Measuring idiosyncratic risk absorbing capacity of companies' A welfare optimization approach

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ABSTRACT

Financial Institutions require measurement of concentration risk to ensure their funds are not concentrated with one sector, or investments surrounding one sector. To develop this idea, tools like Gini coefficient are adequately utilized, besides, the Gini Coefficient also support in Income inequality measure. However, Gini coefficient do not serve good with negative values and "adjusted gini coefficient" can only be applied with large bootstrapped samples.so unlike, the other papers, in this research, and alternative strategy for portfolio weight selection was considered, here, variance of the bootstrapped OLS regression coefficient series was considered as proxy to "adjusted gini measure". Traditionally, the aggregate "employee costs" can adequately serve as measure of income inequality or idiosyncratic diversification; provided the explanatory variables were also idiosyncratic in nature. The study clearly explained that how the cement companies in India can be compared based on their self-absorbing capacities to handle such idiosyncratic wage risk burden.

JEL codes – C22, C61, D 81

Keywords: OLS, Bootstrapping, Risk optimization

I. INTRODUCTION

It is well known that accounting information is idiosyncratic in nature and diversification of portfolios using the volatility of these information improve if the resampling process is adopted. The conscious effort to reduce "wage gap" across companies with homogenous products is a tenacious economic activity and therefore the "wage governance" model adopted by authorities must resolute with some concrete measures to eradicate these differences. Optimal taxation across intra-industry on income of employees is a daunting task. The present paper, is providing a useful measure to establish a traditional n-portfolio optimization (risk minimization) model to reduce "idiosyncratic risks" across intra-industry level. The difference is that instead of using weights through some traditional means of "capitalization" or other measures of "size" factors, unique weights of "variance of bootstrapped regression coefficients" were utilized.

II. BACKGROUND OF THE PROBLEM

Cement sector in India growing rapidly, under the 12th five year plan , the government of India had decided to increase the capacity from its existing level, uninterestingly, only few big companies like ACC Ltd, Ultratech Cements Ltd absorbed the maximum capacity. Most of the small players face problems and therefore invite "acquirers" for financial justifications. Under such circumstances, the aggregates wages and salaries may require internal adjustments, purely emerging out of the fluctuations in idiosyncratic, specific company-level information. Thus, the present paper will check the strength of these "specific information" on the aggregate wages and how companies prepare themselves to sustain "risk shocks" to minimize the aggregate wage differentials across time.

The focus is one observing the patterns of "idiosyncratic risks and risk weights" pre and post optimal conditions by choosing "income variable" as alternative asset category. The "bootstrapping" can be used a simulation measure to estimate how optimality results vary so that a reasonable justification of optimal redistribution of wages across intra-industry level can be provided.

III. LITERATURE SURVEY

Risk governance at the intra-firm and inter-firm level is a welfare concept. Firms acting like welfare agents, must therefore share the burden of Government and state-agencies working for the welfare and growth of the economy. Numerous studies pertaining to risk sharing, risk absorbing, and risk-bearing power of economic agents are available.

But first let us begin with more mathematical dimensions, according to Bai and Ng (2005) it is possible to consider skewness with less number of observations, under low power a joint distribution of several moments can be used to increase the power. A sieve bootstrap is applicable under linear processes to measure the statistical quantities. In this article author used GARCH (p,q) process to generate the bootstrapped squared returns, instead in the present paper, a use of univariate OLS mechanism to generate the fitted series is conducted, and further derived the conditional volatilities, mean, and conditional covariance's for calculations. Gabrielsen, Kirchner, Liu and Zagaglia (2015) utilized the higher moments to compute the Value-at-risk models, they use Gram-charlier series expansion tests for the same under which the EWMA model was implemented for the conditional variance, skewness and kurtosis. Freitakas (n.d.) expressed the use of concentration risk in banking institution; he utilized gini index, Herfindahl-Hirschman index (HHI), and Berry index in the paper. Scherer

(2012) explained how considering human capital and particularly the employee costs as one of the asset categories and further treated other forms of shadow assets and its implication on the portfolios while mixing with financial assets. Guo (2004) explained the relationships of uninsured income risk considering it as factors related to market frictions along with limited stock market participation and borrowing constraints. Alessi, Barigozzi and Capasso (2007) had used a GDFM, generalized dynamic factor model, which divides the standardized stock returns into two components, common and idiosyncratic, and thus for each the first two moments are calculated, and this is further utilized in GARCH for better analysis. The very reason of considering idiosyncratic factors separately relates very well with the shadow asset pricing models where idiosyncratic information play a critical role in predicting shadow asset prices. The impact of shadow CAPM to solve equity premium puzzle is discussed (Boyle and Ma, 2005), Hara (2001) also utilized the inclusion of new assets to improve the CAPM results, by using marginal rate of substitution in terms of the elasticity's represented by the mean and standard deviation of the new assets with the existing assets in the pricing framework. Stoikov and Zariphopoulou(2005) explained that under incomplete markets, non hedgeable and background risks are sub-additive in nature. Another paper by Stoikov and Zariphopoulou(2004) critically explained that why residual risks provide valuable information in the non-hedgeable portion denoting incomplete markets. Further, the paper claims that the model prescribed can be used for labour income valuation in the path dependent process. Rudloff (2009) explained the incomplete market hedging concept with the black sholesmerton model, since this model use lot of assumptions (restrictive idealization), and due to these assumptions if relaxed in realistic conditions, will leave black sholes model a distorted risk hedging tool.

