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MODELING METHODOLOGY
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Navigating Through Crisis: Validating RiskFrontier® Using Portfolio Selection

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Abstract

Assessing credit risk and ensuring the effectiveness and reliability of credit models are critically important to many risk managers and portfolio managers, especially during financial crises. This validation study examines the measurement accuracy of the portfolio credit risk models employed in Moody's Analytics RiskFrontier.

To evaluate accuracy, we construct various credit default swap (CDS) portfolios with different levels of risk. We then compare the modeled portfolio volatilities obtained from RiskFrontier with the subsequently realized portfolio volatility over the crisis period of January 2008 through May 2009. We focus on the comparison for three risk measures: instrument unexpected loss, risk contribution, and portfolio unexpected loss.

We find high rank correlations between ex ante and ex post measures of portfolio relevant risk. These findings validate the model's ability to capture changing levels of risk and the co-movements of credit exposures. We find that the choices of accurate and forward-looking probability of default (PD) values, as well as asset correlation measurement, are critical when determining the model's predictive power.

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1 Introduction

The recent financial crisis has forced many credit portfolio managers and risk managers to critically evaluate how they measure and manage portfolio credit risk. Such an evaluation raises the following questions: how has the portfolio model performed during this turmoil? How do we identify hedging counterparties? Where do the worst exposures lie? To answer these questions, credit portfolio and risk managers rely on models that they hope will provide legitimate insights. This leads to another question: how do credit portfolio and risk managers know whether their models are providing appropriate guidance? To this end, they must rely on an effective validation process, which is one of the most important aspects of risk modeling.

A typical validation method compares observed outcomes with model expectations. For example, evaluating whether or not the frequency of exceptions (i.e., occasions when actual credit losses exceed the forecasted critical values) over a specified time period is consistent with the selected confidence interval. A major impediment to this backtesting method is the small number of forecasts available for evaluating the model's forecasting accuracy. Unlike market risk, credit risk is more skewed and fat-tailed. Moreover, the relevant horizon for credit risk is much larger—one year, compared to a few weeks. Reasonable tests of forecasting accuracy require an impractical number of years to produce sufficient observations.

This study employs a different approach to validating a credit risk model. Rather than examine the occurrences of exceptions, we focus on investigating correlations between ex ante and ex post measures of portfolio risk. In theory, accurate portfolio models should produce ex ante forecasted values highly correlated with ex post realized values. Following this principle, we use RiskFrontier to analyze multiple CDS portfolios with different degrees of riskiness with parameters measured as of January 2008. We then compute the rank correlation between the modeled volatilities and the subsequently realized portfolio volatility during the financial crisis period from January 2008 through May 2009. We focus on three risk measures: instrument unexpected loss, risk contribution, and portfolio unexpected loss.

Results show high rank correlations between ex ante and ex post risk measures. For example, we find a correlation of 76% between modeled portfolio unexpected losses and empirical portfolio volatilities, which indicates robust performance in capturing the changing levels of risks and co-movements in credit exposures.

We also conduct various controlled portfolio analyses to explore the importance of different inputs in determining the model's predictive power. This rank correlation approach provides quantifiable measures of forecasting accuracy that can be used for model validation. Our methodology enables credit portfolio managers to identify and choose appropriate credit risk models, and to examine the robustness of specific model assumptions and parameters.

The remainder of this paper is organized in the following way.

- Section 2 presents the validation method.
- Section 3 describes the data for portfolio construction and different PD and correlation inputs.
- Section 4 discusses a comparison of portfolio results under different test scenarios.
- Section 5 summarizes the study and provides concluding remarks.

2 Methodology

This section describes the validation method we used for this study.

A. Portfolio Selection

Our CDS sample begins in January 2008 and runs through May 2009. We use CDS instruments instead of bonds or loans for validation; the CDS market has a large number of liquid names with terms and conditions that are largely uniform. We construct multiple CDS portfolios of different riskiness at the beginning of the sample period and check the correspondence between the empirical and model-generated portfolio volatilities and other risk measures.

We complete the following steps for the validation procedure.

1. Select a total of 100 CDSs from different PD buckets on 1/2/08, even though the daily number of CDSs varies around 1000, for which most of the underlying reference entities are large firms with high credit quality. To differentiate the riskiness of constructed portfolios (as described later), we first define several PD buckets and then randomly choose a certain number of CDSs from each of the PD buckets. We then make the total number of selected CDSs equal 100.
2. Randomly select 80 CDSs from the pre-selected 100 CDSs and populate relevant parameters—for example, Moody's Analytics EDF™ (Expected Default Frequency) credit measure, R-squared, and spread—measured as of January 2008 to create a portfolio.
3. Repeat Step 2 100 times to create 100 portfolios.
4. Run these 100 CDS portfolios through RiskFrontier to obtain modeled instrument and portfolio volatilities. In the meantime, calculate the empirical instrument and portfolio volatilities based on weekly CDS return realizations.
5. Compute the rank correlation of modeled and empirical portfolio relevant risk (i.e., unexpected loss [UL] and risk contribution [RC]).

B. Modeling Risk

The modeled CDS risk measures are direct outputs from RiskFrontier. Instrument stand-alone risk in RiskFrontier is measured by Unexpected Loss (UL), which is defined as the standard deviation of the instrument value at the horizon. Portfolio UL is analogous to instrument UL, describing dispersion of realized losses around the expected loss.

The portfolio UL is written as

$$UL_P = \sqrt{\sum_i \sum_j w_i w_j \rho_{ij} UL_i UL_j} \tag{1}$$

Where ρ_{ij} is the correlation between values of instruments i and j and is calculated through simulation. w_i and w_j are instrument weights in the portfolio.

Risk contribution (RC) measures the marginal contribution of one instrument to the volatility of the portfolio value. In other words, it looks at the effect on the portfolio UL of a marginal increase in the portfolio weight of an instrument. RC is expressed as

$$RC^i = \frac{\partial UL_P}{\partial w_i} = \rho_{ip} UL_i \tag{2}$$

Where ρ_{ip} is the correlation between values of instruments i and the value of the portfolio. In other words, RC, for an instrument, measures the change in portfolio standard deviation (in currency units) resulting from one additional currency unit of this particular instrument.

C. Empirical Risk Measures

The empirical CDS value volatility is defined as the standard deviation of the exposure value over time. The value gain or loss is associated with return realization over a certain time period.

