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"Can Firm-specific idiosyncratic financial data provide a solution to the macro-economic factor-risk optimization problem?"
"Wage regression residuals- Macro-economic factor cost optimization"

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Abstract: *The mysterious debate upon whether the macroeconomic forces are responsible for factor-cost disparities, or are the factor-cost disparities become a macro-economic problem is nerve-challenging for economists and policy makers. As one of the presentation (Hornstein & Fed, 2005) explained the wage disparity by means of reasons like workers heterogeneity, compensation differentials, discriminations and frictions.(Popli& Yilmaz, 2014)speaks in support by relating increase in education labor supply with decreased in the wage dispersion.The latter part of this dictum was considered more ceremonial for the author when he started looking to use his financial prowess in this area. This probing leads to development of the analytical paper, where the challenge are mainly in the confinement of using the factual financial information and its relationship with wage cost differentials and generating the firm-specific factor- risk profiling and optimization with well-known OLS and LAD coefficient estimating tools. Thus, this paper is a combination of the relevant literature survey and the easily defined statistical regression methods to understand the potential in terms of firm-specific idiosyncratic wage costs regression residuals in providing optimal long-horizon macroeconomic factor-risk solution.*

The labor cost differentials need to be analyzed from macroeconomic factor risk perspective. The study in this area is of a recent origin. One of the related paper in this direction (Gori, 2014) recently provided some relationship between macroeconomic imbalances and real labor cost issues in his paper.(Peeters, 2013) made a useful thought in incorporating idiosyncratic risk factors in asset allocation decisions.Industry-wide wage heterogeneity like that of Cement sector in India is combination of systematic economy-wide and firm-level idiosyncratic factors (the latter can be easily observed in the published financial statements). These firm-level financial differentiators can bring a diverse pattern on wage regression. These diverse wage residuals (out of unsystematic wage factors) determine the macroeconomic factor-risk optimization possibilities. This paper converge the thought particularly in the same direction with the more traditional and well known financial portfolio risk optimization techniques with a benefit of robust regression methods like Least Absolute Deviation (LAD) into consideration.

Cement sector in India is growing with a tremendous pace; the mass urbanization fuelled the economy in the past. To match the pace, some companies also made M&A a strategic weapon to penetrate with product diversification.The differences in residual correlations across cement stocks provide an opportunity for portfolio investors and policy makers and this was tested bysuperiority of Least Absolute Deviation (LAD) over OLS technique. With the results it was made clear that how the non-normal and normally distributed residual correlation (termed as impure combination) with that of pure combination (normally distributed residuals) behaved in terms of portfolio-based factor risk optimization in companies.
Keywords: *OLS, LAD, Risk optimization, risk attributes*

I. Introduction & Literature Review

Most promising paper in this subject is by (Eiling, 2012) who explained how industry-specific human capital diversity support in cross-sectional stock returns. It is the motivation of his paper that such work was extended. Several other contributors like (Priestley & Zapatero, 2011) indeed spread knowledge on the said area, they elaborated on intervention of human capital in the traditional CAPM framework with considering local effect of labor costs in asset pricing. A profound work by (Krusell & Smith, 2006) suggested that how "curse of dimensionality" in optimizing macroeconomic wage inequalities and how macroeconomic forces bring the wage inequalities. Similarly, work by (Gori, 2014) in identifying unsystematic macroeconomic factor risks are of great importance in building the empirical dimension in this paper .Several research works on Wage regressions including aspects on Job polarization ((M. J. Boehm, 2013) and wage inequality (Falaris, 2008) can be illustrated and therefore the subject of predicting the employee cost is not fascinating, but using the wage regression residuals correlation matrix with OLS and LAD techniques for Macroeconomic factor risk optimization is definitely an area worth investing the time. Therefore, the author struggled to arrange the literature on how wages regression and factor- risk optimization are studied. (Yufen & Blazenko, 2014) give some relevance to the idea of using unsystematic risk component into portfolio optimization mean-variance framework .One area of considerable importance can be the distribution of household portfolio investments ,where individual savings are important determinant of the portfolio structure, there are papers like (Chen, 2009) and (Li & Smetters, 2011) which talks on the similar lines. But author here, is layering his empirical justification on a more macro-level side of wage residuals (i.e. residuals generated from wage regressions) and how this can aid in the overall portfolio risk optimization at the industry specific level. (Heathcote, Storesletten, & Violante, 2006) this empirical work explain why welfare costs, which is measure to cover the idiosyncratic wage shocks, require to be controlled, (Mckay, 2012) had also stressed on welfare costs by identifying idiosyncratic wage shocks explaining them counter-cyclical in nature.

