C III labels the downgrade of Citigroup by Moody's on September 21, 2011. BSC and LEH denote the collapse of Bear Stearns on March 16, 2008 and the Lehman Brothers bankruptcy on September 15, 2008, respectively.

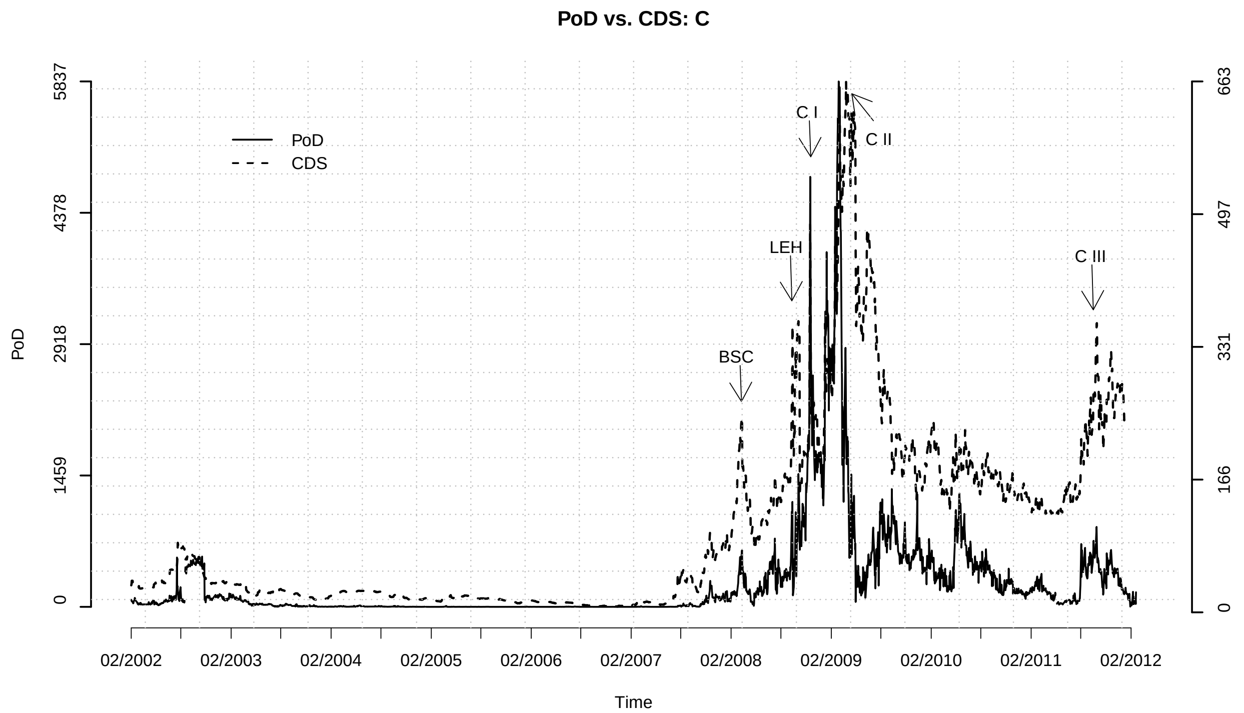
2009, PoDs return to pre-LEH period levels and in end-2010/beginning-2011 even to levels of the pre-BSC period. In August 2011 PoDs begin to increase again to pre-LEH levels as a consequence of the European sovereign debt crisis.

Firm specific events for Citigroup are highlighted in Figure 1 with C I, C II and C III. C I indicates the date when Citigroup was rescued by the US government on November 23, 2008, C II indicates the date when large restructuring of the firm was decided at a general meeting on April 22, 2009, and C III the date when Citigroup was downgraded by Moody's September 21, 2011. For C I and C III we see that the PoDs already signalled very high risks in advance of these events, with levels of around 1800 basis points (BP) for C I and 800 BP for C III. With regard to C II, the decisions seemed to be expected (as PoDs decreased some days before) and once they were actually made led to a sharp decline in investors' risk perception. Added together, we see that the PoD time series are able to signal risks concerning the entire financial sector (systemic risk) as well as firm specific (idiosyncratic) risks in a timely manner.

To check our indicator's predictive power in comparison to other existing indicators, we compare our PoD time series to 5-year CDS since they are a very commonly used measure to derive (risk neutral) probabilities of default for firms and countries. We consider it worthwhile to examine the performances of our equity based default probabilities to the debt based implied default risks of CDS.

In Figure 2, 5-year CDS for Citigroup are plotted against our PoD time series using two different scales. It is obvious that both indicators exhibit very similar dynamics, which is true for the time series of all considered institutions (see Figure 3, and Figures 9 and 10 in the Appendix). Table 1 (Appendix) shows the Pearson and Spearman correlations between CDS

**Figure 2:** Time series of maturity corrected PoDs versus time series of 5-year CDS in basis points for Citigroup from February 2002 to February 2012, using two different scales




*Note*: C I indicates the governmental rescue of Citigroup on November 23, 2008, C II denotes Citigroup's large restructuring measures on April 22, 2009 and C III labels the downgrade of Citigroup by Moody's on September 21, 2011. BSC and LEH denote the collapse of Bear Stearns on March 16, 2008 and the Lehman Brothers bankruptcy on September 15, 2008, respectively.

and the maturity corrected PoDs for the different financial institutions. Pearson correlations are mostly around 70% whereas Spearman rank correlations are mostly above 80%. The size of the correlations is extremely high, taking into account that CDS levels imply a default evaluation over five years[14] while our PoDs describe the possibility of default over six month on average.

A different picture arises if we compare the levels of the PoDs and the CDS. These differ considerably for all considered institutes, most strikingly in high distress times. Exemplarily, this feature is highlighted in Figure 3, in which the PoD and CDS time series for Lehman Brothers are plotted at the same scale. At the time of LEH's bankruptcy, PoD values rose to 2500 BP whereas CDS values rose only to 700 BP. For other banks the differences are even more severe (e.g. see Figure 2).

There is an obvious reason for these differences. In contrast to our PoD estimates, CDS cannot be directly interpreted as probabilities of default, since derivatives on debt based securities are a function of the recovery rate. Given a recovery rate unequal to zero, a CDS spread implies a probability of default of a multiple of its amount.[15] This fact severely complicates the assessment of a firm's resilience based on CDS, since recovery rates may vary across time and firms (e.g. that means, an equal CDS level for two firms can imply two totally different probabilities of default). Here we stress the great advantage of the equity based PoD estimates for which larger indicator values always imply higher risk, no matter if comparisons are made over time, firms or both.[16]

Taking into account the different interpretations of CDS and PoD levels, in the following we evaluate the levels separately for each respective indicator. That is, we compare the indicators only regarding their signalling power of high risk periods and high risk institutions. To do so, it is important to know what can be regarded as a high/low value for the respective indicator. From Table 2 (Appendix) we see that before the crisis (chosen start date for crisis: July 2007) the average PoDs range from 2 BP for WFC to 29 BP for MS and average CDS from 14 BP for BAC to 60 BP for MBI.[17] The average values after July 2007 range for PoDs from 61 BP for GS to 1135 BP for MBI and for CDS from 89 BP for PNC to 1162 BP for MBI. Knowing this, we can now assess that the PoDs' observed maximum values for LEH of 2500 BP and for C of even 5800 BP are extraordinarily high. In contrary, the maximal values of CDS for LEH of 700 BP and for C of 600 BP are only about half as high as the average CDS value for MBI after the crisis. Given LEH and C faced maximum financial distress at