First, let's understand how CDS return is affected by quoted spread changes. Suppose a bank sells a five-year CDS protection on a reference company at a spread of 150 basis points (bps). One year later, the four-year CDS on the same reference entity is quoted at 100 bps in the market. To unwind this five-year CDS contract, the bank could enter into an offsetting position, in which it buys the same reference entity for the next four years. By doing this, the bank earns a positive return because it is charging 150 bps for providing protection against certain risk, while the market is only willing to pay 100 bps. This scenario means that the bank creates a positive premium income of 150-100 = 50 bps annually until a credit event or maturity. The return brought by spread changes, together with the spread received in the past year, comprises the total realized CDS return over one year.

In this study, the return calculation is conducted on a weekly frequency. A mathematical expression for calculating CDS return is as follows: for a CDS position initiated at t-1 at a contractual spread of $S_{t-1, M}$ with maturity M, offset at a T with a position traded at a spread of $S_{t, M}$, the return is given by

$$r_{t-1,t} = S_{t-1,M} / 52 - (S_{t,M} - S_{t-1,M}) \cdot PV1_{t,M} \tag{3}$$

Where

$S_{t, M}$ is the contractual spread at time t with maturity time M

$PV1_{t, M}$ is the present value at time t of a 1 bp premium stream that terminates at maturity time M or default, whichever is earlier.

As mentioned previously, the weekly CDS return from t-1 to t consists of two components. The first component represents the return accrued in one week. The second component refers to the spread difference earned by buying a protection at time t and selling the protection originated at t-1.

Where *PV1* is calculated as follows,

$$PV1 = \sum_{i=1}^{N} DF_{t_i} \cdot Q_{t_i} \cdot S \cdot d_i + \sum_{i=1}^{N} DF_{t_i} \cdot (Q_{t_{i-1}} - Q_{t_i}) \cdot S \cdot \frac{d_i}{2} \tag{4}$$

Where

S is the annual CDS premium (1 bp here)

Q_{ti} is the survival probability at time t_i.

DF_{ti} is the corresponding discount factor for time t_i.

d_i is the accrual days.

The accrual period runs from the previous coupon payment date through the current coupon payment date -1, inclusive. The CDS payment is computed as annual coupon/360 × accrual days. For simplicity, we use 0.25 of a year as accrual days in this study.

In equation (4), the first term represents the expected value of the quarterly premium payment. The periodic payment is the product of the annual CDS premium S and the accrual days d_i. Note that the payment will only be made when the reference entity has not defaulted, going by the payment data. Therefore, we need to adjust the premium payment by survival probability to obtain the expected payment at time t_i.

The second term represents the accrued premium paid up to the date of default, when default happens between the payment dates. We assume that the default only occurs in the middle of the interval between consecutive payment dates, so the accrued payment amount is S multiplied by half of the accrual days $d_i/2$. We must then adjust this accrued payment by the survival probability $Q(t_{i-1})-Q(t_i)$ to capture the fact that the reference entity survived through payment date t_{i-1} but not to the next payment time t_i. The two terms together represent the expected value of an uncertain premium stream.

Some approximations arise when computing weekly returns with real data. Ideally, the offsetting contract should have the same maturity date as the original contract. For example, you sell a five-year protection today. To unwind the position, one week later you should enter into an offsetting position in which you buy protection on the same reference entity for the next five years, minus one week. A CDS contract with such maturity may or may not exist in market. In reality, CDS maturity dates are standard and always fall on March, June, September, and December 20. Figure 1 and Figure 2 show the implication of these standardized maturity dates on weekly return calculation.

Suppose there are two, five-year standard CDS contracts traded on 3/10/2010 and 3/17/2010. Due to the maturity convention of the CDS contract, both would protect the buyer through 3/20/2015.

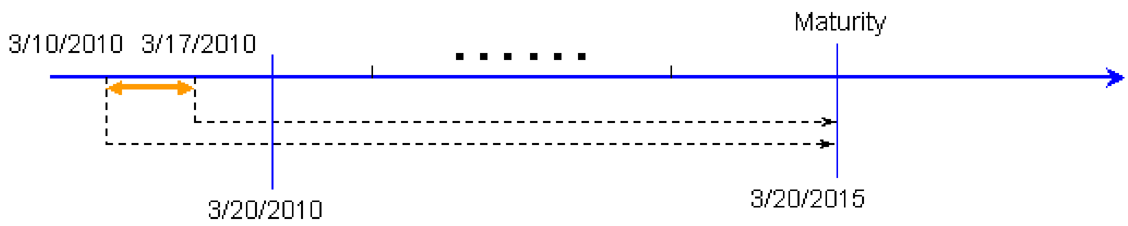

Figure 1 Two Credit Default Swaps with the Same Maturity Dates

Move one week forward; for five-year CDS contracts traded on 3/17/2010 and 3/24/2010, although the trade dates are still one week apart, the maturities of the two contracts become 3/20/2015 and 6/20/2015, respectively, according to the standardized CDS maturity dates.

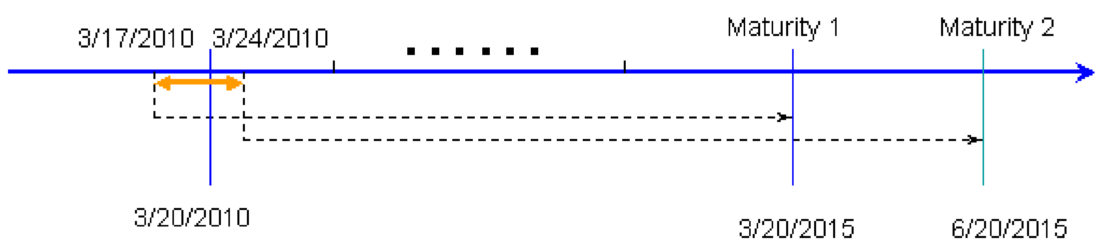

Figure 2 Two Credit Default Swaps with Different Maturity Dates

In this study, we ignore the resulting inconsistency in maturity dates between the original contract and the offsetting contract because its impact on the return calculation is minor. For simplicity, we approximate the offsetting contract with a new issue, five-year contract at the valuation date. In the above case, this means we treat the contract traded on 3/24/2010 as if it expires on 3/20/2015 in order to offset the contract entered into on 3/17/2010.

