Sustainable Risk Management of Financial Institution Investments: A Cbsprcv-At-Risk Capital Framework

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Abstract

Is it possible to propose bootstrapped regression coefficient series which possess time-series element, considering they emerged from the idiosyncratic regression residuals? If it is so, then a generalization of traditional autoregressive conditional volatility based value-at-risk model and thereby ascertaining risk capital under point-back test (Traffic signal approach) can be meaningful. Using above methodology institutions can provide reasonable justification of "risk exposure" towards intra-industry investments with idiosyncratic wage data as a decision variable. The present paper use the similar ideology stated above, considering a robust autoregressive series of bootstrapped regression coefficients as a proxy for empirical conditional systematic (micro-systematic to be precise) risk series and leading to creation of a "Risk capital" measure for Banks to ascertain the "uninsured illiquid securities/assets risk capital buffer" they may have to ascertain under extreme risk prepositions. The paper clearly demonstrates how robust risk capital (Conditional bootstrapped shadow price regression coefficient variance: CBSPRCV-at- risk capital) of shadow assets (human capital costs) makes relevance in modern economic environment of unreliable market framework.

Keywords : OLS, Bootstrapping, Risk optimization, CBSPRCV JEL: G17, C54, C58, D52

Introduction:

Human capital is a critical resources and its vulnerability in terms of endogenous factors seems empirically and structurally relevant and worth investigating, not only from welfare perspective, but also from micro-prudential risk governance perspective. The statistical dimension of using shadow assets as Human capital and aligning them with financial factors in aggregate manner for pricing framework and studying its robustness for risk sharing purposes is a policy dimension which modern banking institutions must develop for a sustainable risk management. On the same premise, an attempt is made to ensure some pragmatic realization can be made using well known statistical modeling framework. More generically as Galor and Moav (2004) explained that why changingeconomic climate from manufacturing to knowledge economy require migrating from physical capital accumulation and pricing to human capital accumulation and pricing. The paper also explains that why economies with lower return to human capital in comparison to physical capital works well under the economic inequality framework while how this economic equality matters when changes in case human capital return component improves in comparison to the former.

With a low frequency data, like annual financial information, it is very risky to use AR (p) models, since, the assumption is that market prices usually take lesser than a year to absorb the information, but here in this paper, we are using shadow prices, or more precisely, a endogenous human capital pricing framework, for which a "market mechanism" for frequent price releases is not available. So it can be worthy to look forward for traditional AR (p) framework for lesser lagged series, at least, to justify the empirical outcomes. An uninsured hedge fund risk having exposure to illiquid securities carries very high autocorrelation and is an excellent case in point. Financial institutions must be restricted in case they default or support through capital by the state, or both (Berger, Bouwman, Kickand Schaeck, 2011). But these measures are not preparing these organization to do micro management of their investments, after all, restricting banks to provide loans will most likely is economically unviable option.

The particular empirical contribution of using human capital assets as proxy for wealth portfolios is case in point (Zhang, 2006). This paper by Zhang (2006) further explained why jointly the accounting of human capital assets and other financial assets is extremely important. A functional coefficient autoregressive models (FAR) are popular in theacademic context (Chen, 2001). Koenker and Xiao (2012) used quantileautoregression with resampling approach as a model proxy to the M-estimation for the unit root tests for heavy tailed series. The quartile regression also hold well in case of data with significant outliers possibilities. Kim (n.d.) explained the use of mean unbiased estimation for biased error removal in case of small sample bootstrap prediction interval estimation in case of AR series. For optimal AR (p) the use AIC, BIC and similar criteria's were suggested. Eakin, McMillen and Buono (1990) in their paper utilized bootstrapped technique for small samples and to generate confidence intervals. Hence, unlike this paper, bootstrap can be used for generation of confidence intervals under a normalization assumption. For prediction interval estimates in a time-series setup, bootstrapping AR (p) volatilities is an improved method, provided the residuals are bootstrapped first for generating conditional volatilities, together a stress on use of predictive root (error) and studentized root was emphasized for bootstrapping purposes. (Pan and Politis, 2014). Levich and Rizzo (1999) presented a more robust test of autocorrelation because the first order autocorrelation can only be measured by DW statistic, further, ACF and PACF are better, but the paper proposed two additional tests namely "P" and "ϕ" vocalized as "Rho" and " PHI" in greek. Scientifically, it is difficult to find enough empirical work done particularly in human asset risk capital using bootstrapped autoregressive regression coefficients. So, connecting various parallel studies in areas of boostrapped auto regression was found to be much relevant. Hence, the research objective is to critically identify the complex risk methodology with the help of statistical tools for the measurement of long term risks associated with the illiquid investments occupied by the financial institutions