The present topic of research also strongly relate with the phenomena of'incomplete asset markets' where the idiosyncratic behavior of wage volatilities can be vital concern. (Finn, Prescott, Lawrence, Eichenbaum, & Fitzgerald, 1997)their work explain this phenomena very well ,the paper clearly states that all endogenous endowments (labor costs) are not fully insurable; the information gaps are primarily due to non-identification on unsystematic firm-specific endogenous components commanding wage predictions.

Cement Sector had seen a faster growth in the last two decadessimply due to rapid urbanization and M&A for product diversification and market penetration. Due to enormous opportunity existed in the cement sector, the demand of skilled employees also increased, this study shed a light whether the employee costs are statistically related with the other published financial variables and if possible, can this be used as a matter to create sound Economy-wide factor risk optimization strategies. The idea seems robust, so the method need to be robust, hence author utilized the OLS and LAD techniques and compare how these two techniques faired in terms of the reducing the portfolio risk raised out of the selected Employee costs and other financial variables relationships.

Regarding use of robust regression in wage prediction, Falaris (2008), adopted the quantile regression technique against identifying the wage inequalities with the help of several variables. The benefit of quantile regression in terms of being robust and being less restrictive was identified with this statistical survey. (M. J. Boehm, 2013) in his paper, utilized multinomial regression, in form of two-stage regression process and stressed on Logit model over OLS model in qualitative assessment of results. (Barde, 2014) in his empirical contribution utilized 2 stage least square and explained the wage spillover effect with spatial auto regressive approach. Another similar paper (M. Boehm, 2012) expressed the use of talent measurement in determining the U-curve related to polarization of high and low level wages. (Matsuoka, 2001) in his paper explained how wage differentials can be related with the foreign ownership shares, it has been found through this study that wage differential among companies having large foreign equities usually have high wage payments. (Belzil & Hansen, 2002) paper is a phenomenal paper, explaining the need for using a Correlated random coefficient wage regression model. The paper exposes the limitation of OLS technique where the residual heteroskedasiticity may pose serious limitations to confirm the comparative advantage between regressors. The author clearly explained how intercepts and slope coefficients determine the relative absolute and comparative advantages in the regression equation. (Stoyanov & Zubanov, n.d.)In their useful paper explained the change in Cobb-Douglas equation by taking to account the impact of Spillover potentials (SPs) in the overall factor productivity framework.

The wage disparities can result into a portfolio plan is a subject more interested for pension companies, hence, some literature like that by (Nkeki, 2014) examine the use of Wage variables over time for pension portfolio optimization. Some studies on cross-country wage differentials like that of (Genre, Kohn, & Momferatou, 2009) explained that some firm level characteristics are responsible for wage differences among companies in the same sector.

II. Methodology

The methodology is based on the three step process adopted under this paper:

1. Selection of explanatory variables and explained variables (Regressors and Regressand) using Correlation matrix. Here, the Employee costs ratio (industry-specific aggregate human costs) is compared with other financial ratios from income statement and balance sheets.
2. Creating the Linear Regression model, showing the comparative advantage of independent financial factors in determining the output of human capital cost. Residual correlation matrix for OLS and LAD regressors and selecting the least correlated residual combinations for portfolio risk optimization purpose. (Here, the portfolio risk is considered as Macro-economic factor-risk combination)
3. Portfolio risk optimization or Factor-risk optimization (as these terms are often used interchangeably in the paper) with residuals values using GRG-Nonlinear algorithm-Under this step the risk attributes (weights) are optimized with the solver optimization tool. The weights are nothing but redistribution of macroeconomic risk capital across cement stocks based on the idiosyncratic diversification opportunity lying due to individual company-specific financial inputs)

Data Source:The last 14 years' time-series databased on annual Income statement and balance sheet of six Cement companies .(sample selected based on 8 cement companies in BSE 500 list in 2014, which was later reduced to 6 companies due to one sample companied failed to pass the autocorrelation test of its growth rates) was acquired from Capitaline database. Total 8 relevant ratios which were considered are as follows:

1. Employee cost/Reported Net profit (EC/RNP)
2. Raw Material/Reported Net profit (RM/RNP)
3. Power & Fuel cost/Reported Net Profit (PF/RNP)
4. Other Manufacturing expenses/Reported Net profit (OME/RNP)
5. Misc. expenses/ Reported Net Profit (ME/RNP)
6. Return on Investment : Reported Net Profit/Total Capital (ROI)
7. Current Ratio : Total Current Assets/ Total current liabilities (TC/TL)
8. Net Current Assets/ Total Shareholders fund (NCA/TSF)

These ratios growth rates were also calculated so that the data can become scale invariant and the issue of Autocorrelation (if any) can be handled to an extent.