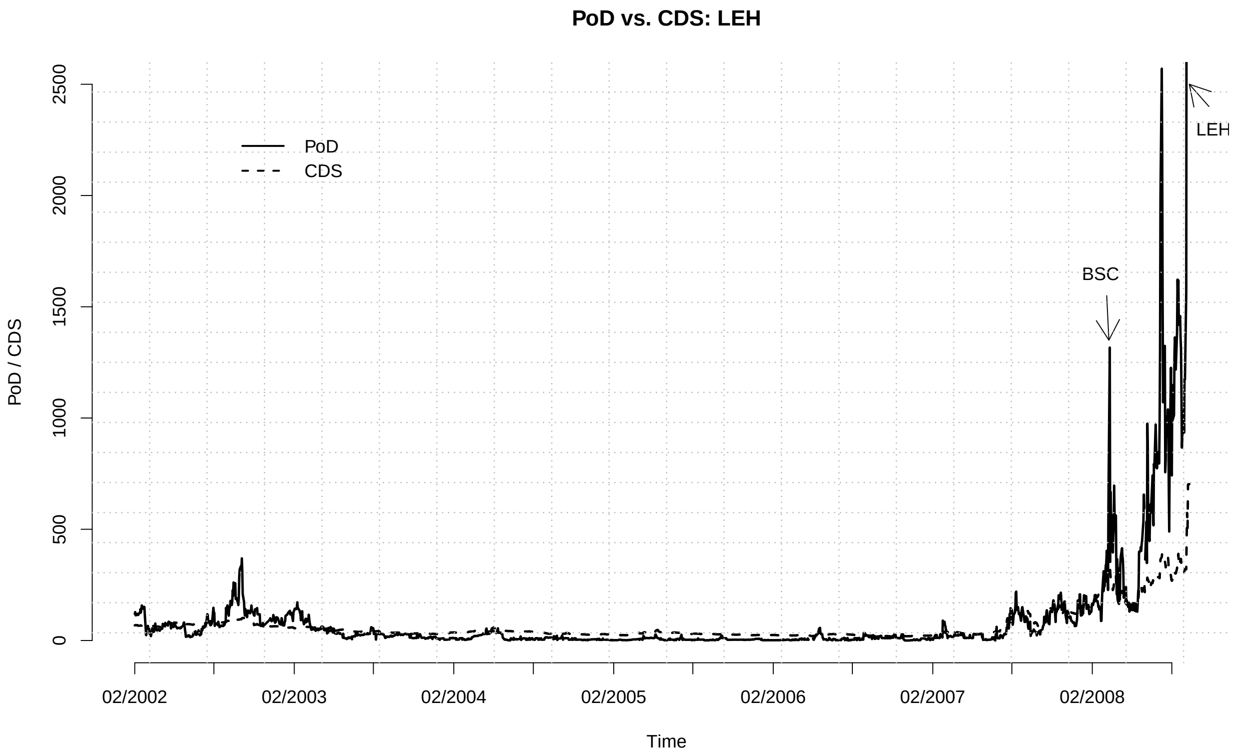
[14]More precisely the CDS-levels exhibit information about the average yearly Probability of Default over the next 5 years.

[15]In more resilient periods, however, CDS levels are in fact higher than our PoD levels. Here the effect of differing maturities comes into play which dominates the recovery rate effect.

[16]Counterparty risk as well as government interventions (too-big-to-fail hypothesis) also drive a wedge between PoD and CDS levels as they distort CDS spreads downwards (see Schweighard and Tsesmelidakis (2012)).

[17]Only taking into account those banks for which CDS and PoDs are available.

**Figure 3:** Time Series of maturity corrected PoDs versus time series of 5-year CDS in basis points for Lehman Brothers from February 2002 to September 2008, using one scale




*Note*: BSC and LEH denote the collapse of Bear Stearns on March 16, 2008 and the Lehman Brothers bankruptcy on September 15, 2008, respectively.

time of the respective maximum values, we obtain a first indication that CDS levels exhibit less signalling power as the levels of the option iPoDs. One possible reason for the weak signals of CDS levels might be differing assumed recovery rates for the different firms.[18]

In order to examine more thoroughly the risk levels indicated by CDS and PoDs, we next apply a 'relative risk analysis'. That is, we examine how large the level of a specific bank's indicator is relative to the indicator levels of the other banks in the system. To do so, we derive in the next section a proxy for the systemic risk in the US financial sector.

## 5.2 Systemic Risk Measure

We derive a systematic measure of financial risk, that is based on separating the common dynamic of all firms' indicators from the individual indicator time series. This takes into account that all banks display historically high indicator levels during crises periods and low

[18] Other reasons might be implied government guarantees or liquidity issues.

levels in boom periods. Hence, we interpret this measure as a proxy for the systemic risk in the overall US financial sector. We later use this proxy to identify especially risky banks in relation to the systemic risk.

Given the strong similarities in the dynamics of our PoD series (see Figure 9 in the Appendix), there is strong evidence for some latent factor predominantly driving the pattern of our dataset. We interpret this unobservable joint factor as systemic or financial sector risk. To segregate the systematic risk of our PoD/CDS data from the banks' individual idiosyncratic risks we apply a principal component analysis (PCA) to our indicator time series and regard the first principal component (PC) as a proxy for the overall financial sector risk. The first PC represents that joint factor which mainly causes the correlation between the variables and likewise explains the largest part of the variation in the dataset and is therefore regarded as the driving force behind the common pattern underlying our data.

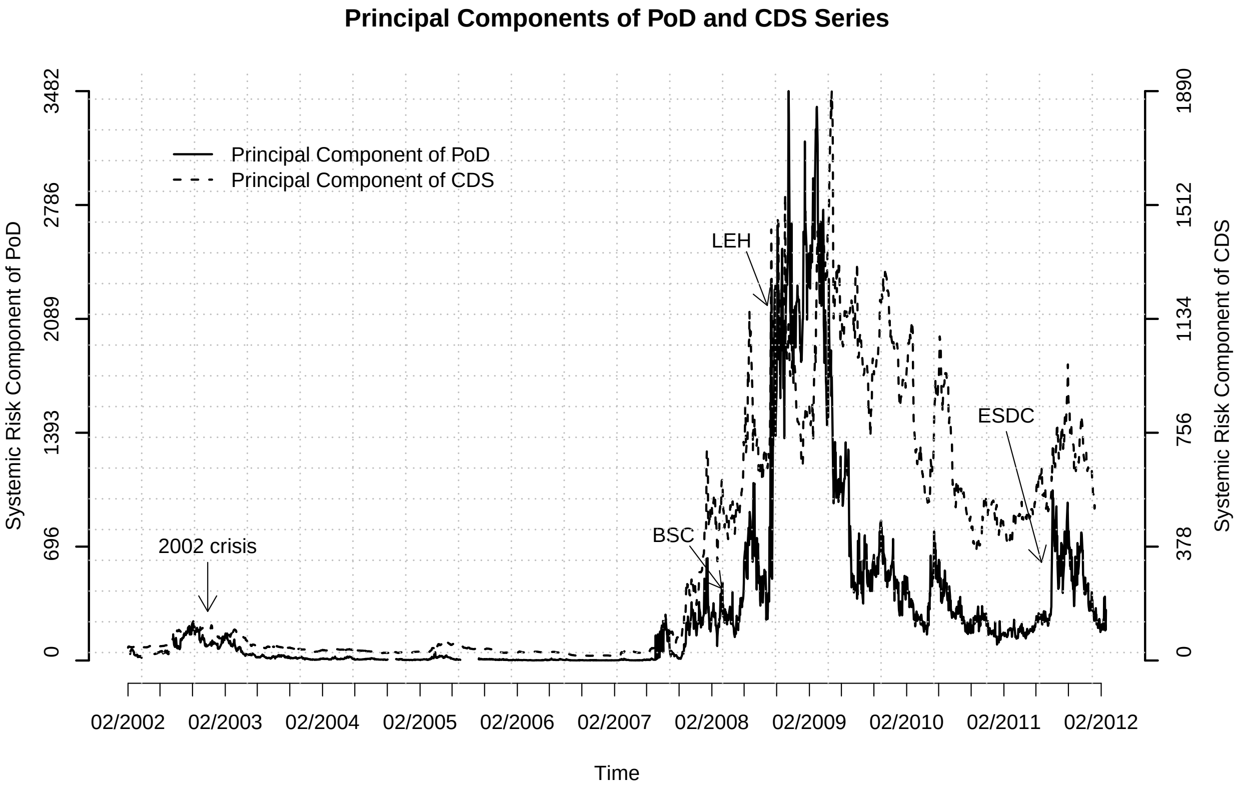
Since the first PC can be regarded as a linear combination of the optimally weighted PoD data, our financial sector risk indicator is a weighted mean of our banks' PoDs. The term optimally refers to the fact that there exists no other set of weights that leads to a PC which accounts for a larger amount of variance in the data. Thereby, we weigh these banks in the sample the most which exhibit the highest percentage of the total variation and, hence, exert the strongest influence on the overall financial sector risk.