Literature Review

The papers concerning use of endogenous firm level aggregate financial information for human capital pricing are rare; most of the papers utilize the subjective variables concerning human resource. But papers on statistical measures and robust pricing models are rarest so far and therefore to begin with,

A fundamental paper by Kreiss and Neumann (1999) examines how the wild bootstrap of non-parametric autoregressive series can be tested with parametric test properties. Fair (2003) provide validation for bootstrapping with dynamic, non-linear, structured equations. Gonçalves and Kilian (2004) explained the use of three types of autoregressive bootstrapping procedures for conditional heteroskadasticity of the first order asymbiotic distribution. Inoue and Kilian (2002) explained the use of bootstrapping in the VaR(∞) models as against the traditional models which used the finite-lag asymbiotic measures. The reasons are that even with infinite lag order, the asymbiotic variance never tend to become zero.

In terms of idiosyncratic human capital risks, papers by Kerbs (2003) explained that how the aspect of human capital idiosyncratic risks are associated with business cycles. Related paper by Atkeson and Phelan (1994) emphasized that how a countercyclical policy is welfare oriented by justifying the idiosyncratic income risks among individuals by reduced correlations among them. There is a stress on individual's storage technology in the event of high unemployment risk. Both Krusell and Smith (1999) and Imrohoroğlu (1989) also advocated the same view of a counter cyclical policy for welfare gains, these phenomena at the individual level can be replaceable by agents at "firm level" where the aggregate counter cyclical policy can be ascertained and that too for aggregate employee costs.

Another yet equally powerful aspect is to relate the shadow pricing like that of aggregate employee costs with the concept of hedging of illiquid securities. Ehrlich, Hamlen and Yin (2008) stated that how the price volatilities demand analyzing micro information aspects including human capital endowments (in form of education levels etc). By far, the decision of buying an objectively riskier asset also relates to the fact that the investor will seek or hold much better knowledge of the endogenous pricing, and therefore subjectively better-off due to educational component achieved. Buss, Uppal and Vilkov (2015) and Hanushek, Ruhose, and Woessmann(2015) also supported the aspect of subjective dimension of investors experience important in his inclination towards investing in illiquid assets. Essentially both the above papers covered the subjective variables into account while accommodating shadow price valuation.

Turning back to the important string of need to concentrate on investing in illiquid securities, Leibowitz and Bova (2009) explained how financial crisis had made portfolio investors finding difficult to fulfill the commitments to their investors, leading to commitment risk exposure. Westerfield and Phalippou (2014) holds the view that proportionately investing in private equity certain increase due to increase private equity premium, and also why illiquid securities diversification is seldom important to reduce the commitment risks.

Yet another concept of portfolio polarization is of extreme relevance, according to Longstaff (2004) when their will be time of infinite illiquidity, the agents selection of portfolio and asset purely depends upon on his or her perception of risks, now, they are more concerned about sustainable risk management, rather than possibility of frequent adjustment of portfolio weights by trading, in the event of trade being ceased, their options were mainly to choose securities or assets with subjective understanding.

Diebold and Chen (1996) discussed the use of supremum tests in case of structural breaks between the asymbiotic versus bootstrapped series.