First step:

1. Selection of Explanatory variables and explained variables (Regressors and Regressand) using Correlation matrix.

Firstly, in order to check the feasibility of considering in the dependent and independent space, the ratios were put into correlation matrix. And thus, the desired ratios were put into dependent and independent categories for further tests. (See Table 1)

The data was converted to a time-series format in Gretl and four important tests were conducted along with OLS parameter estimation with HAC criteria on the Growth rates.

The Heteroskedasiticity test, the Normality tests, the Autocorrelation test at lag 1 and The Volatility Inflation factor test.

The analysis of study continued with stress on selection of right variables for regression equations (mainly three regression equation were studied), regression parameters with p-value, SE of regression and R squared and Adjusted R squared.

Creation of Regression equations:

$$y_{EC/RNPt} = \beta_1 + \beta_2 x_{OME/RNP} + \beta_3 x_{CR} + \beta_4 y_{NFA/TSF} + u_t \qquad \text{eq. 1}$$

Further a second multivariate equation was desired, for which, the second largest regressor with Employee cost/ RNP growth rates was found to be Selling and Admn cost/ RNP growth rates at 0.9786. This exogenous variable also had weak negative correlation.

$$y_{EC/RNPt} = \beta_1 + \beta_2 x_{S\&A/RNP} + \beta_3 x_{CR} + \beta_4 y_{NFA/TSF} + u_t \qquad \text{eq. 2}$$

Third equation will consider multicolinearityissue which exists between S&A/RNP growth rates and OME/RNP growth rates respectively.

$$y_{EC/RNPt} = \beta_1 + \beta_2 x_{OME/RNP} + \beta_3 x_{S\&A/RNP} + \beta_4 x_{CR} + \beta_5 y_{NFA/TSF} + u_t \qquad \text{eq. 3}$$

2. Residual correlation matrix for OLS and LAD regressors and selecting the least correlated residual combinations for portfolio risk optimization purpose.

Concept of Breakdown points in OLS and LAD methods:

The OLS method is based on the following equation-

$$\ell_2 norm = \left\| y_{EC/RNPt} - x\hat{\beta} \right\|_2 = \sum_{i=1}^{n} \left(y_{EC/RNPt} - x\hat{\beta} \right)^2 \qquad \textit{eq. 4}$$

The least square regression estimator has the lowest breakdown point. This is based on several trials of contamination denoted by "m" in the datasets. With least square approach, the breakdown point reaches earlier. (Giloni, Simonoff, & Sengupta, 2006) The range of breakdown point is between 1/n and 0.5). There are two important computational issues with OLS; firstly since it is second-degree normalization process, and square values are used, the computed values are not correctly estimated. Secondly, the breakdown point in the OLS is coming earlier compare to the other robust methods

Usefulness of LAD method:

$$\ell_1 norm = \left\| y_{EC/RNPt} - x\hat{\beta} \right\|_1 = \sum_{i=1}^{n} \left(y_{EC/RNPt} - x\hat{\beta} \right) \qquad \textit{eq. 5}$$

The breakdown point of LAD usually remains high in comparison to OLS method. Usually, LAD being more robust, the algorithm behind running contaminations "m" takes more time for LAD which makes LAD more optimal estimator of regression coefficients than OLS method.

After ascertainment of the four important criteria's the regression parameters p values, normality test p values, heteroskedasiticity p values and autocorrelation test p values, the later job is to create the residual correlation matrix and then

3. Portfolio risk optimization with residuals values using GRG-Nonlinear algorithm

Applying portfolio standard deviation (squreroot of variance) as seen below in equation 4:

Portfolio variance is calculated as: $\sigma_{xy}^2 = \sigma_x^2 w_x^2 + \sigma_y^2 w_y^2 + 2 w_x w_y COV_{xy}$ *eq. 6*

Once the Portfolio variance was calculated, the weights of the portfolio were kept at 0.5, 0.5 (2 asset portfolio), but later a solver simulation was applied to check how the change in the weights minimize the portfolio risk in the given set of portfolios.