Due to data restrictions we could not use the complete set of banks to calculate our PCs. For the PC of the PoDs we used GS, WFC, C, BAC, JPM, AIG, MS, MBI, PNC and STT. No data are available for LEH, BSC, WB, MER, CFC and WM after their takeover or default and also BLK, BX and BK contain too many missing values. For the CDS we took GS, WFC, C, BAC, AIG, MS and MBI for the same reasons just explained. We found that all eigenvector elements are positive and that the first PC of our PoD data explains 79.21% of the total variation and the first PC of the CDS explains 83.66% of the overall variance in the dataset. Given that high explanatory power, we consider the first PC as an appropriate proxy for the systemic risk inherent in the financial sector.

The PCs of our PoD and CDS series are depicted in Figure 4.[19] As for the individual bank time series, the CDS and PoD based PCs exhibit highly similar dynamics but differ sig-

[19]Beforehand, we tested our PoD and CDS series for unit roots (results available upon request). We found that except for the 'crisis banks' which went bankcrupt or were taken over during 2008 (LEH, BSC, WB, MER, CFC and WM), the series are significantly stationary. The crisis banks' indicators, though, rose to very high levels shortly before failure and then abruptly ended, hence, pointing towards unit root behaviour. Nonetheless, theoretically it is hard to justify that the CDS and PoD series are non-stationary. If the series were not mean-reverting, very high values lasting over a lengthy period of time would sooner or later trigger default of the respective company.

**Figure 4:** Systemic risk of PoD and CDS series measured in basis points from February 2002 to February 2012



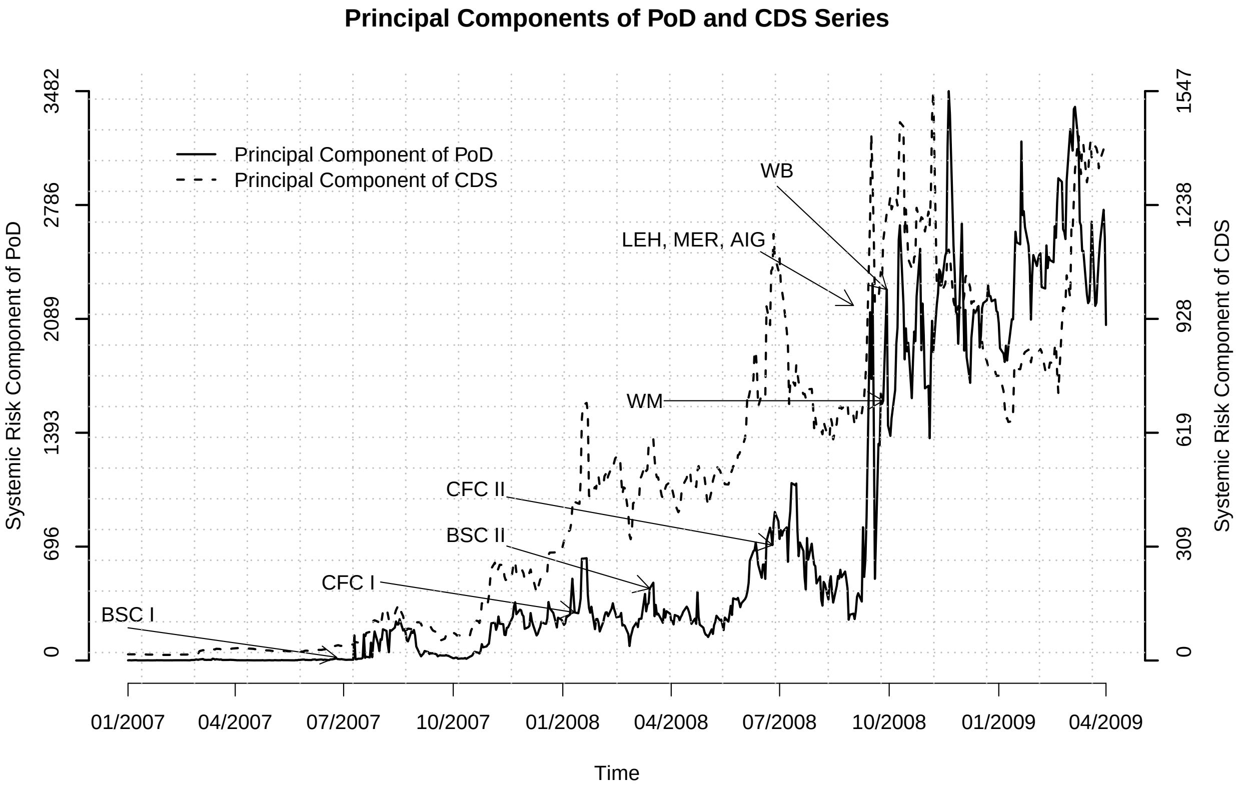

*Note*: 2002 crisis indicates the late consequences of the early 2000s recession, BSC denotes the Bear Stearns takeover by JPM on March 16, 2008 and LEH labels the Lehman Brothers bankruptcy on September 15, 2008. ESDC represents the European sovereign debt crisis.

nificantly in their level during high distress times. Both indicators clearly indicate the late consequences of the early 2000s recession, the takeover of Bear Stearns by JPM on March 16, 2008, Lehman Brother's bankruptcy on September 15, 2008 as well as the worsening conditions in the wake of the European sovereign debt crisis. This shows that the proxies significantly cover the incisive events in the US financial system and, more importantly, the magnified risk prior to the events.[20]

In order to have a closer look at the dynamics of the systemic risk proxy, Figure 5 focuses solely on the crisis period. Important events during the financial crisis are highlighted in order to further back up the signalling power of the indicators. BSC I marks the Bear Stearns

[20]Figure 11 (Appendix) shows that the above mentioned properties do not hinge on the exact choice of banks used for the PC determination. In Figure 11, we used the same specification of banks for the PC determination of the PoDs as used for the PC of the CDS. The first PC of the PoDs explains 72.28% of the total variation in the data, still a very high percentage.