Methodology

The financial statement information (acted as idiosyncratic information) growth rates were used on yearly basis from 2000- 2015 extracted from capitaline database. For selection of companies in the Cement sector, it was made from the top 500 BSE companies as on November 2014, and therefore the top 6 qualified (here qualified means companies whose complete information of all the designated accounting variables for all the required years were available to create the balanced panel data). Thus, the following six cement companies were utilized, namely Associated Cement companies (ACC), Birla Cements Ltd (Birla), Heidelberg Cements Ltd (Heidelberg), Ramco Cements Ltd (Ramco), Shree cements Ltd (Shree) and Prism cements Ltd (Prism). And, together the following were the information used from the accounting books for regression and optimal portfolio purposes. The matrix representation is alsoprovided along with the variable information where m stands for number of observations, hence xmn represents m=year, n as accounting variable. So, for year 2000-01 growth rates where m=1, is presented below.

Hence, out of 14 financial variables, 13 were considered as independent, and EC was considered as Dependent variable in the present analysis.
Use of Principal Component Analysis (on correlation matrix)
The following describe the result of PCA, and accordingly for each sample company a “Univariate Parameter estimation” technique was employed

Table 1:Non-academic staff category and sampling determination

1.	ACC	S&A (5.3954,0.359)
2.	BIRLA	P&F (5.3700,0.394)
3.	HEIDELBERG	ST (5.5434,0.383)
4.	RAMCO	TCA (5.6102,0.372)
5.	SHREE	ST (6.9708,0.355)
6	PRISM	ST (9.070,0.328)

After implementing PCA on the sets of 14 accounting (idiosyncratic variables), the results for the most “independent” variable against the “aggregate employee cost decision variable” were as follows (see above Table 1) , for ACC it was S&A, for BIRLA it was P&F, for HEIDELBERG, SHREE and PRISM it was collectively ST, and RAMCO it was TCA which stood in the first orthogonal category, It is interesting to observe, that the values of first independent component is so high, which clearly prompt the researcher’s inquisitiveness to observe such “idiosyncratic risks” closely.
Before, providing the equations for OLS model, the four tests accompanied OLS were Auto correlation tests, Multicolinearity tests, Heteroskadasiticity tests and Normality of residual tests.

Functional equations are as under:

A) PCA equations:

1. Firstly, a correlation matrix is proposed which will

$$S_x^{\ 2} = \frac{1}{(n-1)} \sum_{i=1}^{n} (x_i - \bar{x})^2 \quad \textit{and} \quad S_y^{\ 2} = \frac{1}{(n-1)} \sum_{i=1}^{n} (y_i - \bar{y})^2 \qquad (1)$$

Then covariance will be $S_{xy}^{\ 2} = \frac{1}{(n-1)} \sum_{i=1}^{n} (y_i - \bar{y})\ (x_i - \bar{x})$

Hence correlation will be:

$$r = S_{xy}^{\ 2} / S_x S_y$$

Now if we have M observations of N demeaned variables $x_1, x_2, x_3, x_4, \ldots\ldots x_{14}$ *where* x_{ij} is the j^{th} observation of the i^{th} variable then the covariance matrix C is an $N \times N$ matrix in which $C_{ij} = \frac{1}{M} \sum_{k=1}^{M} x_{ik} x_{jk}$, thus the only difference between the $S_{xy}^{\ 2} = \frac{1}{(n-1)} \sum_{i=1}^{n} (y_i - \bar{y})\ (x_i - \bar{x})$ *is that each variable x and y has been replaced with its matrix for example in the present example the* X or Y matrices with 14 observations and 14 variables may look like :

$$X = \begin{bmatrix} x_{11} & x_{21} & x_{31} & x_{n1} \\ x_{12} & & & \\ x_{13} & & & \\ x_{1m} & & & x_{nm} \end{bmatrix}$$ *here M and N=14*