After the return of the individual CDS is available, the mark-to-market exposure value and the value change over time can be calculated as

$$\Delta V_t^i = r_{t-1,t}^i \cdot V_{t-1}^i \tag{5}$$

Where V_0^i is the notional amount of the i^{th} CDS in a portfolio at time 0.

The standard deviation of the i^{th} CDS value changes over time is computed as

$$\sigma_T^i = \sqrt{\frac{1}{T}\sum_{j=1}^{T}(\Delta V_t^j - \overline{\Delta V})^2} \quad \text{where} \quad \overline{\Delta V} = \frac{1}{T}\sum_{j=1}^{N}\Delta V_t^j \tag{6}$$

The individual CDS value changes sum to the portfolio value change.

$$\Delta P_t = \sum_{i=1}^{N}\Delta V_t^i \tag{7}$$

N is the total number of instruments in one portfolio.

The standard deviation of portfolio value changes over time is computed as

$$\sigma_T^P = \sqrt{\frac{1}{T}\sum_{j=1}^{T}(\Delta P_t^j - \overline{\Delta P})^2} \quad \text{where} \quad \overline{\Delta P} = \frac{1}{T}\sum_{j=1}^{N}\Delta P_t^j \qquad (8)$$

The empirical risk contribution of the i^{th} CDS to the portfolio *P* is defined as

$$RC^i = \frac{Cov(i,p)}{UL_P} = \frac{Cov(i,p)}{\sigma_T^P} \qquad (9)$$

Where *Cov(i, P)* is the covariance between the value change of the i^{th} CDS and the value change of the portfolio *P*. PD and correlation are critical inputs into a credit risk model. To explore how the quality of inputs affects model predictive power, we run portfolio analysis using several alternative measures in PDs and correlations, described in detail in Section 3.

3 Data

The CDS data we use in the study comes from Mark-it Partners and covers the period of January 2008 through May 2009. In order to obtain enough observations to generate a CDS return series, we require that reference entities must have at least 50 weekly observations during the sample period to be included in the sample.[1] The LGD values are derived from Moody's Analytics LossCalc™.

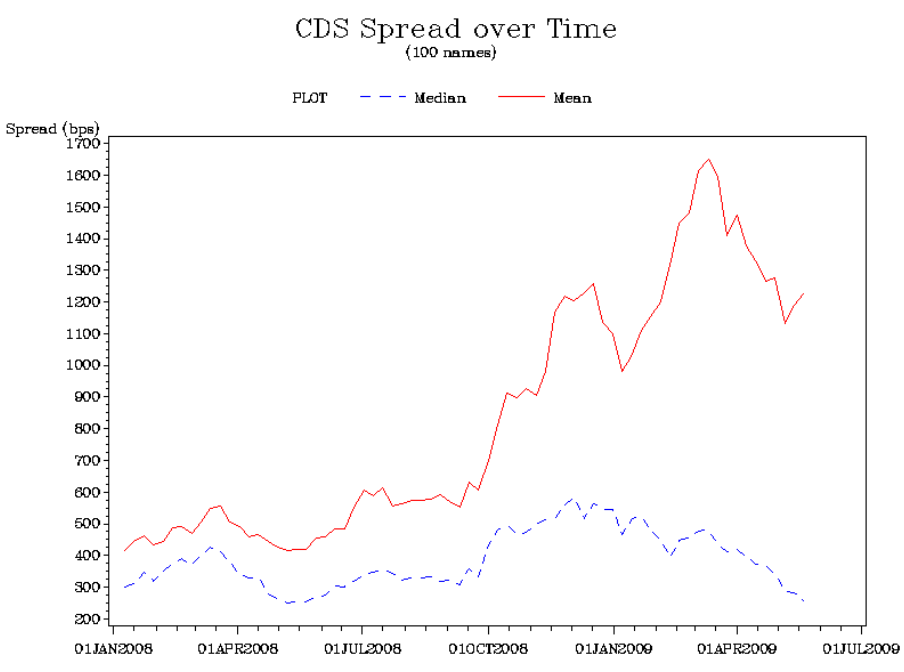

Figure 3 The Mean and Median CDS Spreads for 100 Selected CDSs

[1] See Appendix A for a description of the sample data.

The plot in Figure 3 shows the mean and median CDS spreads of the selected 100 CDSs over time. The average spread substantially increased during the recent turmoil and shows that the sample is representative of the universe. Two empirical return series are plotted separately in Figure 4. The mean and median are taken over all CDS returns at a certain point in time. As the plot shows, while the spreads are not stationary, returns look much more reasonable.

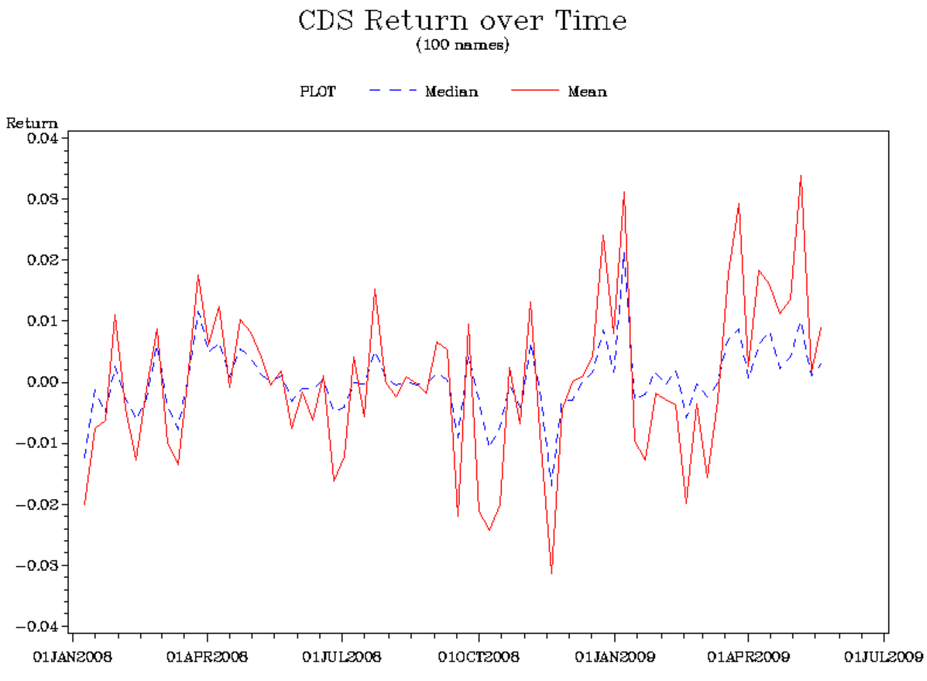

Figure 4 The Mean and Median CDS Returns for 100 Selected CDSs

3.1 Impact of PD and Correlation Model Input

We use alternative measures to examine the impact of PD and correlation model input on model predictive power. For PD inputs, we use the CDS-implied PD (SI EDF) credit measure, the EDF credit measure, random PD, and Rating. For correlation inputs, we use Moody's Analytics GCorr™ (Global Correlation Model) 2008, empirical correlations based on 2005–2007 and 2006–2008 separately, and random correlation