**Figure 5:** Systemic risk of PoD and CDS series measured in basis points from January 2007 to April 2009



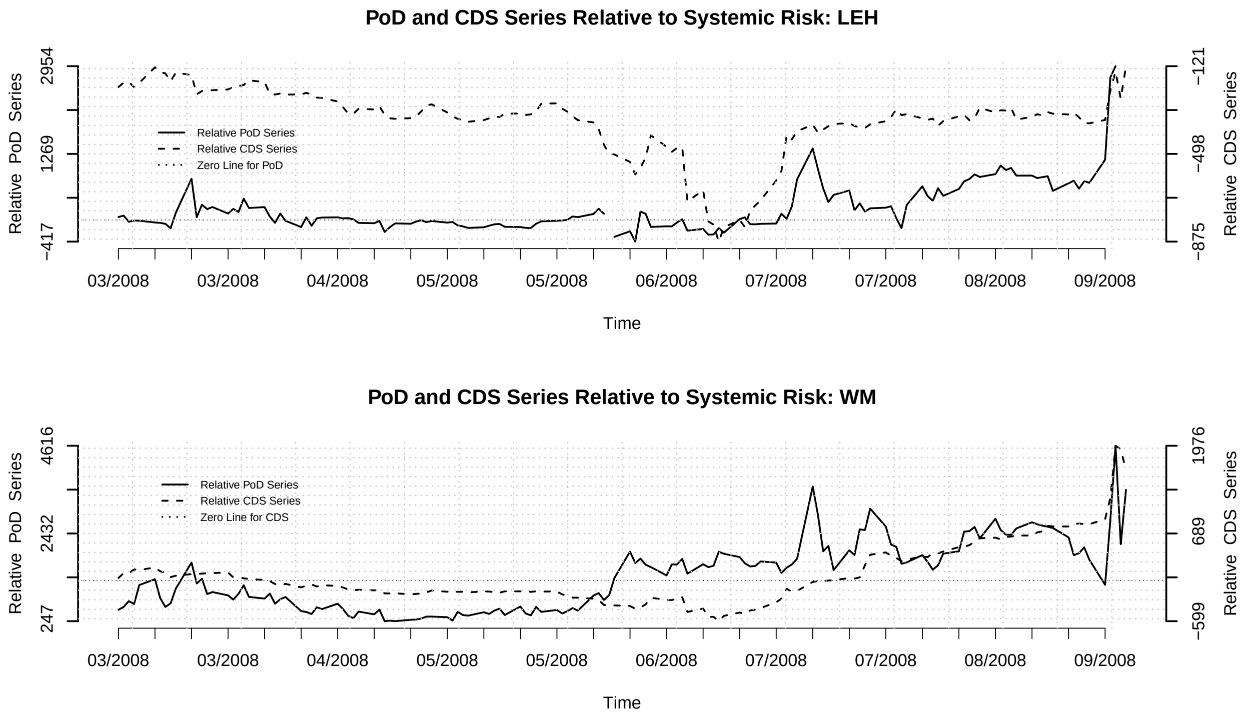

*Note*: BSC I labels the Bear Stearns hedge fund troubles on June 22, 2007, CFC I the announcement of the Countrywide takeover by BAC on January 11, 2008, BSC II the Bear Stearns takeover by JPM on March 16, 2008 and CFC II the Countrywide acquisition by BAC on June 25, 2008. LEH indicates the Lehman Brothers bankruptcy on September 15, 2008, MER the BAC announcement of the Merrill Lynch purchase on September 14, 2008 and AIG the central bank's bailout of AIG on September 16, 2008. WM denotes the bankruptcy of Washington Mutual on September 26, 2008 and WB the first acquisition announcement of Wachovia by C on September 29, 2008.

hedge fund troubles of mid-2007, which were the first forerunners of the financial crisis. CFC I represents the announcement of the Countrywide takeover by BAC on January 11, 2008, BSC II denotes the Bear Stearns takeover by JPM on March 16, 2008 and CFC II stands for the Countrywide acquisition by BAC on June 25, 2008. All four events were accompanied by a significant increase in the systemic risk proxies. More importantly, worsened financial conditions were signalled in advance of the specified events. The biggest surge in the indicator took place in the course of Lehman Brothers bankruptcy (LEH event), the BAC announcement of the Merrill Lynch purchase on September 14, 2008 (MER event) and the bailout of AIG by the Federal Reserve Bank of New York on September 16, 2008 (AIG event). Shortly after the bankruptcy of Washington Mutual on September 26, 2008 (WM event) as well as the first announcement of the acquisition of Wachovia by C on September 29, 2008 (WB event) market conditions even further worsened as indicated by the systemic risk measures.

## 5.3 Relative Risk Analysis

As we could see that the proxy for the systemic risk in the US financial sector provides very conclusive results, we apply this measure to carry out our relative risk analysis. Figure 6 depicts exemplarily the PoD and CDS series of LEH and WM relative to the systemic risk. We consider a period of six months prior to the Lehman event in order to evaluate the predictive power of our financial stability indicator in advance of severe events. Therefore, we subtract the financial sector risk component from the original PoD and CDS series of the respective companies and gain a 'relative risk spread' measured in basis points.[21] This spread indicates whether a company's distress level is considered to be higher or lower compared to the prevailing overall financial sector risk. The upper graph of Figure 6 exhibits the relative

**Figure 6:** PoD and CDS series relative to systemic risk six month prior to the Lehman event on September 15, 2008; measured in basis points




risk spread for the PoD and CDS series of LEH. As illustrated by the zero line, the relative

[21]For the sake of consistency, for the systemic risk calculation we used in this case the same bank sample for the PoDs as for the CDS. However, results remain unchanged if we used the PoD sample of section 5.2.

PoD time series moves constantly around zero but exceeds that value in July 2008, two and a half months before the actual collapse of LEH. Hence, way in advance of the bankruptcy, our indicator is able to signal in relative terms the increased default risk. One trading day before failure, the risk spread even rose to around 29.5%, implying a default probability which is 29.5 percentage points higher than that of the average overall financial sector. In contrast, the CDS spread remains negative over the complete sample, which implies LEH's distress level to be below the systemic one. This clearly underestimates LEH's inherent default risk especially with regard to the looming insolvency.

The lower graph of Figure 6 depicts the relative PoD and CDS time series for WM. Here, both curves signal a relative risk level above the systemic one in the latter part of the sample, which is plausible since WM collapsed on September 26, 2008. However, the PoD spreads are positive over the complete sample, whereas the CDS curve does not cross the zero line before the end of July 2008. In addition, the absolute values of PoD spreads are decisively higher than the CDS ones. These results again back the hypothesis of higher signalling power in the option implied stability measure.