Hence, the symmetric Covariance matrix equation will be

$$C = \frac{1}{M} X^T X$$

In principal component a matrix V of eigenvectors which diagonalizes the Cmatrix like

$$V^{-1} C V = D$$

The columns of V are orthogonal vectors of unit length and they define principalcomponents-i.e. combination of data in directions leading to zero covariance, the diagonal elements of D are the variances of the each of the corresponding principal components.For principal components sorting of elements of D is conducted, and this is similarly applied to V, thus the fraction of the variance explained by each vector will be :

$$f_i = \frac{D_{i,i}}{\sum_{k=1}^{M} D_{k,k}}$$

Creation of Regression equations:

For a simple uni-variate OLS regression look like:

$$y_{EC_t} = \beta_1 + \beta_2 x_t + \varepsilon_t \qquad (2)$$

y_{EC_t} = decision variable (Employee cost)

β_1 = Const (drift)

β_2 = Regression parameter for x_t

x_t =the explanatory variable from PCA decomposition

ε_t = stochastic error term

Bootstrapping formula and MS Excel template

For parameterization and formation of Lorenz curve , a bootstrap technique can be adopted,

For this purpose, the "fitted series" comprising 14 values of y_{EC_t} were taken, and then a 10 observations "bootstrap" series for each "fitted series" of the sample companies after regression was considered.

Bootstrapping With Fixed Matrix X Resampling

In this paper, a fixed x-Resampling method was adopted for 15 observations in the series. Method: in the fixed resampling the bootstrap replication is conducted when matrix X is fixed.

We test the fitted values $\hat{Y}_i$ for the model, by the bootstrap responses. The steps summarized as

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

Step2 : 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* $Y^*_i = f(x_i, \hat{\beta}) + \varepsilon_i^*$

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* $\beta^{*1} \ldots\ldots\ldots \beta^{*b}$

Portfolio optimization equations

To generate Portfolio weights $w_{x_1} = 1 - (w_{x2} + w_{x_3} + w_{x_3} \ldots\ldots w_{x_n})$ *and* $w_{x_1} = \dfrac{\sigma_{x_1}{}^2}{(\sigma_{x_1}{}^2 + \sigma_{x_2}{}^2 \ldots \sigma_{x_n}{}^2)}$

and till w_{x_n} for all the respective sample companies, the $\sigma_{x_i}{}^2$ is the variance of "regression coefficients"of bootstrapped OLS. Here, for each company, post OLS regression of bootstrapped "dependent" series, a total of 10 years (refer as) were used. Thus, the variance of these bootstrapped coefficient series can be functionally defined as

$\sigma_{x_i}^{2} = \frac{\sum_{i=1}^{n}(\beta_{b_i} - \bar{\beta}_{b_n})}{n-1}$ *here,* β_{b_i} represents the "OLS regression coefficient" of bootstrapped β^* as mentioned in the step 1 to 5 in the Fixed Matrix x resampling above.

For EWMA model the following formulae will be employed:

Here Lambda is a decay factor which when applied to lag returns decides whether there will be rapid decay or slow decay of the lagged series. In equal weighted moving average lambda and (1-lambda) attached with Lagged variance and lagged returns remained equal or constant. The value of lambda and (1-lambda) ensures stationary condition of the time series of data selected.

$$\sigma^{2x} n = \omega v + \lambda \sigma_{x^2_{(n-1)}} + (1-\lambda)\mu^{2(n-1)} \qquad (3)$$

EQMA and EWMA model description

For EWMA model the following formulae will be employed:

Here Lambda is a decay factor which when applied to lag returns decides whether there will be rapid decay or slow decay of the lagged series. In equal weighted moving average lambda and (1-lambda) attached with Lagged variance and lagged returns remained equal or constant. The value of lambda and (1-lambda) ensures stationary condition of the time series of data selected.

$$\sigma^{2x} n = \omega v + \lambda \sigma_{x^2_{(n-k)}} + (1-\lambda)\mu^{2(n-k)} \qquad (4)$$

$\sigma^{2x} n$=The n period variance of the index series

ωv= Long term weight*long term volatility

$\lambda \sigma_{x^2_{(n-k)}}$= The λ (decay rate) multiplied with the squared lagged variance

$(n-k)$= the lagged component, in the present paper the monthly lag optimization is conducted within 1-6 lags , i.e. the lags were optimized with the range from 1 to 6 months.