3.1.1 PD Input

This section describes the four alternative measures we use in the study to examine the impact of PD input on model predictive power.

CDS-implied PD (SI EDF)

The first alternative measure we use for PD is the SI EDF credit measure. We assume a Weibull survival function for risk-neutral survival probability and a constant loss given default (LGD) of 0.6, then solve for the default probabilities that calibrate an equality: the present value of expected payments made by the CDS buyer equals the present value of the expected payoff received by the buyer.

Assume the survival probability as a function of the time t (in years) is of the form

$$Q_t = \exp(-(t \cdot h_0)^{h_1}) \tag{10}$$

The present value of fixed payment leg is

$$PV_{fixed} = \sum_{i=1}^{N} DF_{t_i} \cdot Q_{t_i} \cdot S \cdot d_i + \sum_{i=1}^{N} DF_{t_i} \cdot (Q_{t_{i-1}} - Q_{t_i}) \cdot S \cdot \frac{d_i}{2} \tag{11}$$

The CDS seller makes the contingency payoff to the buyer in the event of a default. The expected payment from the contingent leg is

$$PV_{contingent} = LGD \cdot \sum_{i=1}^{N} DF_{t_i} \cdot (Q_{t_{i-1}} - Q_{t_i}) \tag{12}$$

The CDS buyer should expect a fair deal on a probability-adjusted and present-value basis, which means that when the buyer enters the contract, the present value of what he pays should be the same as what he expected to receive.

We can then estimate implied Weibull parameters h_0, h_1 by solving the following equation using CDS spreads of tenors 1, 2, 3, 5, 7, and 10 years.

$$S = \frac{LGD \cdot \sum_{i=1}^{N} DF_{t_i} \cdot (Q_{t_{i-1}} - Q_{t_i})}{\sum_{i=1}^{N} DF_{t_i} \cdot Q_{t_i} \cdot S \cdot d_i + \sum_{i=1}^{N} DF_{t_i} \cdot (Q_{t_{i-1}} - Q_{t_i}) \cdot S \cdot \frac{d_i}{2}} \tag{13}$$

The obtained risk-neutral survival probabilities, Q_t, can be converted into a cumulative real default probability

$$CPD_T = N[N^{-1}(Q_T) - \lambda R \sqrt{T}] \tag{14}$$

Then an annualized PD can be implied from the cumulative PD as follows.

$$PD_T = 1 - (1 - CPD_T)^{1/T} \tag{15}$$

EDF Credit Measure

The second alternative measure we use to examine PD impact is the Moody's Analytics EDF credit measure. All sampled firms are public names, so EDF credit measure information is readily available. We use the EDF value data at the analysis date, January 2008.

Agency Rating

Agency rating is the third alternative measure we use for PD. These ratings come from Moody's monthly rating data. We then convert the ratings to PD values through an EDF rating map, which is estimated monthly by calculating the group median EDF value for each rating category over five years. The EDF rating map used here is as of January 2008.

Random PD Values

For comparison purposes, as the fourth PD input, we also randomly draw values from a standard uniform distribution.

Figure 5 shows the distributions of SI EDF credit measures, EDF credit measures, rating-mapped PD, and random PD, respectively.