Table 3 (Appendix) provides an overview of the relative riskiness of the remaining financial institutions in our sample. We aggregated the information by taking the average of the PoD and CDS spreads for each institution over an interval of one to ten days, ten to twenty days, twenty to forty days and thirty to sixty days prior to the Lehman event. The results substantiate the findings from above that the PoDs are superior to the CDS in identifying the most financially troubled institutions prior to Lehman Brother's breakdown (see highlighted LEH, WB, MER, WM and AIG). In a consistent manner, the PoD spreads of the most resilient banks like GS, WFC and JPM exhibit negative spreads since these institutions weathered the financial turmoils quite well.[22]

# 6 Conclusion

In this paper we applied the so-called option iPoD methodology to a dataset of option prices for 19 of the largest US financial institutions, ranging from February 2002 to February 2012. We showed how to empirically implement the framework in order to obtain consistent and smooth time series of option implied Probability of Defaults (iPoDs). This was achieved by

[22]We also analyzed our PoD and CDS data in relation to the most resilient bank and to the own history of each particular institution. The results are fully in line with the findings in this section and speak as well in favour of our derived financial stability indicator. Results are available upon request.

the appropriate choice of liquidity weights and the use of a suitable maturity cycle. To obtain the time series of RND/PoD estimates, alternately five-, six-, and seven month call option contracts were used. Subsequently, maturity dependence in the time series was removed by applying a non-parametric quantile regression approach to the pooled PoDs.

The time series of PoDs for the different financial institutions were comprehensively evaluated regarding their signalling/predictive power in advance and during crises periods. To do so, we contrasted our indicators to historical events and to time series of 5-year CDS. We found that the iPoD estimates signal very well the occurrence of adverse shocks to the financial sector as a whole as well as to specific financial institutions - in most cases prior to the actual events. Comparisons between 5-year CDS and the option iPoDs showed that both indicators exhibit highly similar dynamics but differ strongly in their levels. We stressed that the differences in the levels are mostly due to the fact, that unlike the option iPoDs, CDS spreads are functions of unknown recovery rates, and that this fact makes the iPoDs a superior financial stability indicator. To prove this we evaluated the signalling power of the two indicators in the identification of the most distressed/resilient banks in advance of Lehman Brother's bankruptcy.

In order to carry out this evaluation, we examined the bank-specific indicator levels relative to the prevailing systemic risk in the US-financial sector. The proxy for the systemic risk was calculated by applying a Principal Component Analysis to the time series of PoDs/CDS. As shown, this proxy provides a valuable self contained financial stability measure, that gives distinct signals regarding the stability of the US financial sector.

The risk analysis relative to the systemic risk proxy finally showed that the iPoD approach was able to identify the high risk banks in advance of the Lehman Brother's bankruptcy and clearly outperformed the CDS in this context.

Given the results from the empirical analyses, we stress the high informational content of the option iPoD framework and its ability to provide valuable risk measures. Importantly, the amount of information provided by the methodology is not restricted to the PoDs, but also provides the corresponding RNDs. The plausibility of the PoD estimates evaluated in this paper, implicitly ensures that also the RNDs provided by the framework are plausible, as the PoDs are a function in the RND shape parameters. The framework is hence highly attractive for usage in multivariate - copula based - risk analyses, in which joint PoDs and joint asset distributions can be derived.

## References


Agmon, N., Alhassid, Y., and Levine, R. (1979). An algorithm for finding the distribution of maximal entropy. *Journal of Computational Physics*, 30:250–258.

Alhassid, Y., Agmon, N., and Levine, R. D. (1978). An upper bound for the entropy and its applications to the maximal entropy problem. *Chemical Physics Letters*, 53:22–26.

Breeden, D. and Litzenberger, R. (1978). Prices of state-contingent claims implicit in option prices. *Journal of Business*, 51:621–651.

Capuano, C. (2008). The option-ipod. the probability of default implied by option prices based on entropy. *IMF Working Paper*, 08(194).

Cover, T. M. and Thomas, J. A. (2006). *Elements of Information Theory*. John Wiley & Sons, 2nd edition.

Figlewski, S. (2008). *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle*, chapter Estimating the Implied Risk Neutral Density for the U.S. Market Portfolio. Oxford University Press.

Hastie, T. and Tibshirani, R. (1986). Generalized additive models. *Statistical Science*, 1:297–310.

Hastie, T. and Tibshirani, R. (1990). *Generalized Additive Models*. Chapman-Hall.

IMF (2009). Global financial stability report: Responding to the financial crisis and measuring systemic risks. *World Economic and Financial Surveys, IMF*.

Jackwerth, J.-C. (2004). *Option implied Risk Neutral Distributions and Risk Aversion*. Research Foundation of AIMR (CFA Institute).

Jaynes, E. T. (1957). Information theory and statistical mechanics. *Physical Review*, 106:620–630.

Koenker, R., Ng, P., and Portnoy, S. (1994). Quantile smoothing splines. *Biometrika*, 81:673–680.

Melick, W. and Thomas, C. (1997). Recovering an asset's implied pdf from option prices: An application to crude oil during the gulf crisis. *Journal of Financial and Quantitative Analysis*, 32:91–115.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29:449–470.

Schweighard, F. A. and Tsesmelidakis, Z. (2012). The Impact of Government Interventions on CDS and Equity Markets. *Working Paper*.

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal*, 27:379–423.

Vilsmeier, J. (2011). Updating the option implied probability of default methodology. *BGPE Working Paper*.

