A Firm Level Robust Credit Rating Migration Modeling Framework : A Small Sample Methodology

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Abstract

Crisis taught us that the capital markets are incomplete, with hidden information, which puts limits to arbitrage and thus controversial aspect of "efficient prices" prompts the valuation scientists to investigate deeper with more robust methodological investigations. In context, did our financial statements reveal something extraordinary, which allowed our "credit raters" to apply for robust measure of rating calibration ? The present paper proposed a "destabilizing" framework which can bring some benefit (if jointly there are lot of disturbances) in the flexible dynamic system. The dynamic system is a representation of the unknown latent factor. The human capital price as factor price was considered as an unknown factor. The model used here, utilized in a disintegrated fashion, two separate latent factor pricing models. The two latent pricing models (namely market-based and internal-information based) with respect to conditional volatility of latent prices (prices derived from single-variate market-based and internal-information based) showed marked differences, and it was observed that for sample companies under robust setup, the internal information based model yielded better credit rating annual forecast compared to the market-price based model.

Keywords : **OLS, EWMA, rating migration, bootstrapping, non-parametric**

JEL Classification : C1, C520, C580, E370

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Let us put a straight question - how can empirical experiments be conducted with only six listed companies; the answer lies that if the experimenter picked up the "target sector or industry" which is more vulnerable to the problem - "the NPA crisis" and simultaneously, as per the published information, only few companies comply with the requirement of the historical data framework. Therefore, it is evident that selection of the sample will ultimately reduce to its minimum, and any methodological survey can only be experimented within the available information set.

Credit rating agencies in the past faced some challenges like default - correlation, rating - migration, and equity - based credit rating framework, all jostling for one thing - identifying the "unobservable factor flexibility or dynamism." Firstly, the moment of such unobservable factors are random, but not independent, and thus, non-Gaussian in nature, limiting the use of asset-correlation prepositions of Gaussian - copula out of context. Secondly, the even bigger challenge is that how to bring those idiosyncratic prices into the modeling framework directly and see their impact in the rating - transitions.

According to Aulin's (2012) concept of cybernetics and dynamic system theory, any dynamic system (even asymbiotically) will never be stable and will always self-steer, self-regulate, steer from outside or 'disintegrate'. This was also explained in depth by Aulin (1989) particularly referring to the state - space models. Hence, the

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notion of considering the hidden Markov process constituted with macroeconomic and idiosyncratic factors together needs to be "disintegrated," and that is purposely devised for the present paper.

Such empirical issues are important since the sustainable human capital volatility (as a proxy for illiquid asset category in the present paper) is an important ingredient for the long-term stability of the economy. It is important to note that such incomplete information as per our traditional general equilibrium models provides stability or equilibrium under unscrupulous and highly speculative equity prices.

Literature Review

Thom (1984) and Anderson and Blundell (1982) together highlighted the benefit of a flexible dynamic system in terms of unrestricted preferential ordering and dynamic adjustment due to “conditional information”. Wu (2008) also mentioned about the use of simulation optimization using several algorithms employing local and global optimum. Furthermore, the paper highlighted the use of hybrid simulation, which can be used for agent-based and discrete simulation based modeling approaches. Earlier, Bonabeau (2002) discussed about the agent-based models particularly referring to counterintuitive results while explaining the example of ticker size reduction and reduction of spread.

The behavioral or psychological biases in return demand an evolutionary feedback-loop, and at times, remain hidden - Markov type structures. Gass (1983), in terms of flexible systems, explained some validation techniques out of which scenario or sensitivity building was considered ; this is also thought to be appropriate in the present paper. Oliva (2003) discussed that model calibration under system dynamics using iterative (automated) process and similar simulation using illiquid human capital is measured using bootstrapped samples.