With context to the policies post financial crisis, the emergence of firm's having close networks become relevant, but there is caveat, as revealed under the work by (Carney ,1998) it could lead to contagion as well, so the remedy is to devise a mechanism to "segment" the firms to absorb the risks and only send the impact to an extent which can be further absorbed easily by the other firms. In a way, risk sharing is possible, only when the firm in the network had a tendency to absorb the part of the shock and also under the segmented system only optimize and share the risks to the other networked player lexicographical. This paper further claims the phenomena of "trust" or moral norms on which networks are ready to share the risk burden. Economically, it also reduces the transaction costs, of insurance against risks.

Miyamoto(1992) stressed on providing genetic utility theory and correlated with relative and absolute utility models. The objection to complete market equilibrium is critically explained in case of Inter-generational equity markets (Ball and Mankiw, 1921).

Yet another contribution by Das(2006) devoted on "bounded optimality" using artificial intelligence or complex simulations is a case in point, and supports the current research of the use of bootstrapping method as simulating the agents behavior of optimal risk sharing. The notion of cognitive science with simon's "satisficing" attitude is relevant as it closely relate to the notion of any decision which is Pareto-optimal may in reality be a "bounded" decision or not perfectly optimal in mathematical sense.

To support the optimal risk sharing views, Bleman and Xu (2009) discussed how the joint venture parties (principals) and take economic benefit by optimizing their risks, the authors used relative profitability index to measure the joint utility benefits.

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Now shifting the emphasis again on more mathematical dimension, Maćkowiak and Wiederholt (2009) explained that the firms will shift their emphasis from aggregate information to idiosyncratic information in case the volatility in the latter found to be more in comparison to the former. Another very powerful statement observed in this paper was that market frictions imposed by theagents are not due to limited information but by not paying proper attention to the changes in the information.

Regarding the use of banking portfolio decisions, the paper by Mline (2000) stressed on "incentive based" regulatory risk capital mechanism as a healthier method for management of credit risks accounted due to banking investments, however, it depends upon the apportioning of assets between realized (liquidated) and unrealized (non-traded) used for portfolio investment by banks. Hence, it is important that the shadow assets investment and pricing must be taken care of while deciding the suitable regulatory risk weights (mainly ex post) for financial institutions. Problem is that such shadow prices usually do not governed by some pre-specified accounting rules; hence, their pricing is heavily dependent on the idiosyncratic information of the investing companies.

Krakowski (2005). Explicitly provide the evidence that in terms of inter-country impact of informal economy, the effect of intensity of labour legislations was most important regression factor. Beside this paper also claim that when the size of informal economy is large in a state, then formal regulatory measures for social redistribution in terms of taxation fails. Hence, some measure to accumulate the aggregate idiosyncratic information to generate valuations for such informal, shadow assets like aggregate labour costs will be relevant from the policy perspective. In large informal economy, to assess whether the welfare phenomena, enough quantitative mechanism and additionally to assure that whether companies as economic agents (tax paying authorities) be able to assess shadow asset prices vulnerability (for present research, the aggregate employee costs) due to specific idiosyncratic factors (the other aggregate financial information available in formal reports) under simulated environment is required. Essentially under such circumstances a statistical robust policy prescription can be validated. Such self-sustaining risk absorbing companies should then be proportionately burdened with the lower taxation. Since, these companies lower the state or bureaucratic agencies burden of redistribution. For that matter, a comparative portfolio of such shadow assets prices must be required and suitable optimization weights criteria can be ascertained.

Also, the claim of the author in the present paper is to not to target hidden business transactions which could be illegal by nature, but to look into measures of pricing shadow assets from the more formal publicly available idiosyncratic financial information.

So a welfare governing taxation policy should be on basis of self-sustainability of the companies as economic agents, and not mere on the fact of their business income alone. So, a company may be earning well, but being self-sustainable, in terms of managing shadow assets, can be burdened less with taxation. Such companies or corporate entities naturally will be favourable for financial institutions as they find their investments being less effected by internal idiosyncratic shocks.