# Appendix

**Figure 7:** 40%- and 90%-Quantile of the PoDs for different time to maturities and the respective fitted functions

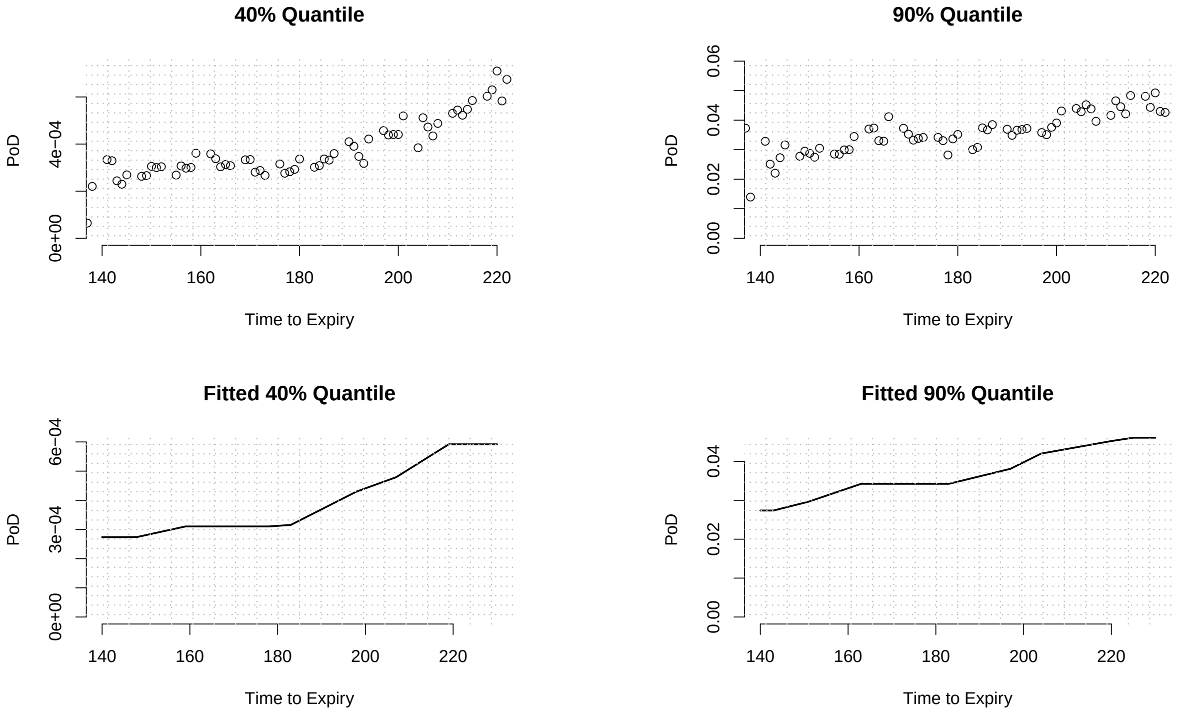
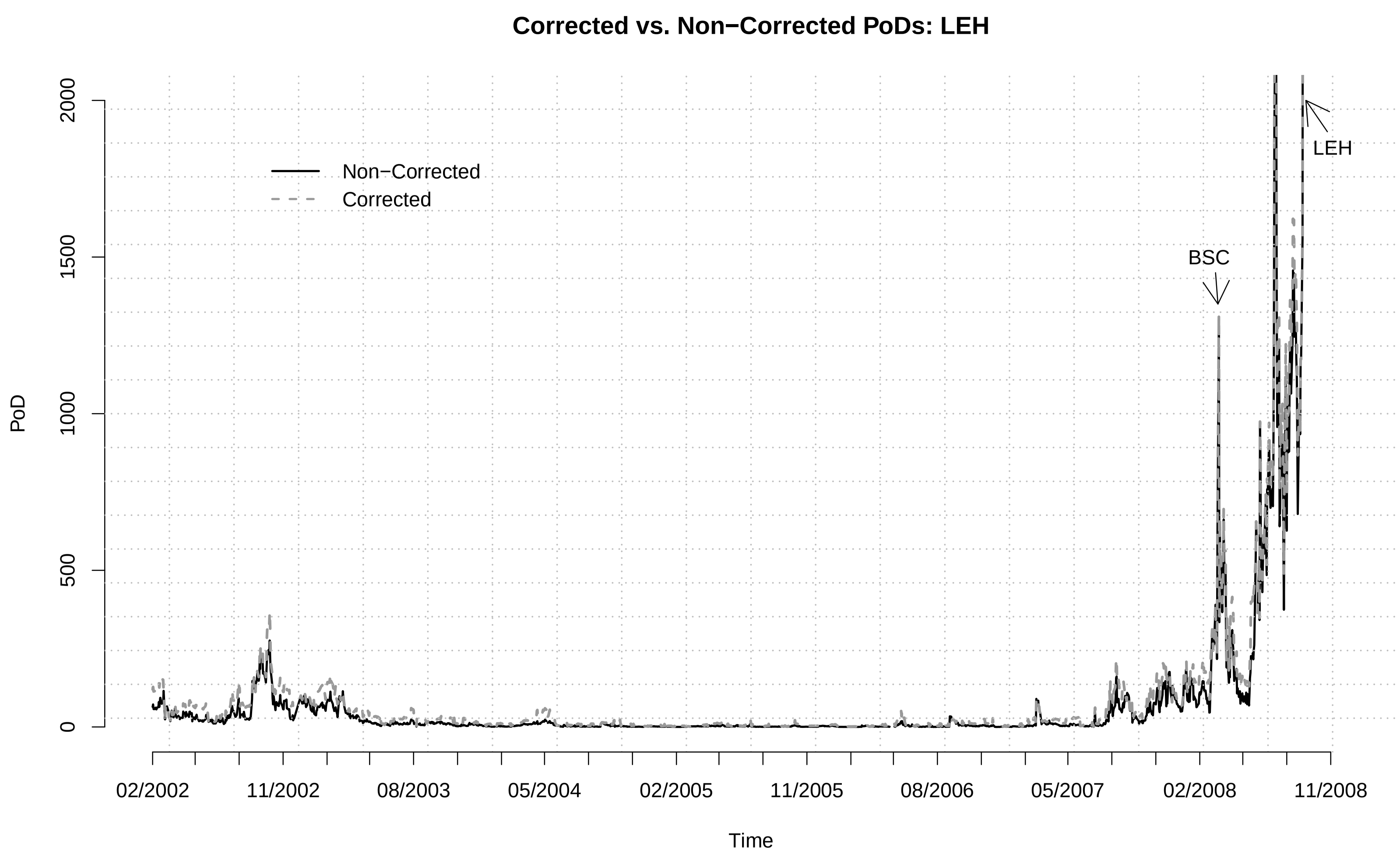


**Figure 8:** Maturity corrected and non-maturity corrected PoD time series for LEH measured in basis points from February 2002 to September 2008




*Note*: BSC and LEH denote the collapse of Bear Stearns on March 16, 2008 and the Lehman Brothers bankruptcy on September 15, 2008, respectively.

**Figure 9:** PoD time series for all financial institutions measured in basis points from February 2002 to February 2012