Empirical and theoretical papers on the concept of hidden- Markov (state space models) using latent factor dynamics are very scarce. To begin with, Constantinide and Duffie (1996) rejected the notion that there is consumer's disaggregate to aggregate labour income ratio which is stationary and with low persistence in case of labour income shocks. Therefore, time varying equilibrium is achieved with hedging by bond like instruments and other suitable assets (but assumption of risk free arbitrage is self contradictory). Rajgopal and Venkatachalam (2007) clearly reflected that under a time series framework, the earnings quality and idiosyncratic volatility had some relationships, and this increased the stock returns. However, the paper failed in terms of differentiating the greater inclination of hidden assets valuations towards internal financial information in comparison to the stock returns. Gómez, Priestley, and Zapatero (2016) and Gori (2014) stressed on including the labour component in the CAPM framework. Together in a similar string, Martellni and Milhan (2015) shared the limitation of consumption pricing models and Wei (2009) and Constantinide and Duffie (1996) provided justification on inelastic labour supply reducing monetary policy shocks under equity is a relevant point in justifying pricing of human capital.

Hedge funds use illiquid pricing, which was demonstrated by Healy and Lo (2009), Lee (2014), and Jurek and Stafford (2015). Badea (2015) explained that procyclical risks are difficult to predict ; Gabaix (2011) justified that fat-tailed distribution of firm level activities impacts aggregate shocks.

However, several papers have been written in terms of credit risks and macroeconomic variables. According to Morgan (2002), bank's opacity brought larger default premium and there existed a distinctive asymmetry with relation to bank's bond issue ratings by different credit rating agencies. Peter and Fallis (2014) explained how the German banking industry, due to exposure of 'soft' creditors relationships had remained immune to the financial crisis. Tobin (1978) clearly mentioned that arbitrage is an incomplete exploited opportunity since acquisitions of capital and its disposal is not instantaneous and a state of equilibrium is difficult to reach. Castro (2012) commented on the use of factor dynamics with a mixed model approach while criticizing BASEL 2 using single factor model for credit assessments. In continuity with the subject of unobserved factor autocorrelated dynamics and non-Gaussian distribution properties, Wendin and McNeil (2006) proposed a realization of hidden Markov process (state space models) with robust calibration using MCMC (Markov chain Monte Carlo) simulation. The interesting outcome, however, is hyper parameters like upgrade migration correlations and downgrade migration correlations, which are used effectively in terms of predicted conditional idiosyncratic asset volatility through internal financial information and stock prices in the current work.

Wei and Zhang (2006) demonstrated the importance of frailty factors in terms of violation of joint stochastic probabilities associated with the credit-risk models. Frailty factors according to them are those unobservable latent factors that have correlation among firms. Wei and Zhang (2006) and Ali, Hwang, and Trombley (2003) commented on fundamental value to stock price ratio and its relationship with mispricing and risk proxies.
There was a use of discrete time-maximum likelihood (DTML) framework with time-homogenous Markov chain process (Gavalas & Syriopoulous, 2014). Schwaab, Koopman, and Lucas (2011) associated "barometers" which are those set of empirical outcomes that are different from macroeconomic indicators. The paper relates the magnitude of latent frailty factors with the early warning signal under micro-prudential setup.

For this purpose, a robust methodology involving several statistical techniques for risk measurement in a small sample set up (as explained in the beginning, only six Indian listed companies in the textile sector are considered for experimental purposes).

Broad Research Objective Framework

The present paper will mainly discuss the methodological impact as to how such sustainable human capital volatilities under bootstrapped prediction can provide basis for our credit rating agencies that can utilize hidden asset volatilities and correlation in comparison to the market model for better credit governance at the granulated levels.

Methodology

Most of the earlier work on credit rating models with unobservable variables utilized the state space model with the assumption that such unobservable (latent) factors have autocorrelated dynamics under usually high-frequency time-scales. However, all these above-mentioned strings of research took the mixed modeling approach, that is, utilized macro - economic factors and idiosyncratic factors together. Secondly, use of bootstrapped inputs differentiated dynamic arrangements of variables into flexible systems allowing changes which are scenario-built.

As indicated earlier, in the present work, the analysis proceeds as follows :

(1) Empirical Model Building Process

(i) Initially, after gathering the last 16 years (starting from 1999 - 2000 till 2014-15) aggregate information of six textiles companies converted for first differences (based on market capitalization ending January 21, 2015), PCA (principal component analysis) was conducted for factor decomposition and single-factor modeling.