Bakk-Simon, Borgioli, Girón, Hempell, Maddaloni, Recine and Rosati, (2011) paper discusses the size of European banking system in terms of shadow banking, the regulatory arbitrage is a key concern, it is important as the paper reveals, that regulatory arbitrage may make the unregulated sectors more vulnerable. As this paper puts in credit intermediation, securitization and maturity transformation which can fuel shadow banking operations further.

In addition banks tend to invest in shadow assets since that provide a relatively better capital buffer since market-linked investments are vulnerable to extreme fluctuations.

The premise of this paper is based on two dimensions of Modern economics, one purely mathematically on selfish, market-based rationality (only for the purpose of utilizing the essential tools) and then rephrasing the genesis of potential optimization outcomes in relevance to the welfare objective. i.e. risk sharing, cooperation, equality and other postulates of modern welfare economics. Hence, as a reader one should make firmly clear that beside the boundaries of mathematical assessments, this work deeply cherish the emotional and social dimensions towards solving the welfare redistribution objective.

The mere emphasis in this work is to focus on how modern day financial institutions and other agents like public limited companies (acting as welfare agents) bring effective robust measures supporting the preexisting optimal taxation policies and other welfare measures adopted by the state.

IV. 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 also provided along with the variable information where m stands for number of observations, hence X_{mn} represents m=year, n as accounting variable. So, for year 2000-01 growth rates where m=1, is presented below.

Income statement idiosyncratic information:

X_{11} =Sales Turnover / Operating Income (ST), X_{12} =Other Income (OI), X_{13} =Raw Materials (RM), X_{14} =Employee Cost (EC), X_{15} =Power & Fuel Cost (P&F), X_{16} =Other Manufacturing Expenses (OME), X_{17} =Selling and Administration Expenses (S&A)., X_{18} =Miscellaneous Expenses(MISC), X_{19} =Reported Net Profit(RNP)

Balance sheet idiosyncratic information :

$X_{1,10}$ =Total Shareholders Funds (TSF), $X_{1,11}$ =Total Current Assets (TCA), $X_{1,12}$ =Total Current Liabilities (TCL), $X_{1,13}$ =Net Current Assets (NCA), $X_{1,14}$ =Revenue expenses in forex (REFx)

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 "Uni-variate Parameter estimation" technique was employed.

PCA results for Uni-variate Parameter estimation are provided below the following order (Company name, The Variable acronym, Eigen value, Eigen vector)

ACC	S&A (5.3954,0.359)
BIRLA	P&F (5.3700,0.394)
HEIDELBERG	ST (5.5434,0.383)
RAMCO	TCA (5.6102,0.372)
SHREE	ST (6.9708,0.355)
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.

Autocorrelation test:

The use of serial correlation is to measure any lag relationship with the dependent series in order to ensure that the dependent series is independent and identically distributed with stationarity properties

The paper used the Breusch-Godfrey test for first-order autocorrelation at lag 1 for annual data series.

Multicolinearity tests:

Multi colinearity test implies that within independent variables there lies no "strong dependencies", if it appears that there exist multicolinearity then the regression may be spurious. To test that initially correlation matrix can be prepared to confirm the least correlation among independent variables and high correlation with the dependent variables. Usually, in multivariate regression, this remove the problem of multi-colinearity.

In the present paper, however, Variance Inflation factor is utilized, in case VIF is more than 10 for any of the independent variable, it denotes a multi-colinearity issue.

Heteroskadasiticity tests:

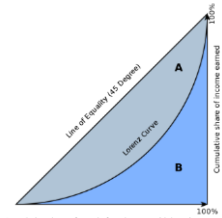
The heteroskadasticity usually relate with residuals, in case residual or error series are non-normal or their variance distribution are non-normal, then under these conditions it is reflection of latent factor impact. i.e. some information-gap is administered in the regression setup.

White's test is used under which the squared of error distribution is considered to be the sum of their independent variables, their square values and their cross products, the R-square obtained from this combination is tested with F-statistic, in case there exist a significance, it assures heteroskedasiticity.

Normality of residual tests:

In connection to error distribution, it is important that the distribution of errors must be normal, that will allow the "long-memory" effect to persist mean-reversion is slow.

Lorenz Curve and Ginni Coefficient



Lorenz curve depicts in income inequality with respect to income and population. The ginni coefficient as the name depicts is the degree of inequality sin form of ratio which lies between 0 and 1.

Ginni coefficient (G) is the half of relative mean absolute difference by equation it can be represent as :

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2\sum_{i=1}^{n}\sum_{j=1}^{n}x_i} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2\sum_{i=1}^{n}x_i}$$

From Ginni coefficient above , bootstrapped ginni coefficients can be generated by either taking the random series of original ginni coefficients itself or taking the "variables" under study and then calculating its value.