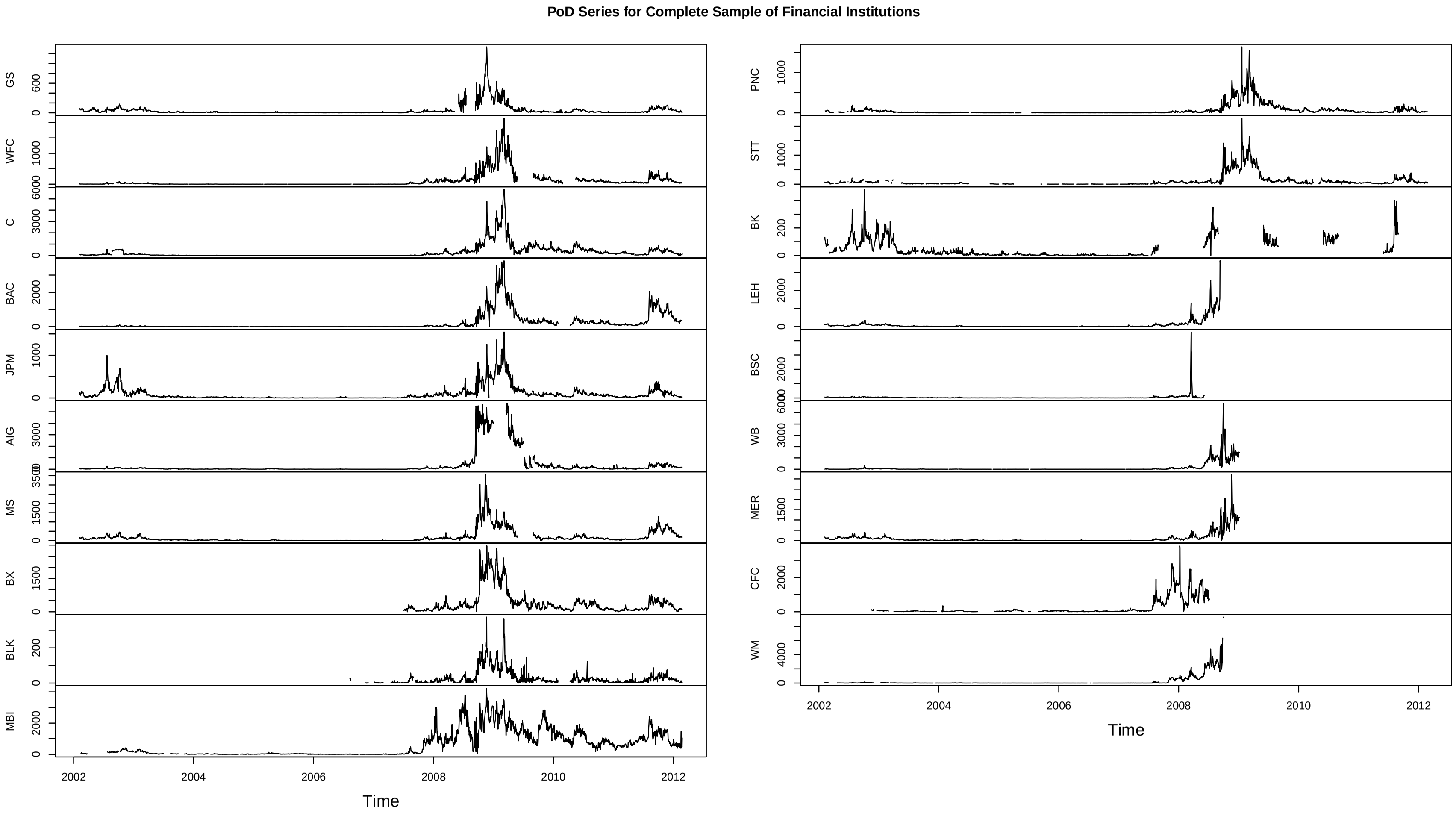


**Figure 10:** CDS time series for all financial institutions measured in basis points from February 2002 to February 2012

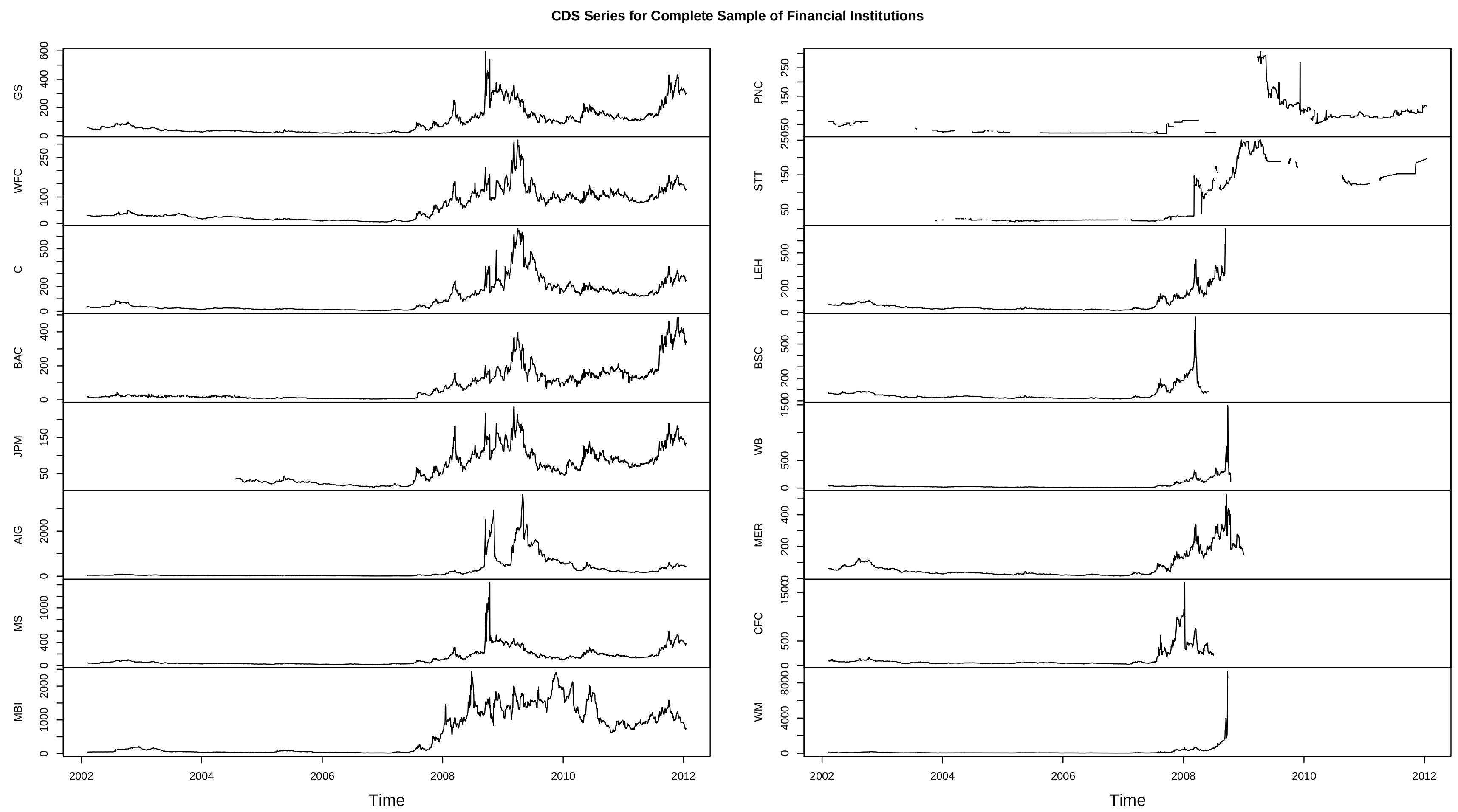
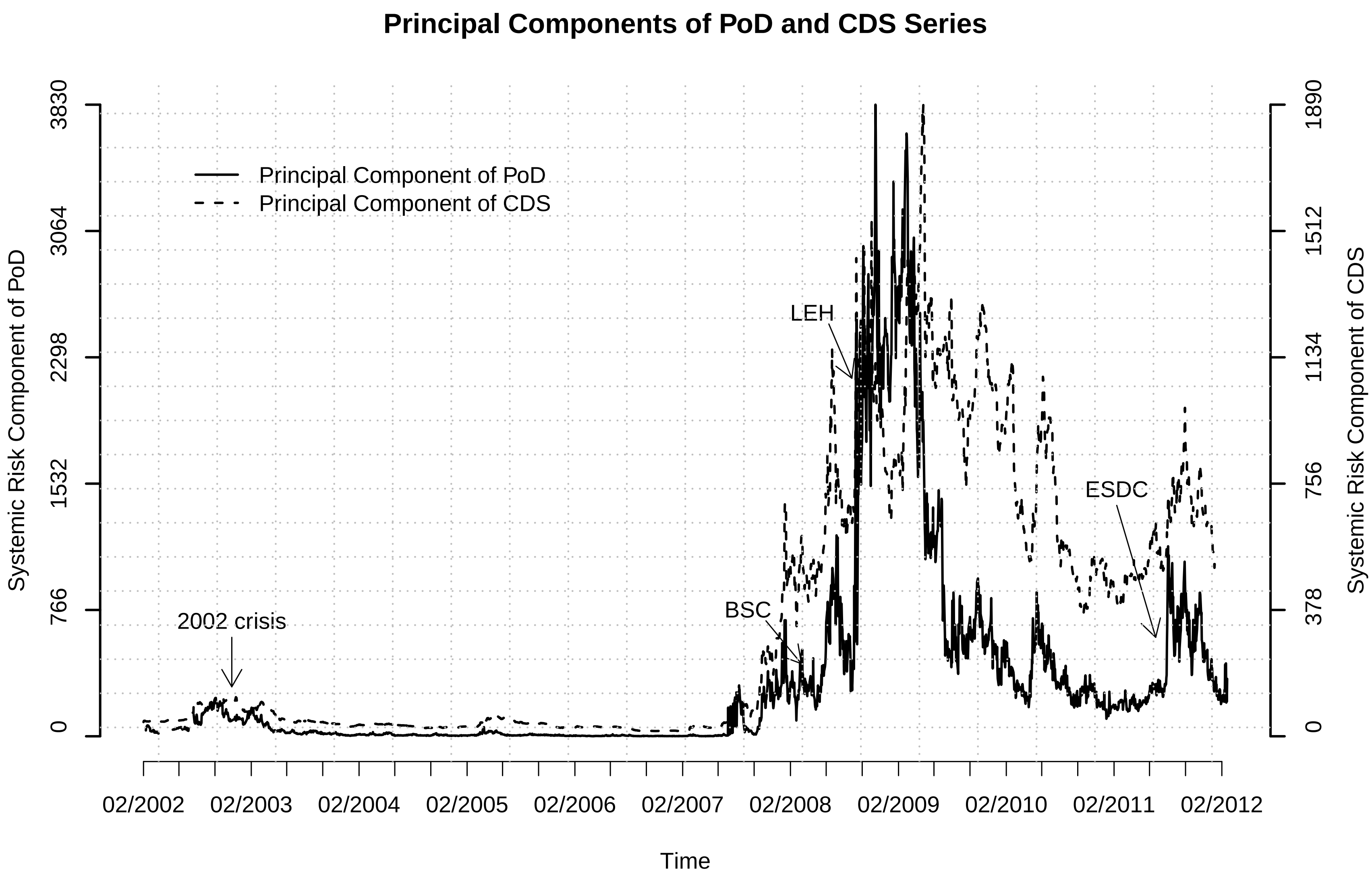