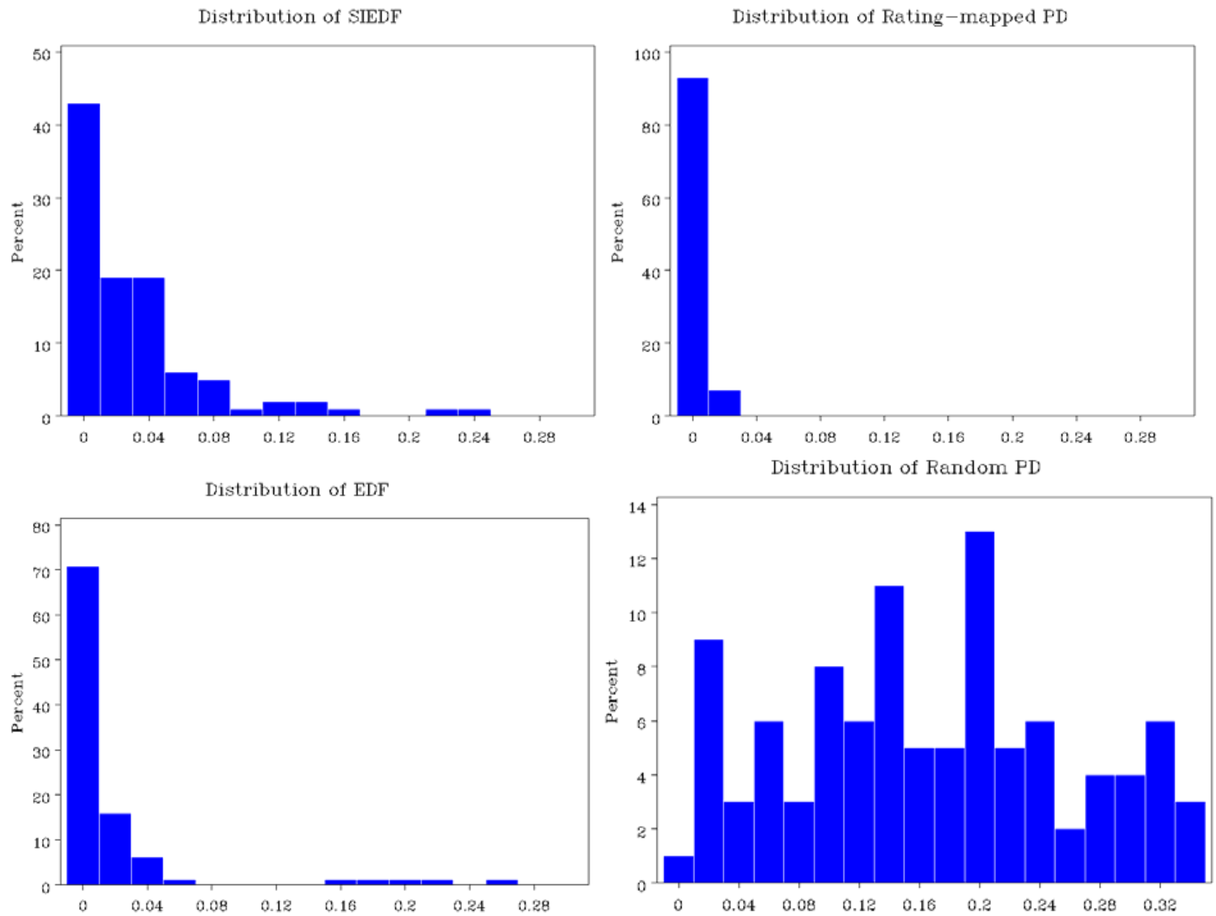

Figure 5 Distributions of SI EDF Measures, EDF Credit Measures, Rating-mapped PD, and Random PD

Rating, EDF credit measure, and SI EDF credit measure represent different methodologies used to assess credit risk. They are highly, but not perfectly, correlated, as shown in Table 1. In general, the randomly drawn PDs are not correlated with the other three measures.

Table 1 Rank Correlations Among Alternative PD Measures

Spearman Correlation Coefficients			
	Rating	SI EDF Value	EDF Value
Rating	1		
SI EDF Value	0.57	1	
EDF Value	0.43	0.83	1

3.1.2 Correlation Input

This section describes the four pair-wise correlation matrices we compare in order to examine the impact of correlation input on model predictive power.

GCorr 2008

The first matrix is the modeled asset correlation from GCorr 2008. GCorr is a multifactor model that assumes co-movements among asset returns are driven by a set of common factors. Unlike historical correlations containing random noise, in addition to useful information, a well-constructed multifactor model produces more accurate forward-looking correlation measures. The GCorr model parameters are estimated once a year to reflect the most recent dynamics of the firms' businesses and industries. When this study was conducted, the up-to-date GCorr model was GCorr 2008, estimated on asset return data from the previous three years.

Empirical Correlations: January 2005–December 2007

The second correlation input is empirical pair-wise correlation based on asset return data from January 2005 through December 2007. We choose this sample pattern to match the one used in GCorr 2008 global correlation estimation.

Empirical Correlations: January 2006–December 2008

The third correlation matrix is also empirically estimated but based on a more recent dataset covering the period from January 2006 through December 2008 and is the latest data available when this study was conducted. The empirical correlation matrices are ensured to be positive definite.

Random Correlation

The fourth zero correlation matrix assumes all the pair-wise correlation between names is zero.

4 Portfolio Analysis Results

To test the rank correlation between modeled and realized risk measures, we define a base scenario where SI EDF values are the PD inputs for both empirical and modeled risk calculation, GCorr 2008 provides correlation input, and LGDs come from the LossCalc model. The following portfolio analysis results are all obtained under the base scenario, unless otherwise specified.

We first examine the correspondence between risk measures at the portfolio level. We use 100 test portfolios; each dot displayed in Figure 6 represents one test portfolio. The x-axis shows the portfolio's empirical UL rank among 100 portfolios, and the y-axis indicates the corresponding modeled UL rank for the same portfolio among the portfolio group. Figure 6 shows that the modeled portfolio ULs are highly correlated with empirical portfolio UL. The rank correlation is 76.4%.

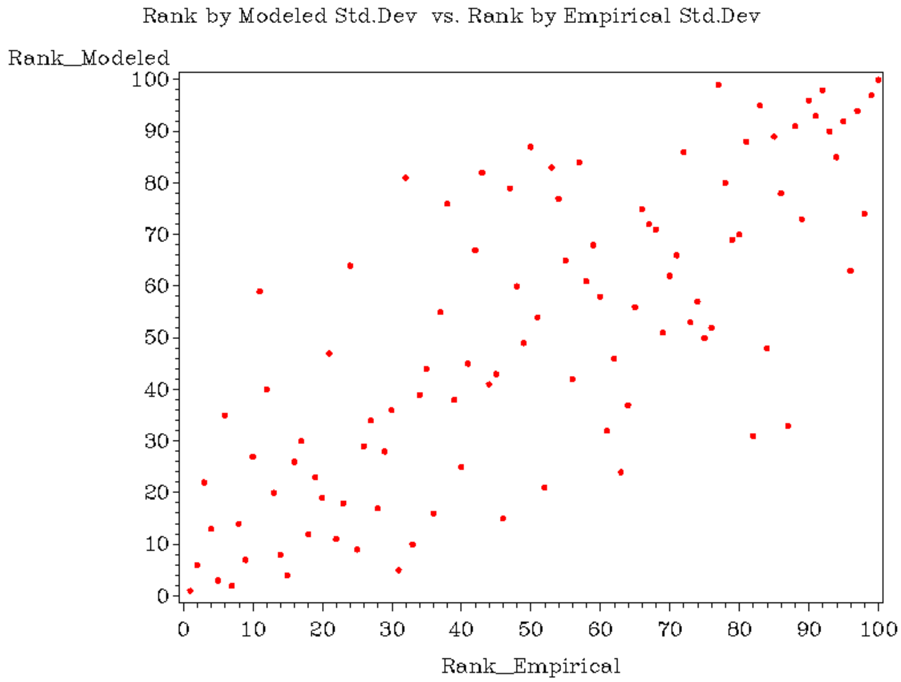

Figure 6 The Comparison of Portfolio Ranks by Modeled UL and Empirical UL

Note that the levels of modeled standard deviations and empirical standard deviations can be different. The empirical standard deviation captures some information updated during the time period (i.e., the standard deviation is calculated from single realizations of weekly returns). The borrowers' characteristics are not constant over time, so the estimated standard deviation is an average over the sample period. In contrast, the modeled standard deviation is computed based on all the information available at the beginning of the time period. We compute the standard deviation by keeping the borrowers' characteristics fixed at the analysis date and simulating to horizon. Despite these differences between the empirical and modeled standard deviations, the rank ordering is high, indicating that the model provides a useful description of portfolio risk.