NOTE : In the present study instead of bootstrapping (small resample) ginni coefficients, an alternative method of bootstrapped regression coefficient was employed to see the impact of change in the optimization or risks in terms of pre and post bootstrapped phases.

The weights utilized in the pre-optimization levels were actually taken from the average of bootstrapped regression coefficients of each of sample company bootstrapped regression results.

These average of bootstrapped regression coefficients were thus used a weights under pre-optimization for the bootstrap phase.

Under pre-bootstrap phase, the actual regression coefficient were weighted for the division of portfolio capital. And later were optimized using GRG non-linear algorithm.

What is GRG non-linear algorithm:

In simple terms, Generalized reduced gradient method is suitable under conditions when ordinary least square does not provide solutions. It provides a local solution and it confirms that further convergence is not possible.

How is Maxi-min strategy explained:

Maxi-min strategy under redistribution strategy in terms of say imposing more flexibility to the firms as welfare-generating efforts (here optimization of risks strategy is utilized as an approachagainst the more commonly used measure like gini coefficient etc).

Here the pre-post top three riskiest companies were considered (maximum risks) and then within these three companies out of given sample, the one which has minimum relative movement of risks under post-optimization phase was considered to be more "stable" enterprise thus enabler of welfare in the present paper.

This is how the issue of welfare optimization and risk absorption is interlinked and une methodologically.

Functional equations are as under:

PCA equations:

Firstly, a correlation matrix is proposed which will be described as

$$r_{x,y} = \frac{cov_{x,y}}{\sqrt{cov_{x,x}}\sqrt{cov_{y,y}}}$$

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 :

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

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 C matrix like

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

The columns of V are orthogonal vectors of unit length and they define principal components-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:

$$y_{EC_t} = \beta_1 + \beta_2 x_t + \varepsilon_t \qquad (1)$$

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_{ECt} were taken, and then a 10 observations "bootstrap" series for each "fitted series" of the sample companies after regression was considered.

For this the spreadsheet formula used was :
=INDEX(SERIES,ROWS(SERIES),RAND()+1,COLUMNS()+1 and thus a 5 columnar bootstrap series was constructed, the "mean" of these observed columnar values were utilized for Bootstrapped Gini coefficients.

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 , $\hat{Y}_i = f(x_{i,}\hat{\beta})$

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 $Y^*{}_i = f(x_{i,}\hat{\beta}) + \varepsilon_i^*$

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*

$\sigma_{x_i}{}^2 = \dfrac{\sum_{i=1}^{n}(\beta_{b_i} - \overline{\beta}_{b_n})}{n-1}$ *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.

A mean-variance Portfolio optimization equation will thus look like :
for N risky assets
considering return of an asset as random variable, here Return $R_n = \dfrac{S_{(1)} - S_{(0)}}{S_{(0)}}$ *t= 1,2,3 ..n* $S_{(0)}$ *,and* $S_{(1)}$ are the bootstrapped idiosyncratic dependent variable values at time $t_{(0)}$ and $t_{(1)}$ respectively. *Also is the return from the bootstrapped* $\sigma_{x_i}{}^2 = \dfrac{\sum_{i=1}^{n}(\beta_{b_i} - \overline{\beta}_{b_n})}{n-1}$ *series as mentioned earlier.*

Let weights $w_{x_1} = \dfrac{\sigma_{x_1}{}^2}{(\sigma_{x_1}{}^2 + \sigma_{x_2}{}^2 \ldots\ldots \sigma_{x_n}{}^2)}$ *of these portfolios are as calculated earlier from bootstrapped OLS regression coefficient series. Where* $\sum_{i=1}^{n} w_{x_n} = 1$*,*

The rate of return of portfolio can be described as :

$$R_p = \sum_{i=1}^{n} w_n \overline{R}_n \; and \, \sigma_p{}^2 = \mathrm{var}(R_p) = \sum\sum w_i \; w_j \,\mathrm{cov}(R_{i,} R_j)$$

Let Ω denotes the correlation matrix, hence $\sigma_p{}^2 = w^T \Omega w$, when n=2,
Matrix equation will look like :

$$(w_1, w_2)\begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}\begin{pmatrix} w_1 \\ w_2 \end{pmatrix} = w_1^2 \; \sigma_1{}^2 + w_2^2 \; \sigma_2{}^2 + 2\rho_{12} w_1 w_2 \sigma_1 \sigma_2$$, wher

ρ_{12} represents correlation coefficient.

Thus, this can be repeated for multiple asset combinations, by taking the asset combinations as $n(n-1)/2$ pairs of above risks combined..