(ii) The use of single-factor modelling (with decomposed set of independent annual financial information using PCA) was used.

(iii) Model validation was ascertained with root means square error (RMSE) - scale variant and mean absolute percentage error (MAPE) - scale invariant error measurement techniques were used one after the other.

(iv) For forecasting purposes, bootstrapping (fixed *X* resampling with replacement) was utilized for generating 10 different resamples for each sample company. Markovich (2008) and Wood (2005) supported this view that small resamples may be helpful in retaining the original properties of distribution of the population.

(v) Furthermore, an attempt to calculate the bootstrapped (equal weighted moving average (henceforth, EWMA) volatility of predicted employee costs was calculated for each resample. Moosa and Bollen (2002) and Pasaran and Zafforoni (2005) emphasized on "equal weights" method as unbiased rolling filters since, in the bootstrapping arrangement, the posterior probabilities are not based on assigning unequal weights, because the possibility of lagged information can be sequenced randomly.

(vi) Ang's (2014) approach of optimal asset allocation in the long run comprising of labor income risks was considered at the "firm-level".

(2) Disintegrated "Latent Factor" Modeling Approach : As discussed earlier, using flexible dynamic systems approach, the current paper uses parsimonious pricing model based firm-level employability volatility using current market price (Model - CMP) and firm-level employability volatility using internal financial information with single-factor derived after PCA decomposition (Model - Others). So, the present paper will essentially show the difference between the Model - Others and Model - CMP with relation to the 'default intensities' (a nomenclature commonly used in credit risk modeling). For the prediction process, the small - resample for maintaining the non - parametric properties of frail factor autocorrelation flexible dynamics is also highlighted at the end.

(3) Important Equations and Description : In the fixed resampling, the bootstrap replication is conducted when matrix X is fixed. I tested the fitted values $\hat{Y}_i$ for the model by the bootstrap responses. The steps are summarized as follows :

Step 1: Fit a model to the original sample like to get the $\hat{\beta}$ and the fitted values as, $\hat{Y}_i = f(x_i, \hat{\beta})$.

Step 2: Get the residuals $\varepsilon_i = y_i = \hat{y}_i$.

Step 3: Draw ε_i^* from ε_i and attach to $\hat{Y}_i$ to get a fixed x bootstrap values Y_i^*.

where, $\hat{Y}_i = f(x_i, \hat{\beta}) + \varepsilon_i^*$ (1)

Step 4: Regress the bootstrapped values Y_i^* on the fixed X to obtain β^*.

Step 5: Repeat Step 3 and Step 4 for β times to get $\beta^{*1} \ldots\ldots\ldots \beta^{*b}$.

Dogan (2007) critically examined the use of bootstrapping and likelihood estimation on the small samples. According to him, under the non-parametric estimation in system dynamic modeling, the error term is assumed to be randomly placed with the time-bound unlike the case of parametric methods where the error term is not random within the time-bound.

(4) EQMA Model for Conditional Variance of Fitted Time-Series Data : Using equal weighted moving average for conditional variances (to recollect - here, fitted shadow price series volatility for bootstrapped samples are calculated).

$\sigma^2_x n = \omega v + \lambda \sigma_x^2{}_{(n-k)} + (1-\lambda)\mu^2{}_{(n-k)}$ (2)

$\sigma^2_x n$ = The n period variance of the index series.

ωv = Long term weight * long term volatility.

[1]Volatility = Square root of variance.

$\lambda\sigma_x^2{}_{(n-k)}$ = The λ (decay rate) multiplied with the squared lagged variance.
$(n\text{-}k)$ = The lagged component. In the present paper, the yearly lag is considered.
$(1-\lambda)\mu^2{}_{(n-k)}$ = Here, this is decay representing with the growth rate, this denotes whether there is rapid decay or slow decay, in the case of rapid decay, the mean reversion is fast.
For the present purpose, the decay rate was kept as 0.10 or 10% y.o.y. for 10 years simulated time period.

