CHAPTER – 4

RESEARCH METHODOLOGY

RESEARCH METHODOLOGY

This chapter presents a detail description on the methodology followed to arrive at the study results. Here we give a detail accounts on the nature of data used, sample design, construction of variables, model specifications, econometrics and statistical techniques including robustness tests that are adopted to get the research output. Below we discuss each of these aspects in a comprehensive way:

4.1. Sample Design

Sample design includes the selection and size of sample, study period considered, various sources used of the collection of required data of the study etc. We give a detailed description of each of the aspects below:

4.1.1. Sample Size and Selection Procedure

The study uses a set of moderately balanced panel data consisting 91 manufacturing firms listed and traded on BSE 200 index of Bombay Stock Exchange (BSE) of India. Notably, the required data for eight consecutive financial years were available for 91 manufacturing firms' among 125 such firms initially selected as sample. Besides, as we already mentioned in our first chapter that unlike other emerging markets of Asia, ownership concentration is much more noticeable in manufacturing sectors in case of India (Selarka, 2005; Altaf, 2016). Hence, studies on ownership structure and especially on concentration reasonably prefer manufacturing firms as the sample.

4.1.2. Study Period

The study aims to provide some fresh empirical evidence on the relationship between capital structure, ownership structure and performance of Indian manufacturing firms.

For the purpose of the study the researcher covers a time period of 8 years from 2009 to 2016.

4.1.3. Data Sources

The data are collected from financial databases namely 'Prowess' and 'ACE Equity' developed by Centre for Monitoring Indian Economy Pvt. Ltd and Accord Fintech Pvt. Ltd. respectively. Further, the study also uses annual reports of the sampled firms for different financial years. The required annual reports are sourced from the respective official websites of the companies. Besides, for the purpose, the website of SEBI is also visited and found useful. The various financial and corporate governance related reports, balance sheets, profit & loss accounts are surveyed from the respective websites to meet the data requirement.

4.2 Variables Used in the Study

The study introduces a number of important variables to represent capital structure, ownership structure and firm performance of Indian manufacturing companies. Besides, a set of empirically endorsed and relevant firm specific variables are introduced to control the effects of other possible determinants of corporate performance. Below the variables used in this study are described in details:

4.2.1. Dependent Variables

I. Return on Assets (ROA)

The study uses return on assets as one of the important proxies of accounting performance of Indian manufacturing companies. Return on assets is commonly agreed to be a strong indicator of corporate accounting performance. The ROA has

been considered as a measure of firm performance in innumerable number of empirical investigations like Zeitun and Tian (2007), Stiglbauer (2011), Bistrova et al. (2011), Pouraghajan et al (2012).

II. Return on Equity (ROE)

The present study considers return on equity as another measure of accounting performance of Indian manufacturing companies. The return on equity is also equally recognised as an important measure of companies accounting performance. The studies like Krishnan and Moyer (1997), Perrini et al. (2008), Bokhari and Khan (2013), Goyal (2013) use return on equity (ROE) as a measure of firm performance. It signifies how efficient a firm is in generating returns on the investment it received from its equity shareholders. It is a ratio between net incomes to shareholders equity of a firm.

III. Tobin's Q (TQ)

Besides measuring accounting performance, the present study also measure the market performance or value of Indian manufacturing companies through Tobin's Q. Tobin's Q is the most frequently used measure of firm valuation in most of the past studies like Morck et al. (1988), Demsetz and Villalonga (2001), Vintila et al. (2014), Mishra and Kapil (2017) etc. The study following Ferreira and Matos (2008) and Ting (2013) measures TQ by dividing market capitalization plus total debt with the book value of total assets of a particular firm for a particular year.

IV. Market to Book Value Ratio (MBVR)

The study also introduces market to book value ratio as another measure of market performance of Indian manufacturing companies. MBVR is also used as an important

proxy of firm value in a number of empirical researches like Zeitun and Tian (2007), Zeitun (2009), Stiglbauer (2011).

4.2.2. Independent Variables

I. Capital Structure (CS)

Capital structure is one of the important variables in the study. The capital structure of Indian manufacturing companies is measured by taking the ratio of debt to equity. Debt-equity ratio is a very prominent and commonly used proxy of capital structure or financial leverage in the empirical investigation of corporate finance and governance. Firm financial leverage is in fact proved to be an important determinant of a firms' profitability and agency costs (Grossman and Hart, 1986; Jensen, 1986; Stulz, 1990). Many empirical studies which attempt to interlink other corporate governance parameters and corporate performance also consider firms' financial leverage (mostly in the form of debt to equity ratio) as control variable. Therefore, capital structure is both theoretically and empirically supposed to have crucial significance towards performance of firms. In this present study we attempt to interlink capital structure measured by debt-equity denoted by CS with the performance of Indian manufacturing companies.