The plot in Figure 7 shows that the rank correlation between empirical risk contributions and modeled risk contributions ranges between 0.68 and 0.83. The empirical risk contribution is defined in Section 2.

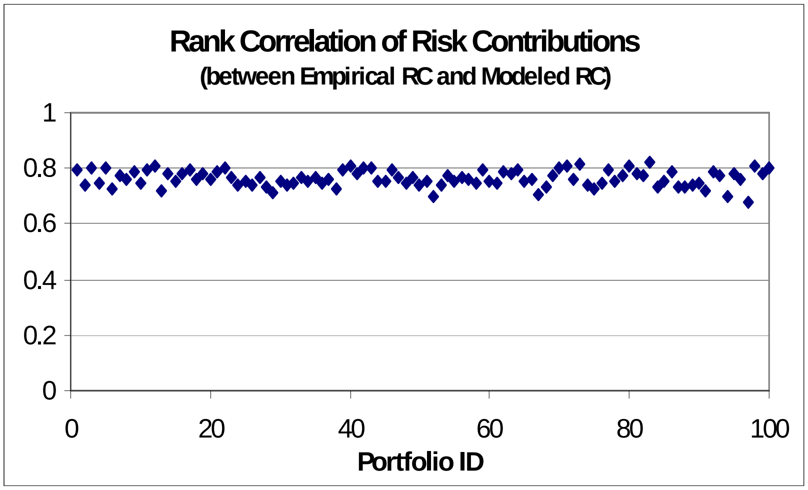

Figure 7 Rank Correlation of Risk Contributions

The two bar charts in Figure 8 show the impact on portfolio UL rank correlations with the change of PD and correlation inputs. We replace the PD inputs in the *Base Scenario* with random PD, rating, and EDF level, respectively, and keep LGD and correlation unchanged, then compute the modeled portfolio UL using RiskFrontier.

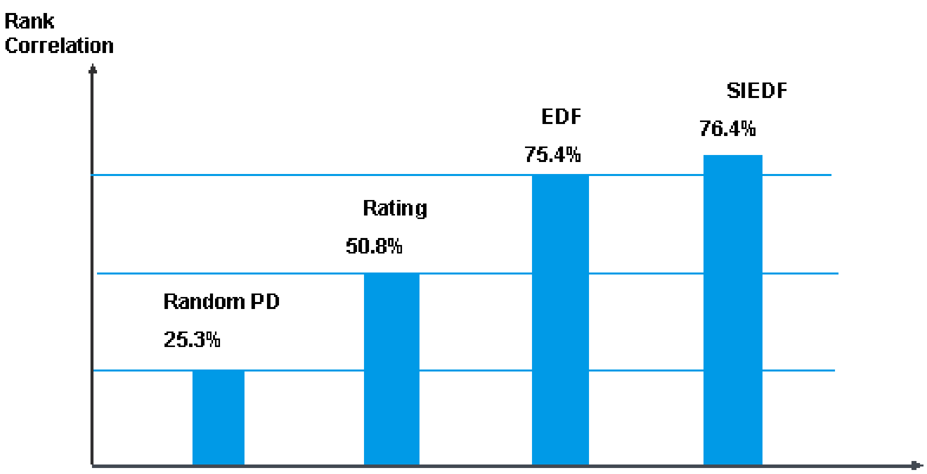

Figure 8 PD Impact on Portfolio Rank Correlations

The highest rank correlation (76.4%) is achieved when the SI EDF credit measure is used as the PD input. The EDF credit measure results in slightly lower rank correlation than the SI EDF measure. With rating-mapped PD as input, there is 50.8% of rank correlation between the modeled and empirical portfolio ULs, about 25% lower than with EDF measure and SI EDF measure.

Continuing this exercise, we now replace the correlation in the Base Scenario with zero correlation—empirical correlations 1 and 2, respectively. SI EDF measure and LGD remain unchanged. We then run the modified portfolios through RiskFrontier to obtain the predicted portfolio ULs.

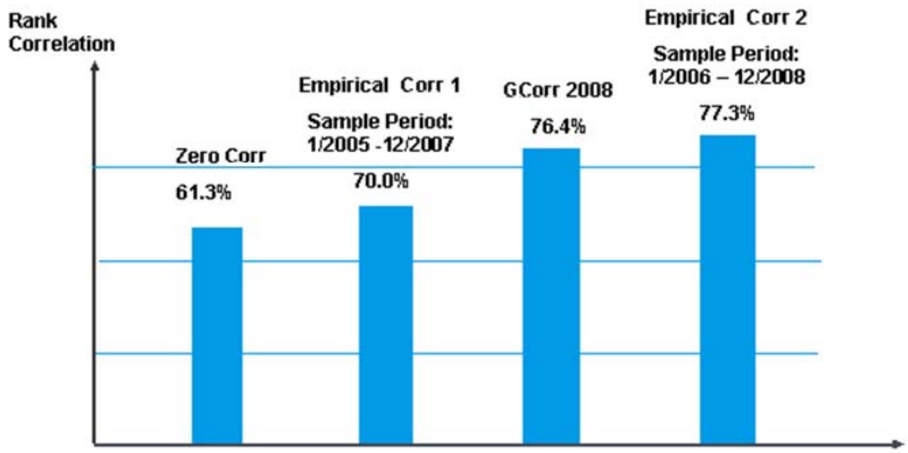

Figure 9 Correlation Impact on Portfolio Rank Correlations

Empirical Corr2 generates a rank correlation of 77.3%, slightly higher than *GCorr 2008*. This finding is not surprising given that the data for GCorr 2008 estimation ends at 2007, while the data for computing Empirical Corr2 covers one year of in-sample data. *Empirical Corr1* and GCorr 2008 allow for a more fair comparison because of the same asset return data coverage. Note that the latter outperforms the former by 6.4%, which confirms that the GCorr model produces more accurate estimates of future correlations than historical correlations. With zero pair-wise correlation, there is still 61.3% of rank correlation between modeled and empirical portfolio ULs.