(5) Life Cycle Approach Modeling Equations (Specific Mathematical Interpretations) :

(i) Bootstrapped (proxy to flexible system arrangement) conditional volatility comparison (Smoothed EWMA volatility[1]) Model (Others) & Model (CMP) :

$\overline{\sigma}^2{}^{\text{Resample}}_{x\,\text{model (others)}}$ = Average smoothed bootstrapped Model (Others) volatility.
$\overline{\sigma}^2{}^{\text{Resample}}_{x\,\text{model (CMP)}}$ = Average smoothed bootstrapped Model (CMP) volatility.
$\sigma^2{}^{\text{original}}_{x\,\text{model (others)}}$ = Average original empirical Model (Others) volatility.
$\sigma^2{}^{\text{original}}_{x\,\text{model (CMP)}}$ = Average original empirical Model (Others) volatility.
I_S^{Resample} = Stock-like capital under smoothed bootstrapped case.
I_B^{Resample} = Bond-like capital under smoothed bootstrapped case.
I_S^{Original} = Bond-like capital under original empirical model case.
I_B^{Original} = Bond-like capital under original empirical model case.

Scenario 1 :

$$\left\{\overline{\sigma}^2{}^{\text{Resample}}_{x\,\text{model (others)}} = \left(\Sigma_n^{t=1}\,\sigma^2_{x\,\text{others}}\right) \div n\right\} < \left\{\overline{\sigma}^2{}^{\text{Resample}}_{x\,\text{model (CMP)}} = \left(\Sigma_n^{t=1}\,\sigma^2_{x\,\text{CMP}}\right) \div n\right\} = I_S^{\text{Resample}} \tag{3}$$

Scenario 2 :

$$\left\{\overline{\sigma}^2{}^{\text{Resample}}_{x\,\text{model (others)}} = \left(\Sigma_n^{t=1}\,\sigma^2_{x\,\text{others}}\right) \div n\right\} > \left\{\overline{\sigma}^2{}^{\text{Resample}}_{x\,\text{model (CMP)}} = \left(\Sigma_n^{t=1}\,\sigma^2_{x\,\text{CMP}}\right) \div n\right\} = I_B^{\text{Resample}} \tag{4}$$

(ii) Original (empirical) conditional volatility comparison (EWMA volatility) between Model (Others) & Model (CMP) :

Scenario 1 :

$$\left\{\sigma^2{}^{\text{original}}_{x\,\text{model (others)}} = \omega v + \lambda\sigma_{others}^2{}_{(n-1)} + (1-\lambda)\mu_{others}^2{}_{(n-1)}\right\} <$$
$$\left\{\sigma^2{}^{\text{original}}_{x\,\text{model (CMP)}} = \omega v + \lambda\sigma_{CMP}^2{}_{(n-1)} + (1-\lambda)\mu_{CMP}^2{}_{(n-1)}\right\} = I_S^{\text{Original}} \tag{5}$$

Scenario 2 :

$$\left\{\sigma^2{}^{\text{original}}_{x\,\text{model (others)}} = \omega v + \lambda\sigma_{others}^2{}_{(n-1)} + (1-\lambda)\mu_{others}^2{}_{(n-1)}\right\} >$$
$$\left\{\sigma^2{}^{\text{original}}_{x\,\text{model (CMP)}} = \omega v + \lambda\sigma_{CMP}^2{}_{(n-1)} + (1-\lambda)\mu_{CMP}^2{}_{(n-1)}\right\} = I_B^{\text{Original}} \tag{6}$$

(iii) Credit-Rating Migration Model

$$\left[I_B^{\text{Original}} => I_S^{\text{Resample}}\right] = \text{UPGRADE}$$

$$\left[I_B^{\text{Original}} => I_B^{\text{Resample}}\right] = \text{NO CHANGE}$$

$$\left[I_S^{\text{Original}} => I_S^{\text{Resample}}\right] = \text{NO CHANGE}$$

$$\left[I_S^{\text{Original}} => I_B^{\text{Resample}}\right] = \text{DOWNGRADE}$$