V. ANALYSIS RESULTS

To ascertain the pre and post optimal welfare weight change, the following step-by-step analysis was conducted,

Firstly, the PCA results are highlighted, since Univariate model was created, only the first variable in the eigen value/eigen vector was considered. (kindly refer Table 1 for this purpose).

Principal component analysis conducted on growth rate series of 13 explanatory variables, and 1 (aggregate employee costs) as explained variable.

Researcher task was to effectively observe the impact of these idiosyncratic information variables on the movement of Employee costs (as a measure of wage diversification risks), hence, an OLS regression was implemented, for ACC , please note that the Univariate information is attached with the Table itself, for ACC the OLS results were not favorable with respect to unexplained variation, explained variation and regression coefficient. Besides, there was the presence of autocorrelation, resulting in adoption of AR(1) model, under which all the results have significantly improved. To be quoted again, the methodology requires the “ residual series” for bootstrapped purposes. For, BIRLA, the results were also favoring OLS results, although explained variation was little lower, but the author strictly want to maintain the univariate parameter estimation, which assures the applicative model remain consistent among sample companies. For HEIDELBERG, the OLS results lead to Non-normality of residuals and hence the GARCH (1,1) was inserted, (GARCH model captures the conditional (markovian) property of variables under study and thus absorbs through coefficients attached with persistence and decay parameters, and use Bayesian likelihood assumptions) which improved the results as can be witnessed (see above Table 2). Following which for RAMCO surprisingly, for OLS, results were poorest, However, the normality of residuals, heteroskedasiticity and autocorrelation tests were negative, regression coefficient although weakly sensitive still showing significant percentage, but explained variation was very low at 17.92%, and similarly unexplained variation (hereafter it represents drift or alpha or intercept value, usually demonstrates that there are some hidden variables which are not captured and therefore a drift is experienced in the dependent series, contrary to this explained variation or R-square is the variation of dependent variable with the variation of independent variable, this higher R-sqaured values improve the model fitness) were at 0.1264 but significantly impacting the relationship (0.00213).

For SHREE, the unexplained variation was lowly insignificant (0.06), regression coefficient was strong, rest of the tests were negative, and atlast for PRISM the results were all confirming OLS implementation effectively for parameter estimation. Hence, leaving RAMCO, the rest of the companies in the cement sector performed well under OLS setup.

Fitted Series analysis

A close analysis of “fitted growth rate series” describing the regressed aggregate employee cost movement explain how it differs across companies and reasons for measuring concentration risk become apparent. It is evident, that PRISM cement contain one “outlying” value, because of which the variance observed was significantly high.

After the individual fitted series were gathered the next step was to arrange the ‘ten’ times regression taken with bootstrapping process, and therefore, the most evident aspect of Fixed matrix bootstrapped resampling is that OLS was conducted for all the 10 resampled data, the results are depicted below

After applying bootstrapping, the above results of bootstrapped regression coefficients were observed, ACC bootstrapped coefficients were although on the higher side, closer to one, most of the time, but interestingly variance was among the highest (0.010177), compared to that PRISM was the lowest with (0.000434), to give an idea, the difference was as high as 23.45 times in the variance values. This shows how important the “diversification” is and for that matter “income inequality” at intra-industry level. The second highest variance of bootstrapped regression coefficient was observed for SHREE at 0.005743 (compared to ACC it was (1.77 times lower of ACC) and for HEIDELBERG whose variance was at 0.004013 stood at third highest position (2.53 times lower of ACC). RAMCO was at 0.002603 respectively .So it is worth noting that bootstrap process which simulates the real-life prepositions clearly account for ACC, SHREE and HEIDELBERG to follow the Maximin strategy.

MAXIMIN Strategy : Here, the three highest (“maximum”) variances of bootstrapped regression coefficient observations will be used for creating portfolio weights, and on the fitted series (pre-bootstrapped) of aggregate employee costs, the portfolio return and risk will be calculated. Later, the portfolio risk will be minimized using “GRG nonlinear” algorithm using solver in MS excel. The whole idea is to select the company whose “post optimized shift” in terms of portfolio weight assigned was (“minimal”). This is ideally considered as a “Welfare policy mechanism” as shift of “idiosyncratic risk capital transfer” will be minimum with this company compare to other two in the sector.

As per the maximin strategy (kindly see the results in Exhibit 1 above), it is closely observed that the weight of ACC is maximum at 51.06%, followed by SHREE at 28.81% and HEIDELBERG at 20.13% (due to virtue of being at the variance level as discussed earlier), and the Portfolio risk of the three asset portfolio stands as 2.899. Thus, now as a welfare mechanism, the results will be compared with the Post optimization phase.