II. Ownership of Domestic Promoters (ODP)

Ownership of domestic promoters is measured by the percentage of ownership stake held by the Indian promoters. The domestic promoters, by virtue of their considerable ownership rights, experience and expertise, are supposed to exert positive influence on the financial performance of firms by actively monitoring the activities of management. The acronym used to denote ownership of domestic promoters is ODP.

III. Ownership of Foreign Promoters (OFP)

Quite similar to the domestic one, a foreign promoter is also supposed to be highly aware, knowledgeable and competent in monitoring the management of affairs of the firm which he/she invested in. By working as an active monitor of the management the foreign promoters are also supposed to influence the functioning and thereby financial performance of a corporation. In this present study, we consider the foreign promoters' ownership as one of the important ownership type which is attempted to interlink with the performance of Indian manufacturing companies. The variable ownership of foreign promoters is denoted by OFP in the study.

IV. Ownership of Institutional Investors (OIIN)

The category of institutional shareholders consists of banks, non-banking financial institutions, mutual fund companies, insurance companies etc. These financial institutions keep professionally qualified and highly experienced investment experts who undertake great deal of efforts in terms of rigorous monitoring and active participation in the management of affairs of the invested company to ensure good return on their investments. Therefore, institutional shareholding is another component of firm ownership that influences financial performance and valuation. In this study institutional ownership denoted by OIIN is also considered as an important proxy of ownership structure.

V. Ownership Concentration (OWN_CON)

The study, following Cubbin and Leech (1983), Demsetz and Lehn (1985), Bruton et al. (2010), Brendea (2014) introduces Herfindahl-Hirschman Index (HHI) to measure ownership concentration. The HHI index as a variable is constructed by summing up the squares of the fractions of equity held by each shareholder with at least five per

cent ownership stake. The study considers a shareholder with at least five percent of ownership as large. Now, simply summing up all the fractions of ownership by each shareholder with at least five percent of the shares implies a shareholder with five percent of shareholding and a shareholder with say, fifty percent of ownership as equally powerful in terms of influence they exert in the management of affairs of a firm. Application of HHI index permits us to capture this difference. For example, for five shareholders with 20 percent of shareholdings each, the HHI will be 0.2, whereas for two shareholders with 50 percent of shareholdings each, the HHI will be 0.5. Higher HHI index indicates higher ownership concentration and vice-versa.

4.2.3 Control Variables

I. Age of Firms (AGE)

Age of firms, both theoretically and empirically, is known to have very strong connection with their efficiency, level of profitability and valuation. Age of firms is correlated with operational efficiency and performance of firms in number of empirical studies like Katz (1982), Hannan and Freeman (1984), Loderer and Waelchli (2010) etc. Therefore, this variable should be considered while modeling the relationship between capital structure, ownership structure and corporate performance.

II. Firms' Liquidity (LQDT)

The theory of corporate finance advocates important implications of firms' liquidity on operating efficiency and financial performance. The relationship is also sufficiently endorsed by number of empirical investigations like Saleem and Rehman (2011), Niresh (2012), Lartey et al. (2013) etc. This study takes firms' liquidity measured by quick ratio as a control variable. Therefore, in this research investigation

liquidity measured by quick ratio is considered as an important firm specific characteristic which is supposed to have crucial bearings to the performance of companies.

III. Assets Utilization Efficiency of Firms (AUE)

The assets utilization efficiency is measured by asset turnover ratio which is derived from dividing annual sales by average total assets of firms. It represents how efficiently the management of a firm is utilizing its assets to generate sales (Ang et al., 2000) and thereby to enhance performance of firms. It also reflects the existence of agency problem between owners and managers and the monitoring efficiency of large owners towards easing out such problem. ATR has been used as a popular proxy of agency problem in number of studies Li and Cui (2003), Matusin et al. (2014). As this variable has a direct association with the performance of companies, we introduce this variable as one of the control variables of this empirical investigation.

IV. Size of Firms (FS)

Size of firms is an important moderating variable which is supposed to confound the relationship between firm performance and any other variables. The firm size is used as a control variable in many important corporate governance studies like Farooque et al. (2007), Zeitun (2009), Santos et al. (2014), Maqbool and Zameern (2018). Following these empirical researches in this present study we also include firm size in the set of control variables.