(iv) Migration Ratio (in times)

$$\text{migration ratio}_{\text{Smoothed Resampled}} = \frac{\bar{\sigma}^{2}\ {}^{\text{Resample}}_{x\text{model (CMP)}}}{\bar{\sigma}^{2}\ {}^{\text{Resample}}_{x\text{model (others)}}} \qquad (7)$$

$$\text{migration ratio}_{\text{Original}} = \frac{\sigma^{2}\ {}^{\text{Resample}}_{x\text{model (CMP)}}}{\sigma^{2}\ {}^{\text{Resample}}_{x\text{model (others)}}} \qquad (8)$$

Analysis and Results

Refer to Table 1 in case of regression diagnostics (post PCA implementation). Firstly, for Model - Others, we can easily witness that the regression coefficients of Arvind Mills, Bombay Dyeing, and Grasim Industries are 1.0035, 0.8253, and 0.7467, respectively and in all cases, the p - values are below 0.05. The remaining three companies namely, Vardhaman, SRF, and Raymond are found with weak regression coefficients and insignificant p - values. As it appears, Model - Others for SRF, Bombay Dyeing, and Grasim Industries has functional model limitations with regard to very low R-squared values.

For Model CMP (see Table 2), SRF has reasonably interesting outcomes, that is, beta is at -0.0341, but p - value is 0.082 and R square value is better than what it is for Bombay Dyeing and Grasim Industries. SE of regression is also on the lowest level. For Raymond, although the covariate value is highest at 0.1659 (but weak p - value of

Table 1. Ten Resampled (Model-Others) "Regression Coefficients" for Textile Sector Companies

(Figures are in Absolute Numbers)

Companies (INDEPENDENT variable)	UNEXPLAINED VARIATION	BETA (*p* value)	EXPLAINED VARIATION	RMSE	MAPE	*SE* OF *R*	NORMALITY OF RESIDUAL	AUTOCORRELATION	HETEROSKADITICITY
ARVIND(ST)	"0.0439 (0.1787)"	"1.0035 (<0.0001)"	0.8998	3.87%	0.77%	0.1277	0.047* (Close to 0.05)	0.5407	0.7434
BOMDYE(P&F)	0.0088 (0.8435)	0.8253 (<0.00001)	0.5428	7.37%	4.5%	0.1763	0.9741	0.6541	0.3271
GRASIM(ST)	0.0149 (0.5122)	0.7467 (0.00001)	0.5696	3.38%	9.48%	0.1194	0.0749	0.1303	0.5789
RAYMOND(ST)	"0.0509 (0.4226)"	B1 FIRST DIFF (AR1)"-0.7952 (0.2165)"	0.5889	18.08%	172.57%	0.2895	0.085	NA	NA
SRF(ST)	0.1383 (0.00638)	0.1172 (0.5715)	0.0305	2.64%	0.25%	0.1055	0.5452	0.8935	0.5383
VARDHAMAN (ReEx)	0.0023	B1 (SECOND DIFF AR1)-0.0169(0.8116)	0.4388	41.19%	214.20%	0.4492	0.1418	NA	NA

Note : SRF with very low R-squared value.

Table 2. Ten Resampled (Model-CMP) “Regression Coefficients” for Textile Sector Companies

(Figures are in absolute numbers)

Companies (INDEPENDENT Variable)	UNEXPLAINED VARIATION	BETA (*p* value)	EXPLAINED VARIATION	RMSE	MAPE	SE OF R	NORMALITY OF RESIDUAL	AUTO CORRELATION	HETEROSKADITICITY
ARVIND (SP)	"0.1341 (0.063)"	"0.1048 (0.2372)"	0.4879	18.63%	3.22%	0.2866	0.4789	NA	NA
BOM DYEING (SP)	(0.792)	0.0277 (0.7412)	0.0081	16%	26.57%	0.2596	0.6387	0.2761	0.3718
GRASIM (SP)	0.0662 (0.255)	-0.068 (0.1926)	0.0667	7.33%	23.67%	0.1758	0.0565	0.6853	0.8239
RAYMOND (SP)	"0.0048 (0.9786)"	B1 (THIRD DIFF AR(1)"- 0.1659(0.7527)"	0.7383	154.77%	4.52%	0.8981	0.2079	NA	NA
SRF (SP)	0.1735 (<0.00001)	-0.0341 (0.082)	0.1449	2.34%	0.81%	0.0991	0.5937	0.9836	0.3898
VARDHAMAN (SP)	0.0384	B1 0.0205, B2 SP1 0.0468, B3 SP2 0.1632, B3 SP3 0.0870, B4-lag1 - 0.3272, B5-lag2 01309, B6-lag3 0.3033	0.4259	41.23%	15.38%	0.2617	0.1418	NA	NA

Note : Bombay Dyeing and Grasim Industries with very low *R*-squared values.