From a risk management perspective, for those interested in maintaining the least volatile portfolios, the following Power Curve graph, shown in Figure 10, shows how accurately RiskFrontier can help detect the ten safest portfolios approximately 1.5 years in advance.

We construct the curves using the following steps.

1. Sort 100 CDS portfolios according to their realized, unexpected losses: on the y-axis, plot the 10 actual safest portfolios (i.e. with smallest ULs).
2. Sort these portfolios based on model predicated UL: on the x-axis, plot the portfolio ID starting from the least volatile portfolio to the most volatile portfolio.
3. Repeat step 2 for different PD input scenarios.

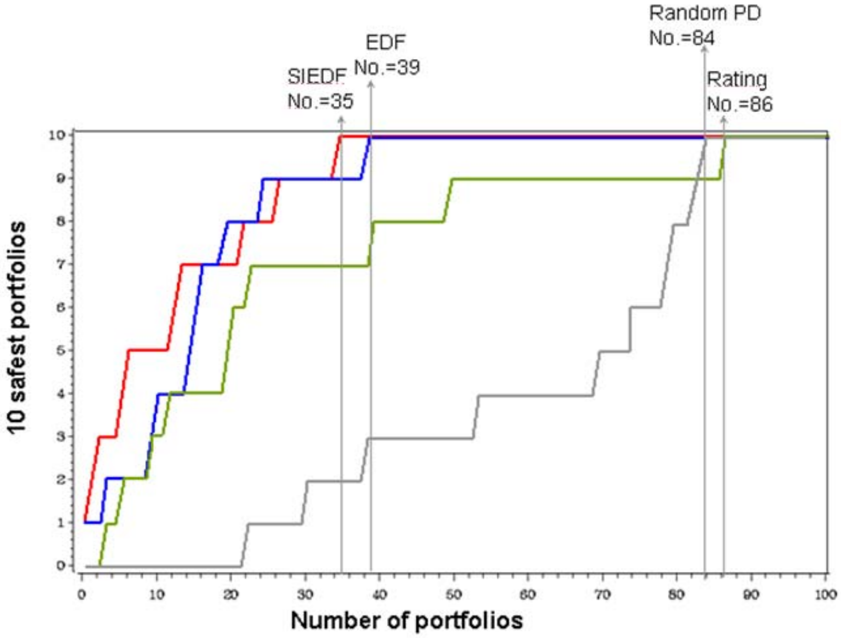

Figure 10 Selection of Ten Safest Portfolios Using Different PD Measures

The vertical line indicates the point at which the line jumps. For example, the label "SI EDF, No.=35" refers to the following case: with SI EDF credit measure as PD input, the ten actual safest portfolios fall into the group of 35 safest portfolios predicted by RiskFrontier. A good model will produce a steep line because it can correctly rank the portfolios according to their riskiness.

5 Conclusion

Evaluating the accuracy of a model's credit loss forecasts is critically important for risk managers and credit portfolio managers. However, validating credit risk models remains more difficult than backtesting market risk models. Credit risk models generally rely on a time horizon of one year or more and therefore produce a small number of forecasts for actual comparison.

Our validation study employs a different approach, focusing on examining the rank correlations between ex ante and ex post measures of portfolio relevant risk. The proposed method is straightforward and general enough to use with other types of credit risk models. It also provides quantitative measures of input quality.

Based on the RiskFrontier portfolio tool, our validation results show a rank correlation as high as 76% between the portfolios' predicted unexpected losses and subsequent realized volatilities. Within each portfolio, we find the rank correlations between modeled risk contributions and realized risk contributions to be high, ranging from 68% to 82%. Running portfolios under different input scenarios, we find that accurate and forward-looking PDs and asset correlations are important in determining the model's predictive power.

From a risk management perspective, for those interested in maintaining the least volatile portfolios, we show how effectively RiskFrontier can help detect the ten safest portfolios approximately 1.5 years in advance.

Appendix A : Sample CDS Data

Figure 11 through Figure 14 provide statistics snapshots of CDS data sampled on January 2, 2008.

In summary, 65% of the reference entities underlying 100 sampled CDSs are from the U.S. The average CDS-implied EDF measure (SI EDF) is approximately 3%, with 40% of the underlying reference entities investment grade. The average R-squared value is 28.5%, and the average LGD value is close to 60%