The analysis is based on two sets of correlation results:

One set of five portfolios comprise of "Non-normal and Normal" residuals

Another five set of portfolio comprise of Normal set of residuals. Table 8 to Table 15 is constructed to display the results of pre-post optimization for OLS and LAD frameworks.

III. Comparative Analysis & Presentation

Comparing the regressors and the intercept position in the OLS, in the robust regression i.e. LAD method it is important to note that out of 6 cement companies only Shree cement its β1 or unexplained variation higher than that of OLS regression. None of the p values in both OLS and LAD however found significant. (Refer, Table 2 to Table 7)

In terms of comparative position of Normality of residuals of OLS and LAD, while ACC and Heidelberg cements were found Normal in both estimations, India cements residual distribution too remain the same in OLS and LAD setup. Birla cement residuals were Non-normal in OLS, changed to normal in LAD, while, Shree cements was normal in terms of residual in case of OLS shifted to Non-normal in case LAD estimation.

With regard to position of regressors, the first regressor i.e. either OME/RNP or PF/RNP were having the higher information efficiency in both OLS and LAD estimation methods. But, as witnessed in the Table 1, the intercept and TC/TL and NCA/NSF were having quite dissimilar results across the two estimation methods. (Refer, Table 2 to Table 7)

At last, comparing the LAD median dependent variance with the OLS mean dependent variance, clearly confirmed LAD superiority in terms of error reductions.Meanwhile, as per Gretl results, AIC, BIC, SIC criteria's also backed the LAD superiority in many respects. (Refer, Table 2 to Table 7)

Another useful dimension to be added with regard to aggregate factor-risk measure is that companies whose residuals were normally distributed supported more in terms of optimization.

Before proceeding to the risk analysis, the author presented the results in two-important dimension: First, the pre-optimized and post-optimized results are compared between OLS and LAD regression, second within Pre and Post phases, A combination of Normally and non-normally distributed residuals portfolio risk (Impure combination) and only normally distributed residual portfolio risk (pure combination) were analyzed. This helped in determining whether the normally distributed residual risk were showing superior results in the post optimization phases

Portfolio risk analysis: In order to comprehend whether the LAD regression outperformed in terms of portfolio risk reduction, the first stage of :

Pre-optimization with "impure" combination

Top 5 OLS least residual correlations		Top 5 LAD least residual correlations	
ACC vs. Birla	-0.5125	Shree vs. Birla	-0.4699
Ramcovs. Birla	-0.3762	Ramcovs. Birla	-0.4457
Shree vs. India	-0.3640	ACC vs. Birla	-0.4025
India vs. ACC	-0.3728	India vs. ACC	-0.3401
Shree vs. Birla	-0.2300	Shree vs. India	-0.2358

It is well conceived by the above numbers, that LAD witnessed more negative correlation component among the residuals, and clearly explain its robustness. As per the Table 1 and 2, on pre-optimization stage for impure combinations, LAD portfolio risks were found on the higher side.

Post-optimization of Impure portfolio risks across OLS and LAD residuals

Comparing the gross component first, the overall average performance of portfolio risk reduction for both models were a change of mere 4 basis points, since LAD outperformed by 40.95% while OLS numbered at

40.99% respectively. Even, at the individual portfolio risks level the change appeared to be insignificant. However, as per the change in the risk attribution (the weights of the portfolio) it was found more in LAD with 3.4758% compared to 2.3584% with that of OLS.

Pre-optimization of Pure combinations: This combination was conducted for the top 3 correlations, since in case of LAD, only three stocks correspond to the Normal residual profile. From that perspective, the correlations profile is as under:

Top 3 OLS least correlated residuals		Top 3 LAD least correlated residuals	
ACC vs. Shree	-0.0688	ACC vs. Birla	-0.4025
ACC vs. Heidelberg	0.1079	Heidelberg vs. Birla	-0.1283
Heidelberg vs. Shree	0.2064	ACC vs. Heidelberg	0.0123

It is good to note, that again the component of LAD correlations were found more on least negative side.
Again on the Portfolio risk at the pre-optimized stage, LAD stand with the highest portfolio risks.