Table 3. Ten Resampled “Conditional Volatility” for Textile Sector Companies

(Figures are in percentage numbers)

Companies	% (EC/TC)	Original	SAM 1	SAM 2	SAM 3	SAM 4	SAM 5	SAM 6	SAM 7	SAM 8	SAM 9	SAM 10	AVERAGE	STDEV
ARVIND (SP)	12.95%	20.59%	37.38%	34.97%	20.16%	14.99%	24.07%	22.90%	35.82%	35.99%	31.19%	21.14%	27.86%	8.10%
BOM DYEING (SP)	11.37%	2.28%	42.14%	36.11%	20.23%	26.12%	36.08%	36.54%	31.54%	29.67%	38.51%	40.29%	33.72%	6.81%
GRASIM (SP)	6.89%	5.62%	23.07%	11.48%	20.17%	20.20%	20.39%	19.67%	22.31%	22.32%	19.61%	23.69%	20.29%	3.43%
RAYMOND (SP)	17.57%	83.01%	135.27%	140.67%	20.16%	102.45%	146.71%	123.87%	155.70%	129.07%	118.14%	154.30%	122.64%	39.63%
SRF (SP)	8.57%	14.08%	27.26%	19.64%	20.17%	16.48%	16.73%	22.22%	17.83%	15.59%	18.02%	21.02%	19.50%	3.46%
VARDHAMAN (SP)	10.17%	22.81%	58.51%	63.51%	20.16%	64.69%	55.73%	62.90%	52.03%	61.85%	53.71%	44.83%	53.79%	13.34%
OTHERS														
Companies	**% (EC/TC)**	**Original**	**SAM 1**	**SAM 2**	**SAM 3**	**SAM 4**	**SAM 5**	**SAM 6**	**SAM 7**	**SAM 8**	**SAM 9**	**SAM 10**	**AVERAGE**	**STDEV**
ARVIND	12.95%	20.43%	25.69%	21.54%	20.19%	20.35%	19.97%	23.75%	19.72%	22.87%	25.51%	20.65%	28.33%	10.77%
BOM DYE	11.37%	25.90%	33.62%	29.07%	20.17%	25.54%	23.61%	29.04%	33.13%	24.70%	25.76%	24.55%	20.06%	3.65%
GRASIM	6.89%	14.87%	15.50%	21.00%	20.16%	15.00%	14.39%	17.00%	16.74%	12.27%	16.79%	19.79%	13.67%	3.50%
RAYMOND	17.57%	20.18%	37.32%	45.77%	20.16%	38.92%	44.01%	49.03%	49.49%	42.83%	36.26%	39.25%	23.04%	7.37%
SRF	8.57%	18.04%	14.94%	19.63%	20.16%	23.62%	22.70%	20.10%	19.63%	21.17%	27.63%	23.74%	16.45%	2.72%
VARDHMAN	10.17%	22.27%	24.66%	26.82%	20.16%	22.70%	22.70%	23.05%	34.77%	29.02%	22.77%	30.12%	33.34%	12.37%

0.7527), high *R* square of 0.7383, but SE of regression is also very high, which leaves Raymond and SRF to be slightly close contenders in terms of Model CMP volatility.

Considering the superiority of Model - Others with comparison to Model- CMP (and making MAPE the scale invariant measure), few key observations are like this (See Table 1 and Table 2). So far, in terms of MAPE, SRF is found with the lowest values for both the models. However, in Model - Others, it is 0.25% compared to 0.81% in the Model- CMP case. Arvind Mills, Bombay Dyeing, and Grasim Industries witnessed a much lowered MAPE value while comparing the Model - Others with that of Model - CMP. Raymond Industries and Vardhaman appeared with dissimilar rather strikingly contrasting results in comparison to the rest of the four companies.