**Figure 11:** Systemic risk of PoD and CDS series measured in basis points from February 2002 to February 2012; same banks used for principal components of PoD and CDS series




*Note*: 2002 crisis indicates the late consequences of the early 2000s recession, BSC denotes the Bear Stearns takeover by JPM on March 16, 2008 and LEH labels the Lehman Brothers bankruptcy on September 15, 2008. ESDC represents the European sovereign debt crisis.

| Company | Pearson correlation coefficient | Spearman correlation coefficient |
|---|---|---|
| GS | 0.62 | 0.78 |
| WFC | 0.73 | 0.91 |
| C | 0.69 | 0.94 |
| BAC | 0.69 | 0.92 |
| JPM | 0.70 | 0.89 |
| AIG | 0.78 | 0.90 |
| MS | 0.73 | 0.89 |
| MBI | 0.86 | 0.94 |
| PNC | 0.85 | 0.82 |
| STT | 0.64 | 0.82 |
| LEH | 0.84 | 0.83 |
| BSC | 0.49 | 0.77 |
| WB | 0.74 | 0.79 |
| MER | 0.68 | 0.90 |
| CFC | 0.92 | 0.71 |
| WM | 0.82 | 0.77 |

**Table 1:** Pearson and Spearman correlations between maturity corrected PoDs and CDS from February 2002 to February 2012

| | Avg.PoDs | Avg.CDS | Avg.PoDs (before) | Avg.CDS (before) | Avg.PoDs (after) | Avg.CDS (after) |
|---|---|---|---|---|---|---|
| GS | 33.10 | 96.76 | 9.41 | 36.51 | 61.33 | 166.53 |
| WFC | 78.81 | 61.30 | 1.89 | 20.37 | 172.91 | 108.64 |
| C | 242.16 | 103.72 | 24.26 | 22.82 | 488.33 | 197.47 |
| BAC | 187.13 | 80.26 | 2.42 | 14.13 | 402.87 | 155.62 |
| JPM | 69.33 | 66.80 | 26.41 | 22.40 | 114.45 | 95.36 |
| AIG | 277.52 | 263.05 | 13.27 | 28.78 | 590.85 | 534.54 |
| MS | 154.60 | 123.87 | 28.76 | 36.54 | 306.87 | 225.02 |
| BX | 345.03 | NA | NA | NA | 345.03 | NA |
| BLK | 16.26 | NA | 0.72 | NA | 17.70 | NA |
| MBI | 585.63 | 570.69 | 26.24 | 60.38 | 1134.84 | 1161.69 |
| PNC | 45.63 | 60.48 | 5.92 | 27.40 | 87.00 | 89.49 |
| STT | 81.30 | 80.81 | 11.53 | 18.96 | 137.68 | 133.96 |
| BK | 29.16 | NA | 19.03 | NA | 74.63 | NA |
| LEH | 74.90 | 67.94 | 17.32 | 39.59 | 328.62 | 192.04 |
| BSC | 23.30 | 56.34 | 7.32 | 37.78 | 113.75 | 163.75 |
| WB | 112.96 | 48.54 | 4.15 | 21.29 | 484.12 | 160.13 |
| MER | 82.49 | 71.11 | 22.73 | 38.87 | 290.66 | 184.04 |
| CFC | 205.47 | 117.23 | 21.93 | 57.14 | 896.36 | 432.82 |
| WM | 167.47 | 149.36 | 3.84 | 49.75 | 378.26 | 570.68 |

**Table 2:** Average PoDs and CDS over entire sample period before July 2007 (before) and after July 2007 (after)

| Company | PoD (1-10) | CDS (1-10) | PoD (10-20) | CDS (10-20) | PoD (20-40) | CDS (20-40) | PoD (30-60) | CDS (30-60) |
|---|---|---|---|---|---|---|---|---|
| GS | -938.50 | -535.36 | NA | -519.02 | NA | -528.68 | -698.31 | -699.39 |
| WFC | -401.63 | -571.10 | -327.75 | -552.55 | -439.10 | -555.66 | -641.59 | -720.22 |
| C | -138.22 | -529.06 | -122.76 | -508.60 | -259.61 | -518.29 | -414.85 | -694.79 |
| BAC | -393.72 | -568.17 | -416.62 | -550.93 | -517.67 | -551.79 | -689.16 | -723.82 |
| JPM | -437.54 | -579.70 | -382.36 | -568.95 | -449.17 | -564.82 | -649.29 | -730.84 |
| AIG | 386.14 | -203.66 | 213.20 | -313.80 | -174.74 | -402.92 | -399.65 | -606.62 |
| MS | -403.90 | -473.37 | -315.92 | -452.86 | -391.65 | -441.07 | -608.45 | -617.60 |
| MBI | 133.66 | 475.78 | 319.97 | 534.20 | 1142.67 | 592.61 | 1888.70 | 836.88 |
| PNC | -492.93 | NA | -421.74 | NA | -521.31 | NA | -782.65 | -927.36 |
| STT | -473.26 | -581.62 | -403.34 | -568.91 | -528.81 | -533.36 | -751.63 | -743.98 |
| LEH | 1294.84 | -282.63 | 846.63 | -324.13 | 445.47 | -348.05 | 203.89 | -514.05 |
| WB | 424.74 | -376.51 | 635.05 | -388.34 | 373.34 | -400.79 | 230.02 | -583.92 |
| MER | 12.27 | -366.53 | 25.49 | -355.08 | -117.97 | -381.52 | -437.81 | -558.62 |
| WM | 2423.84 | 1172.43 | 2561.60 | 694.21 | 2172.71 | 362.79 | 1991.85 | -102.63 |

**Table 3:** Average PoD and CDS spreads with regard to systemic risk prior to Lehman event on September 15, 2008