Post optimized pure Portfolio risks

Comparing the results of LAD and OLS from the standpoint of top three most uncorrelated normally distributed residuals based portfolio risk optimization, the LAD results were found more promising with a reduction of 25.3579% compared to the top three OLS residuals at 16.3359%. A Big change of 9.022% or 902 basis point. As far as risk attribution is concerned, the change of 54.63485 was with OLS, while for LAD the change was of negative 3.97% in the case of LAD. The ACC vs. Shree witnessed the highest risk reduction of 44.4709% in case of OLS, while for LAD Birla vs.Heidelberg contributed to a change of 32.4724% as far as the portfolio risk reduction imperative is concerned.(Refer, Table 8 to Table 15)

One of the important benefit of conducting OLS and LAD model comparison is to study the intercept and regressor coefficients. Both these statistical outcomes, explain how the economic assets should shift with regard to risk associated with macro-economic factor-risks (company specific labor cost risks) and at the portfolio factor-risks level, how an optimized allocation (in terms of portfolio attributes) can be helpful to the economy. Clearly, the robust regression method like LAD if improve the portfolio risk i.e. Minimize the portfolio factor-risk with least attributional change, then this can certainly be a great economic tool for economic disparities with regard incomplete market structures existing due to idiosyncratic factors like labor wage differentials as explained several times in this paper.

Some important empirical outcomes:

1. The OLS and LAD residuals impure risk combinations behave almost in the similar manner across pre and post optimization phases.
2. The residual correlation of OLS residuals were more stronger than residual correlations of the LAD model
3. The normally distributed residuals correlations for LAD and OLS were again being significantly different.
4. The LAD portfolio risk values for both impure and pure combinations were significantly higher that the OLS ones.
5. The LAD pure portfolio residual risk optimization yielded much better results in comparison to the OLS residual case.

From cement sector point-of-view, the visible differences exist between 2nd and 3rdregressors, namely, Current Ratio and Net Current Assets/Net Share Capital. Other Manufacturing expenses/Report net profit, and Power & Fuel costs dominated in terms of having strong relationships with the Employee costs/Reported net profit ratio. It means that across the top 6 companies selected from India, it shows that employee costs worked as variable costs, and no innovative ways so far of making use of technology in reducing workforce for improving the productivity in the cement sector is considered. Another thoughtful dimension, is that since the employee cost and other financial variables have generated residuals of different degree and distribution, which simply implies in the highly non-dynamic sector like Cement thatthere can still be some opportunity for the portfolio investors, and therefore, the study is conducted, to examine the OLS and LAD methods together to verify how far the LAD being robust estimator can also benefit in the strategic portfolio risk reduction.

The industry-specific human capital costs heterogeneity definitely provided the macroeconomic risk reduction advantages. Not only does internal financial factor redistribution seems important, the emphasis on the use of robust tests like LAD, and the impact of Normality of wage or human capital cost residuals also allowed researcher in implementing a policy-tool for macroeconomic factor-redistribution stability .

The extremely important outcome of this study explained that why robust tools like LAD model is important since it shows how the "factor-weights need to be redistributed with minimal distribution rate" by therefore reducing or optimizingfactor-risks in the long term.

IV. Conclusion & Future Scope

As stated in the introduction, the results confirmed that robust regression tool like LAD provide the basis for using Normality residuals. Further, the wage costs (employee costs) differential as stated can provide a significant opportunity to portfolio investors. More so, the insurance companies can make use of it to study how the wage patterns can impact the investor returns in the fundamental sector like Cement in India.

The author therefore conclusively admitsthat :

"Unsystematic risk exposures seldom make the wage residuals an easy choice for macroeconomic factor risk optimization". This is constructively explained in the present paper.

The impact of Non-normal distribution on OLS give inefficient regressors values, hence, such limitations demand a non-linear robust estimation methods. Also, the vector properties in the time-series can be studied, since, the financial ratios gathered, may have lagged relationships which cannot be ignored. Sectors like Steel, Power, and Cementetc can be included, to broaden the scope. The variable of Employee cost/Reported net profit, is a cost variable, which is aggregated, and its volatility need to be tested against qualitative factors concurrently with the financial variables as stated in this article. Decomposition or shrinkage of residual correlation matrix with factor models like principal component analysis for wage residuals can be of empirical importance.

In the end author wish to conclude that Factor modeling using internal financial information and generating policy level optimization strategies can regenerate interest to the scholars, policy leaders in assuring importance of statistical dimension in solving the long term economic problems of the state.

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ANNEXURES
(on Request)