It can be inferred from the Table 3 that in almost three textile companies, the firm-level volatility is higher for Model - Others compared to Model-CMP. Arvind Mills, Raymond, and Vardhaman have the Model-Others volatility lower than that of Model-CMP volatility. This is interesting as it can be seen that Raymond is having higher proportion of employee costs in companies (average of human capital percent of total capital). It is witnessed that except for Arvind Mills, the remaining five companies have their bootstrapped average volatilities at a lower level in terms of Model-Others. However, these results compared to the original model present a

Table 4. Andrew Ang Approach (2014) Applied Towards Comparing the Differences in Model Volatilities Across Original and Bootstrapped Cases (Single Horizon Basis)

ANG (2014) APPROACH OF ASSIGNING SPECIFIC RISK-MINIMIZATION STRATEGY FOR "ILLIQUID HUMAN CAPITAL RISKS"									CREDIT-RATING MIGRATION
Companies/Sectors	ORIGINAL MODEL			Bond-Like Versus Stock -like Capital Arrangement	SMOOTHED BOOTSTRAP Model		Bond-Like Versus Stock -Like Capital Arrangemeznt	Chance of Predicted Firm-Level Employment Volatility Derived from Fundamental Factors Exceeding that of Stock Price Based Model Under Bootstrapped Scenario (ROBUST MEASURE)	DOWNGRADE, UPGRADE, NO-MOVEMENT
	% (EC/TC)	EWMA			EWMA				
TEXTILES		OTHERS	CMP		OTHERS	CMP			
ARVIND ST	12.95%	20.43%	20.59%	STOCK-LIKE CAPITAL	22.02%	27.86%	STOCK-LIKE CAPITAL	NO CHANGE	NO-MOVEMENT
BOMDYE(P&F)	11.37%	25.90%	2.28%	BOND-LIKE CAPITAL	26.92%	33.72%	STOCK-LIKE CAPITAL	REDUCE	UPGRADE
GRASIM INDUSTRIES(ST)	6.89%	14.87%	5.62%	BOND-LIKE CAPITAL	16.86%	20.29%	STOCK-LIKE CAPITAL	REDUCE	UPGRADE
RAYMOND ST	17.57%	20.18%	83.01%	STOCK-LIKE CAPITAL	40.31%	122.64%	STOCK-LIKE CAPITAL	NO CHANGE	NO-MOVEMENT
SRF(ST)	8.57%	18.04%	14.08%	BOND-LIKE CAPITAL	21.33%	19.50%	BOND-LIKE CAPITAL	NO CHANGE	NO-MOVEMENT
VARD REFx	10.17%	22.27%	22.81%	STOCK-LIKE CAPITAL	25.68%	53.79%	STOCK-LIKE CAPITAL	NO CHANGE	NO-MOVEMENT

TABLE 5. Credit-Rating Migration Ratios (Single Horizon Basis)

	Model (Others)	Model (CMP)
TEXTILES	Ratio (Original/Bootstrap)	Ratio (Original/Bootstrap)
ARVIND ST	1.08%	1.35%
BOMDYE(P&F)	1.04%	14.79%
GRASIM(ST)	1.13%	3.61%
RAYMOND ST	2.00%	1.48%
SRF(ST)	1.18%	1.38%
VARD REFx	1.15%	2.36%

different picture. It is ,therefore, customary to use the resampling method for robust model validation and assessment. Moving ahead, the last component of the paper describes the life cycle portfolio approach (according to Table 4), where a firm decides to shift from low risk asset class investments to high-risk asset class investments or vice versa depending upon the 'magnitude' of volatility measured between Model - Others and Model CMP.