By observing the GRG nonlinear optimization applied to the pre-optimized weights, it is clearly witnessed that the change happened to portfolio risks (here referred as idiosyncratic risk which changed from 2.8992% to 2.8030%, a drop of 3.31%), but most importantly the weights were also shifted or altered. Table 4 below will make the comparative picture.

Looking at last the comparative figures of the pre-optimal weights and post-optimal weights (refer the Table 4 at the end of text), it is evident that the maximum change happed with HEIDELBERG at 63.57%, to recollect , as per the variance HEIDELBERG stood at third position. Continuing with the above table, as per the percentage shift ACC stood second with 17.49%, but the SHREE cement accounted for mere 13.43% change which clearly earmarked SHREE as being best performing company so far the welfare mechanism in terms of burden of "idiosyncratic risk transfer" is concerned. To reframe among bootstrapped time series, SHREE has been lowest in terms of disposal of "risk burden" is concerned.

VI. CONCLUSIONS

Based on the results submitted, and replacing the portfolio fitted series values in absolute terms, the real "monetary analysis" can be administered. The focus of the present analytical outcome was to devise a sound measure by which the companies internal idiosyncratic risks can provide meaningful interpretation for policy makers to differentiate the performance of these companies from the point of view of "risk absorbing capacity". Bootstrapping provided as simulated environment and optimizing on "variance weights" of bootstrapped coefficients thus assured that listed companies in India can be tested against their accounting data, and a meaningful Welfare policy perspective can be introduced. Out of the sampled six cement companies, SHREE cements emerged to be leading in terms of "self-absorbing idiosyncratic risks" on time-series basis

VII. LIMITATIONS

The condition of "outlier" appearing in the fitted, independent and residual series can create spurious analysis, and therefore diagnostic bootstrapping techniques, eliminating outliers can be a better method which has not been implemented, more companies can be added in the sample size. Also, the bootstrapped observations should be extended to reasonable size so that parameterization possibilities can be created. The disaggregation at the unit level for each company can be an extended work which can prove more effective at the company, industry and government level for better governance of wage related idiosyncrasies.

VIII. IMPLICATIONS AND SCOPE OF PRESENT RESEARCH

The paper firmly focused on the intra-industry aggregate measures of idiosyncratic risk absorbing possibilities. The selection of portfolio, must account for non-tradable asset long term hedging, otherwise, the loss in absolute monetary terms cannot be discounted fully. The use of bootstrapping results, thereby utilizing regression coefficients explain the extent to which the internal accounting information can be exploited to create meaningful welfare measures at the interfirm level. More cohesive welfare measures can be advocated for companies whose time-series adjustments as stated in paper, increase the "redistribution burden" to the state and policy makers from the traditional equity and efficiency perspective. From the standpoint of portfolio management at Industry level, the empirical work can support in long term adjustments which industry require ensuring such "idiosyncratic risk burden" could be self-absorbing and state does not have to interfere and impose additional "taxes like arrangements" for redistribution policy to be effective.
As can be witnessed in the results that "Shree cement" under maximin setup as an alternative methodology for measuring welfare optimization produced the best results.

REFERENCES

Alessi, L., Barigozzi, M., &Capasso, M. (2007).Generalized Dynamic Factor Model+ GARCH Exploiting multivariate information for univariate prediction (No. 2006/13).LEM Working Paper Series.

Bai, J., & Ng, S. (2005). Tests for skewness, kurtosis, and normality for time series data. Journal of Business & Economic Statistics, 23(1), 49-60.

Bakk-Simon, K., Borgioli, S., Girón, C., Hempell, H. S., Maddaloni, A., Recine, F., &Rosati, S. (2011). Shadow banking in the euro area: an overview. ECB occasional paper, (133).

Ball, L., &Mankiw, N. G. (1921).Inter-generational risk sharing in the spirit of Arrow. Debreu, and Rawls, with applications to social security design, Harvard Institute of Economic Research DP.

Blenman, L. P., & Xu, M. (2009).Joint Ventures, Risk Sharing and Optimal Contract Design.

Boyle, P. P., & Ma, C. (2005).Mean-preserving-spread risk aversion and the CAPM.Department of Accounting, Finance and Management.

Carney, M. (1998). The competitiveness of networked production: the role of trust and asset specificity. Journal of Management Studies, 35(4), 457-479.

Chang (2004). Bootstrap unit root tests in panels with cross-sectional dependency. Journal of Econometrics, 120(2), 263-293.

Chen, B., Gel, Y. R., Balakrishna, N., & Abraham, B. (2011).Computationally efficient bootstrap prediction intervals for returns and volatilities in ARCH and GARCH processes. Journal of Forecasting, 30(1), 51-71.

Das, S. (2006). On agent-based modeling of complex systems: Learning and bounded rationality. Department of Computer Science and Engineering. La Jolla, CA, 92093-0404.