$(1-\lambda)\mu^{2(n-k)}$= here this is decay representing with the Growth rate, this denotes whether there is rapid decay or slow decay, in case of rapid decay the mean reversion is fast.

Standarddeviationat nth variableunder-root of ((squared stdev of n-1 variable* Decay rate (long term weight*v (long term volatility) +squared return of n-1 temp variable* (1-Decay rate)) Here, W (long term weight*v (long term volatility) had been kept 0.

INDIVIDUAL VaR 11th year equations:

$$\sqrt{\begin{matrix} \text{VaR}_{\text{anuual}} & x & \\ Z\ _x & & \bar{r}_i\ \ P \end{matrix}} \qquad (5)$$

POINT BACKTEST for check of Normality condition:

For 99% C.I.= $np \quad \sqrt{np \quad np^2}, np \quad \sqrt{np \quad np^2},$ (6)

For 11th year the ranges as per point back test rule are as follows:

For 99% confidence level lower limit is -0.84 while maximum limit of breaches is 1.14.

Use of Traffic signal violations:

To estimate the risk capital based on Point back test values, the following formula is employed:

Risk capital *=min (VaR 11th year, S (Factor of 3, 3+ (5-x)*0.2 or 4) multiplied by Average of 10 years VaR values)*

Individual Risk Capital

$${}^{I}RC_{xannual} \quad MIN \quad VaR_{11}th_{xannual}, \quad S \quad MeanVaR_{xannual} \qquad (7)$$

Findings and discussion

Table 2:

The bootstrapped Regression coefficients (figures in absolute terms)

BOOTSTRAPPED Value-at-risk (Average of 10 years)

	ACC	BIRLA	HEIDELBERG	RAMCO		SHREE	PRISM
Sample 1	0.05	5.04	1.80		0.88	0.76	4.15
Sample 2	0.09	1.71	2.69		1.49	0.36	4.36
Sample 3	0.12	2.05	4.44		1.40	0.26	2.17
Sample 4	0.08	0.93	1.91		0.47	0.21	1.56
Sample 5	0.08	1.17	2.82		2.60	0.43	2.45
Sample 6	0.10	2.21	3.08		1.56	0.32	3.66

Sample 7	0.13	0.66	3.58		2.56	0.30	2.72
Sample 8	0.08	2.14	1.22		3.99	0.44	3.62
Sample 9	0.07	1.32	0.78		3.35	0.45	2.39
Sample 10	0.14	1.29	1.78		4.08	0.49	2.07
AVERAGE	10.27	4.40	3.05		7.85	0.03	6.51
STDEV	12.03	3.72	1.85		17.36	0.00	6.49

In terms of bootstrapping samples of conditional volatilities risk capitals of aggregate prices of human capital, it is formally revealed that Shree cement emerged as having the least risk exposure, while ACC and RAMCO were at very high countercyclical idiosyncratic capital buffer. This is a fundamental aspect to ascertain the susceptibility of financial institutions (under non-market risks) for a greater damage in case robust long term sustainable measures are not adopted.