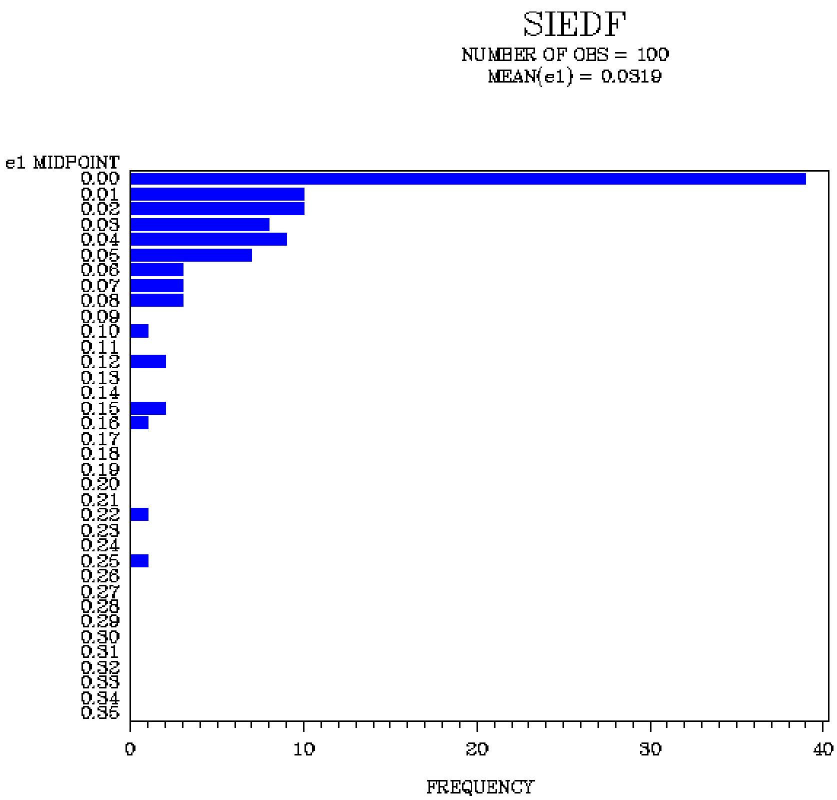

Figure 11 Statistics Snapshot for SI EDF

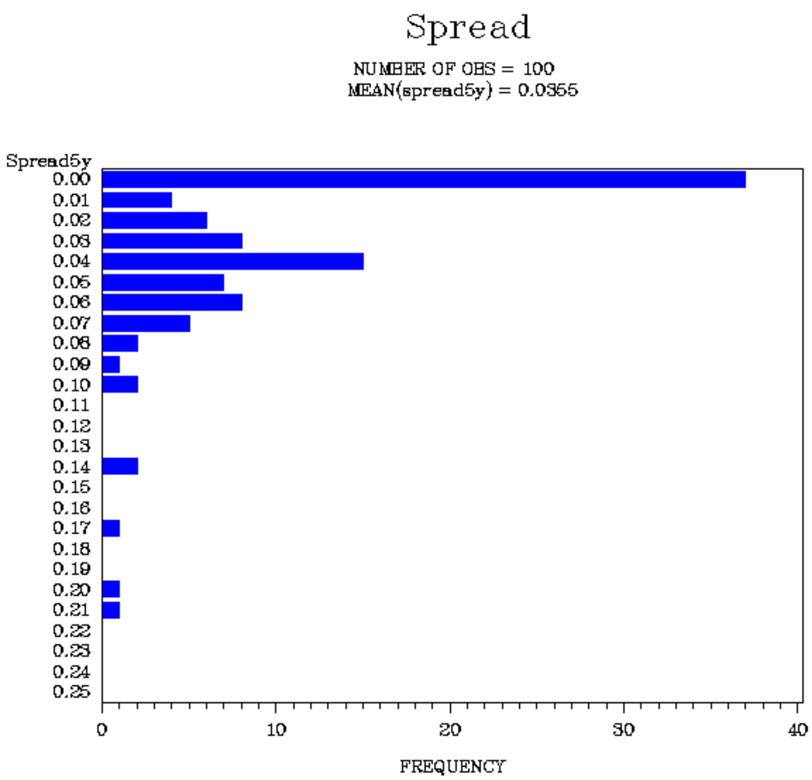

Figure 12 Statistics Snapshot for Spread

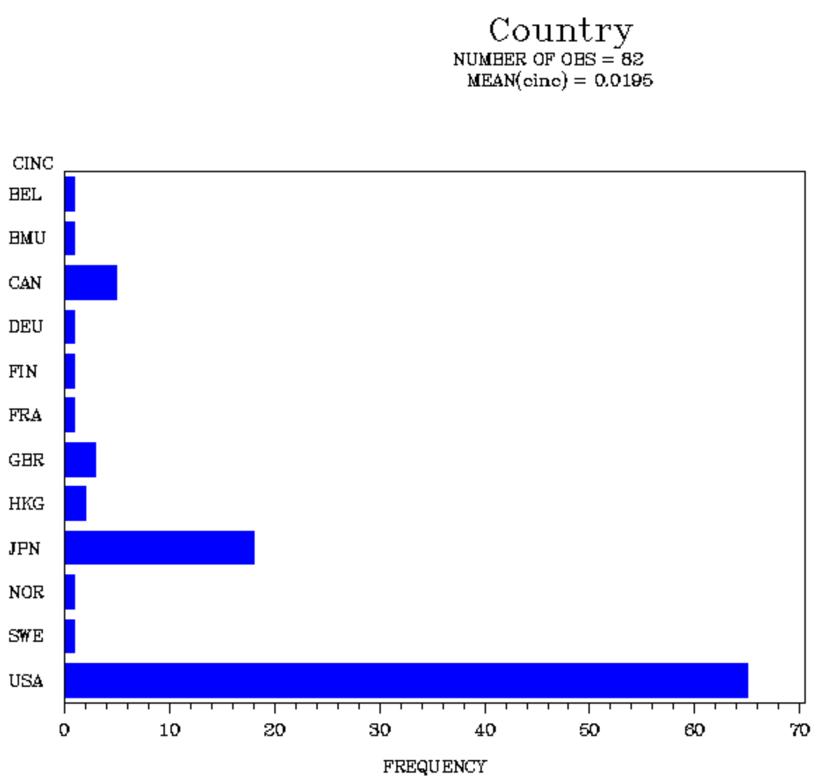

Figure 13 Statistics Snapshot for Country

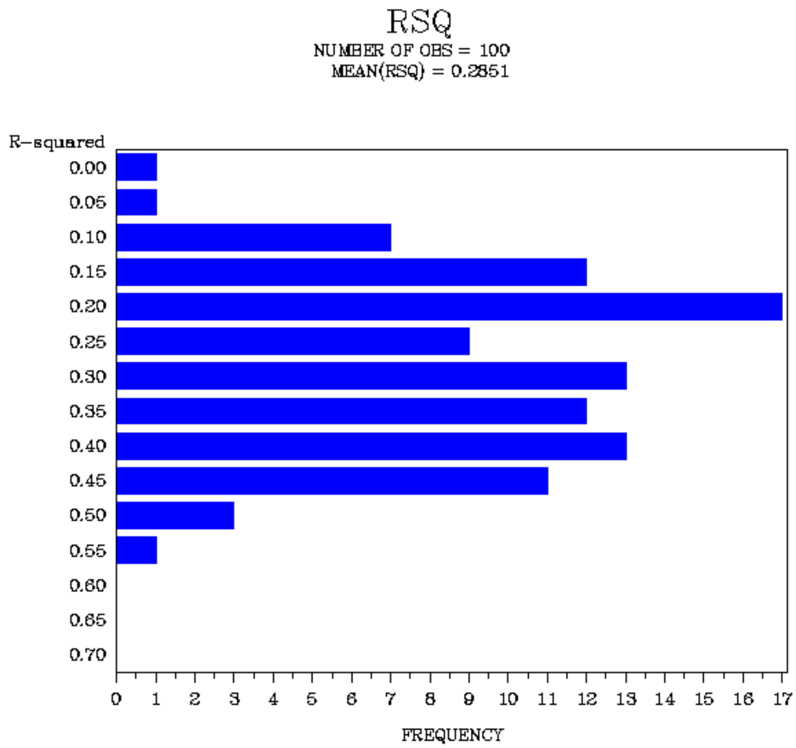

Figure 14 Statistics Snapshot for R-squared

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