As seen in Table 5, in case of Bombay Dyeing and Grasim Industries, as inferred from the above results, the proportionate change from original empirical volatility to bootstrapped volatility for the two companies for Model - Others is 1.04 times and 1.13 times (lowest in comparison to all five stocks leaving Arvind Mills at 1.08 times ; while for Model-CMP, the change is from 14.61 times and 3.61 times, highest among all the six stocks), which proves to be better in managing their idiosyncratic (factor) risks in comparison to rest of the sample companies.

The Ang (2014) approach can also support in relating the 'rating migrations' with reference to the change of direction (in reference to whether the original empirical volatility of Model-Others and Model CMP comparative “change” /or “do not change” asset-investment approach at the smoothed bootstrap levels). Such relative idiosyncratically rating migrations model is of strategic importance and can provide an interesting dimension in the default risk management of long-term investment portfolio risks of financial institutions. It is clearly seen that smoothed bootstrapped model is actually replicating a “flexible dynamic system” of non-bayesian equilibrium properties, while the original model is the initial condition (based on historical data) defining the current state of factor elasticity.

As can be observed, with respect to Bombay Dyeing and Grasim Industries, the idiosyncratic robust volatility-based risk rating has improved or upgraded, while no movement is found in the remaining companies. As per long term portfolio management, including illiquid assets (for original empirical model) Arvind Mills, Raymond, and Vardhaman should acquire stock like alternative investments for long-term portfolio risk balancing/minimization, and on the contrary, Bombay Dyeing, Grasim Industries, and SRF should invest more in bond-like investments. For robust smoothed model out of six sample companies, SRF is found with bond like investment requirements, which clearly explains the benefits of using robust methodologies for long term portfolio management.

Research Implications

For strategic credit risk management, it is empirically seen that the idiosyncratic firm level employment volatility derived from internal published financial information has stronger explanatory power in comparison to the firm level employability volatility predicted through current market price route. This also assures that default correlations are not jointly stochastic, there is hidden Markovian (state space model tendency) particularly due to the impact of idiosyncratic information. The use of a flexible dynamic model (with 'disintegration') proves worthy in so far linking with parsimonious and statistical relevancy of low frequency autocorrelation of unhedged illiquid volatility.

Conclusion

Use of a small sample, although justified, retains the original distribution properties of the time-series (in terms of non-normality) but under dynamic optimization, particularly for bootstrapped time-series regression, limiting likelihood tests (autocorrelation tests etc.) for lower lags can be questioned. Considering quarterly or monthly data, including certain macroeconomic (exogenous) factors, could make the human pricing model more meaningful, but at the same time, requires maintaining the degree of freedom issues since balance sheet publications happen usually on low time - intervals. Model calibration in terms of Balras test of error statistics in terms of bootstrapping results, Hausmen test of endogenity were missing and can be incorporated in future studies.

The overall results demonstrate the dominance of Model - Others in terms of high explanatory power, low conditional smoothed bootstrapped volatility, and also high upgrade and stable rating migration scenario. For credit-risk management, the bottom-line is that a factor-level price volatility strategy is desirable considering the fact that macroeconomic policies fail to adequately account for credit-defaults at the individual firm-level funding programs. Flexible system approach with dynamic parameter estimation using bootstrapping method clearly explains how the behavior of the outcomes changes (as per the initial modeling "original model" structure). Model - Others outperforms even under endogenously randomized set up of explanatory variables, compared to Model - CMP, claiming that human capital pricing is extremely important to reduce the ambiguity-aversion of investors, particularly in long-horizon cases.

The long term portfolio management using robust smoothed bootstrapped shadow prices clarifies the importance of micro management of mispricing information for insurance against long term default risks. By predicting such robust human capital risks and linking with well-established rating migration models provides a meaningful strategic tool for default risk volatilities and its management.

Limitations of the Study and Scope for Further Research

The study is confined to dynamic system by involving bootstrapped conditional volatility estimates. However, a small sample size cannot be considered as policy prescription, more number of companies within the sector is desired. The context of small bootstrapped size of companies puts limits to only non-parametric environment.

The risk governance of illiquid assets like human capital (as factor prices) using two different pricing models gives a whole new dimension of considering factor pricing models in the investment risk management for long term as well as mitigation with use of robust measures for its validation and practice.

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