Freitakas, E. The impact‘s of loan‘s portfolio concentration and diversification to the banking sector. Seven years of Bulgaria's membership in the European Union, 5.

Gabrielsen, A., Kirchner, A., Liu, Z., &Zagaglia, P. (2015).Forecasting Value-at-Risk with time-varying variance, skewness and kurtosis in an exponential weighted moving average framework.Annals of Financial Economics, 10(01), 1550005.

Guo, H. (2004). Limited stock market participation and asset prices in a dynamic economy. Journal of Financial and Quantitative Analysis, 39(03), 495-516.

Hara, C. (2001). Equilibrium Prices of the Market Portfolio in the CAPM with Incomplete Financial Markets. working paper, University of Cambridge.

Krakowski, M. (2005). Determinants of the informal economy: the importance of regional factors. Discussion paper, Hamburg institute of International business, Hamburg : Germany.

Maćkowiak, B., &Wiederholt, M. (2009).Optimal sticky prices under rational inattention. The American Economic Review, 99(3), 769-803

Milne, A. (2002). Bank capital regulation as an incentive mechanism: Implications for portfolio choice. Journal of banking & finance, 26(1), 1-23.

Miyamoto, J. M. (1992). Generic analysis of utility models. In Utility theories: Measurements and applications (pp. 73-106). Springer Netherlands

MR, N., MIDI, H., & IMON, A.(July, 2009) Estimating Regression Coefficients using Weighted Bootstrap with Probability. WSEAS TRANSACTIONS on MATHEMATICS, Vol 9(7).

Rudloff, B. (2009). Coherent hedging in incomplete markets. Quantitative Finance, 9(2), 197-206.

Scherer, B. (2012). Asset allocation with shadow assets.The Journal of Wealth Management, 15(3), 30.

Stoikov, S. F., &Zariphopoulou, T. (2005).DYNAMIC ASSET ALLOCATION AND CONSUMPTION CHOICE IN INCOMPLETE MARKETS*. Australian Economic Papers, 44(4), 414-454.

Stoikov, S., &Zariphopoulou, T. (2004).Optimal investments in the presence of unhedgeable risks and under CARA preferences.Preprint. Department of Mathematics, University of Texas, Austin..

FIGURES AND TABLES

Table 1.Regression Diagnostics (Post PCA selection)

Companies	OLS (α=unexplained variation)	OLS (β=Covariate)	*Explained variation*	*Np=Normality of residual*	*Ap=Autocorrelation*	*Hp=Heteroskadasticity*
ACC (S&A)	-0.00543 (0.8913)	0.8588(0.00847)	0.5561	0.3439	***0.000446***	0.12168
ACC (S&A) AR(1)	-0.0037 (0.876)	0.8759 (0.0003)	0.7861	0.9266	0.2414	NA
BIRLA (P&F)	0.0182 (0.3589)	0.51137(<0.0001)	0.672	0.1844	0.3986	0.2415
HEIDELBERG (ST)	0.1433 (0.7974)	0.9562(0.0689)	0.3265	***0.00399***	0.3314	0.242
HEIDELBERG (ST)-GARCH (1,1)	0.00909(0.0027) α (0)=0.005959(0.3572) α (1)=0.2920 (0.1813)	β (1)=1.00 (1.00579e-12)	NA	0.1758	NA	NA
RAMCO (TCA)	0.1264(0.00213)	0.2076 (0.020)	0.1792	0.19415	0.1079	0.4287
SHREE (ST)	0.1172(0.060)	0.7405(0.00003)	0.6413	0.6987	0.5723	0.2062
PRISM (ST)	0.0084(0.8597)	1.366(<0.00001)	0.9767	0.4601	0.5563	0.2062

Table 2.Fitted Y* post-bootstrap with dependent variables-A snapshot.