Table 3:
Bootstrapped Risk Capital (figures in absolute terms)

Bootstrapped Risk Capital (Average of 10 years)

	ACC	BIRLA	HEIDELBER	RAMCO		SHREE	PRISM
Sample 1	0.21	20.16	1.80		0.88	0.76	4.15
Sample 2	0.38	6.85	2.69		1.49	0.36	4.36
Sample 3	0.49	8.18	4.44		1.40	0.26	2.17
Sample 4	0.32	3.73	1.91		0.47	0.21	1.56
Sample 5	0.31	4.67	2.82		2.60	0.43	2.45
Sample 6	0.40	8.83	3.08		1.56	0.32	3.66
Sample 7	0.53	2.64	3.58		2.56	0.36	2.72
Sample 8	0.33	8.56	1.22		3.99	0.44	3.62
Sample 9	0.28	5.28	0.78		3.35	0.45	2.39
Sample 10	0.56	5.18	1.78		4.08	0.49	2.07
AVERAGE	41.07	17.60	12.20		31.40	0.10	26.04
STDEV	48.12	14.87	7.40		69.45	0.02	25.94

Going further with the risk capital understanding, the capital buffer actually stood up till 10 paisa per Rupee (1/10th of INR) with 2 paisa as the standard deviation. For the rest, the figures explain the enormous exposure of shadow assets price volatilities measured through idiosyncratic resources.

It pertains to the simple fact, that human capital risks particularly at the aggregate level are not correlated significantly with the other financial data, and companies under extremely badeconomic cycles, a creation of counter-cyclical buffer (just like individual storage capacity in form of precautionary assets) is to be seriously looked at,financial institutions regardless of size of fixed assets and earnings must ensure to represent with a robust measure of showing individual strength of risk absorption capacities periodically under bad economic situations.

Conclusion

So far this experimental study based on the resampled conditional volatilities of aggregate prices derived from idiosyncratic information (micro systemic per se), bring enough empirical reasons to justify a need to work diligently in the area of sustainable risk management policy framework for financial institutions investments. Moral hazard and contagion are the biggest challenges of today's times for the central banking machinery and hence a regulatory amendment to incorporate a "hidden illiquid and uninsured asset pricing model" and its related volatility base risk capital buffer arrangements must be looked at with more rigor and seriousness in the coming times.

Limitations

Firstly, there is no dearth of complicated mathematical modeling surrounding the topics of bootstrapping in the field of economics and finance, the financial statements and the related information are subject to economic justifications of the particular state and worth to be commented. Secondly, bootstrapping techniques for small samples can also be utilized for parameterization by using them to extrapolate the given data series. Shadow prices in form of human capital require knowledge of some subjective analysis including education, experience of the employees in improving the productivity but certainly this is not utilized currently under this research and restricted to annual financial information and the related information therein.

Implications & scope of the present research

The main thrust is on a policy dimension, to aid existing measures taken to safeguard individual financial institutions under any predictable financial crisis. Such proactive amendments require some innovative yet tractable and easily adaptable and replicative models. The present paper is therefore providing a contribution in this direction and creatingan additional sustainable risk management measure for financial institutions long term investments.

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ANNEXURE A :

"Fitted" aggregate employee costs data of the Six Cement companies in India

(Figures are in percentage terms)

Year	ACC-SA	BIRLA-P&	HEID-ST	RAMCO-T	SHREEST
2000-01	0.04863	0.004253	0.157858	0.076658	0.134054
2001-02	0.129105	0.034609	0.199261	-0.02383	-0.26318
2002-03	0.087555	-0.00604	0.062968	0.010083	0.432428
2003-04	0.088822	0.018381	0.133297	0.018633	0.039012
2004-05	0.098495	0.044504	0.108571	0.1299	0.177408
2005-06	-0.06452	0.005075	0.207241	0.01721	0.129681
2006-07	0.479658	-0.02628	0.266286	0.394036	0.887906
2007-08	0.197948	0.037723	0.190246	0.119862	0.475563
2008-09	-0.02136	0.062685	0.159183	0.07736	0.249632
2009-10	0.020854	0.019463	0.126008	0.108768	0.278114
2010-11	0.031027	0.104159	0.076087	-0.08308	-0.03375
2011-12	0.333861	0.084618	0.17272	0.05362	0.621398
2012-13	0.121691	0.080137	0.155207	0.087866	-0.04433
2013-14	0.061868	0.125151	0.079459	0.00384	0.05641