ACC	BIRLA	HEIDELBEI	RAMCO	SHREE	PRISM	acc(S&A)	BIRLA(P&F)	HEI(ST)	RAMCO(TCA)	SHREE(ST)	PRISM (ST
0.063465	-0.06826	0.221232	0.037047	0.221232	-0.03732	0.057773	0.00824341	0.395157	0.17111627	0.144544	0.376881
0.112176	0.053122	-0.0144	-0.05515	-0.06619	0.039207	0.153359	0.06708042	0.072382	-0.053192368	-0.28377	-0.11544
0.041287	0.039207	0.029327	-0.06619	0.221232	-0.06826	0.104003	-0.011702	0.165139	0.022507197	0.466266	-0.06769
0.055352	-0.0144	-0.17832	-0.06826	-0.05515	0.114588	0.105509	0.03562744	-0.03397	0.041592014	0.042065	0.170574
0.120566	0.093221	0.037047	0.114588	-0.05515	0.082839	0.116999	0.0862597	0.169358	0.289961912	0.191291	0.141407
-0.08355	0.114588	-0.06619	0.093221	0.029327	-0.0144	-0.07664	0.00983617	0.003701	0.038416357	0.139828	0.280963
0.492209	0.053122	0.029327	0.114588	0.039207	0.039207	0.569767	-0.0509353	-0.05193	0.879567065	0.957385	0.302722
0.297131	-0.0144	-0.0144	-0.17832	0.037047	-0.03732	0.235135	0.07311652	0.486731	0.267555917	0.512776	0.154242
-0.08627	0.221232	0.221232	0.093221	-0.17832	0.082839	-0.02538	0.12149732	0.247616	0.17268329	0.269166	-0.27284
0.042706	0.221232	-0.06826	-0.03732	-0.03732	-0.0144	0.024772	0.03772304	0.172789	0.242791013	0.299877	3.030734
0.028067	-0.06826	0.037047	-0.06826	0.029327	0.039207	0.036856	0.20188432	-0.05275	-0.185444459	-0.03639	0.200788
0.425275	0.029327	0.082839	-0.17832	0.082839	0.021171	0.39658	0.1640101	0.148746	0.119690828	0.670023	0.350128
0.146911	0.039207	-0.03732	0.082839	0.021171	0.037047	0.144552	0.155324	-0.07902	0.196134277	-0.0478	0.062708
-0.03886	0.037047	-0.17832	0.053122	0.039207	0.053122	0.073491	0.24257193	0.367812	0.008571982	0.060824	0.041936
0.084914	-0.0144	0.093221	0.053122	0.082839	0.093221	0.114037	-0.8934324	0.663041	-0.039910687	0.096653	0.124065

Table 3.Bootstrapped (β*) (single-factor regression) and its variances (in %)

Fixed Matrix "X" Bootstrapped Regression coefficients (β*)						
years	ACC-SA	BIRLA-P&I	HEID-ST	RAMCO-T(	SHREE-ST	PRISM-ST
1	0.734876	-0.03469	-0.00119	0.009983	-0.09801	-0.02385
2	0.912056	-0.105	-0.01512	-0.00455	0.11462	-0.02428
3	0.840363	0.070654	0.114193	0.070125	0.087	-0.01005
4	0.748292	-0.01898	0.039061	-0.00733	0.0573	0.031834
5	0.779012	0.010597	0.050447	-0.06493	0.00024	0.02174
6	0.709814	-0.10567	0.077616	0.046992	-0.05454	0.003977
7	0.720548	-0.04476	0.015635	0.038719	0.06993	0.002085
8	0.830184	-0.0734	-0.08794	0.109122	-0.04935	0.0195
9	1.02593	6.47E-05	-0.06734	0.001071	-0.08753	-0.02617
10	0.884157	0.060244	0.060901	-0.03474	0.02281	0.00869
Moments of Distribution of bootstrapped Regression coefficients (β*)						
	ACC-SA	BIRLA-P&I	HEID-ST	RAMCO-T(	SHREE-ST	PRISM-ST
variance	0.010177	0.003786	0.004013	0.002603	0.005743	0.000434

Table 4.Consolidated Top Three Highest (β*) variances of sampled companies and pre-optimal weights and Post-optimal portfolio weights, (risk and return statistics)

	PRE OPTIMIZATION						POST OPTIMIZATION				
							VARIANCE VALUES				
	VARIANCE VALUES						ACC	0.010177			
	ACC	0.010177					SHREE	0.005743			
	SHREE	0.005743					HEID	0.004013			
	HEID	0.004013					Weights based on Var of Bootstrapped Reg coefficie				
	Weights based on Var of Bootstrapped Reg coefficie						accwei				
	ACC	0.510558					ACC	0.421257			
	SHREE	0.288115					SHREE	0.249418			
	HEID	0.201327	0				HEID	0.329326	0		
			1						1		
PORTFOLIO RETURN			-0.81321			PORTFOLIO RETURN			-0.91158		
PORTFOLIO RISK			2.899218			PORTFOLIO RISK			2.803008		

MAXMIN APPROACH									
TAKEN THE MAXIMUM VARIANCE AND CHOOSING THE MINIMUM VARIANCE % CHANGE POST OPTIMIZATION									
	% CHANGE					**absolute percentage change**	**%CH**		
	PRE-OPTIMAL			**POST OPTIMAL**					
ACC	**0.510558**		**ACC**	**0.421257**	**ACC**	**17.4909%**			
SHREE	**0.288115**		**SHREE**	**0.249417**	**SHREE**	**13.4314%**	**minimum wage transfer risk**		
HEID	**0.201327**		**HEID**	**0.329326**	**HEID**	**63.5778%**			

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