The description of all the variables used is given in the table 4.1 below:

Table: 4.1 Descriptions of the Variables

	Variable	Acronym	Measurement
Dependent Variables	**Return on Assets**	ROA	Ratio between net profit after tax of a firm and its average total assets investment
	Return on Equity	ROE	Ratio between net profit after tax of a firm and average shareholders' equity
	Tobin's Q	TQ	The ratio of market value of equity plus book value of debt to book value of total assets
	Market to Book Value Ratio	MBVR	Ratio between market capitalization and net book value, where net book value = total assets value minus outside liabilities
Independent Variables	**Capital Structure**	CS	Ratio of debt to equity capital
	Ownership of Domestic Promoters	ODP	Percentage of shares hold by the Indian promoters
	Ownership of Foreign Promoters	OFP	Percentage of shares hold by the foreign promoters
	Ownership of Institutional Investors	OIIN	Percentage of shares hold by the institutional investors like banks, non-banking financial institutions, mutual fund companies etc.
	Ownership Concentration	OWN_CON	Herfindahl-Hirschman Index (HHI), a variable constructed by summing up the squares of the fractions of equity held by each shareholder with at least five per cent ownership stake.
	Lagged Dependent Variables	ROA_{it-1} ROE_{it-1} TQ_{it-1} $MBVR_{it-1}$	One-year lagged value of dependent variables (ROA, ROE, TQ and MBVR)
Control Variables	**Age of Firms**	AGE	Age of the firm since establishment
	Firms' Liquidity	LQDT	Quick Ratio, a ratio of quick assets to current liabilities
	Assets Utilization Efficiency of Firms	AUE	Asset Turnover Ratio, a ratio of annual sales to average total assets
	Size of Firms	FS	Natural logarithm of total assets

Source: Prepared by the Researcher

4.3 Research Methods

The researcher adopts a very relevant and sophisticated research method to carry out this empirical study. The method includes a number of statistical and econometric tests and estimations. The researcher tries to arrive at meaningful, acceptable, reliable and robust results and for these purposes the study adopts those statistical and econometric tests which are highly recognised, accepted and widely known in the domain of social science research. The study first of all estimates the summary statistics including mean, median, standard deviation, maximum value and minimum value for each dependent, independent and control variables. Regarding inferential statistics, the study applies both static and dynamic panel data regression models along with test of multicollinearity property and heteroskedasticity problem among the variables used in the study. The tests for multicollinearity and heteroskedasticity fall under the diagnostic test and are very crucial for ensuring that the results of the panel data analysis are not erroneous and spurious and therefore the inferences that are drawn based on the findings are correct, reliable and acceptable. Below, we give a detail description on the various statistical and econometric tests used to arrive at the study results:

4.3.1 Test of Multicollinearity

One of the important assumptions of classical multivariate regression analysis is that, the explanatory or independent variables are free from any significant correlation with one another. In other words, the non-existence of multicolleinearity property among the variables is the presumption of a classical regression model. Technically, multicolleinearity is a kind of data property in which two independent or explanatory variables in a multiple regression model are significantly correlated with each other

and degree of such correlation between the independent variables can be linearly estimated with a substantial degree of accuracy or precision. In such a phenomenon, the estimated coefficients of a multiple regression model respond and change erratically with a very small change in the regression model or the data used. Practically, multicollinearity is a condition of the predictor variables that are assumed to be non-stochastic. Moreover, multicollinearity is a feature or property of the sample used in a study rather than the population and for every sample the degree of it can be estimated. As we already mentioned, the presence of multicollinearity property among the variables would lead researchers to spurious and erroneous results which further results into ambiguous and unreliable research inferences.

According to Gujarati (2004) there are specific reasons for which a classical regression model runs with the assumption of non-existence of multicollinearity property among the explanatory variables. Below, we outline these crucial reasons as to why a classical regression model presumes the non-existence of multicollinearity property among the independent variables (Gujarati, 2004):

- If in a regression model the data bears perfect multicollinearity property, the regression coefficients of the independent or predictor variables estimated in the model would be indeterminate and their standard errors would also be infinite.
- If in regression estimation the data set contains quite less than perfect multicollinearity, in such as case the regression coefficients of the explanatory variables so estimated would be determinate but possess higher standard errors. Therefore, the accuracy and reliability of the estimation would become doubtful and questionable.

The present study estimates pair-wise correlation matrix and variance inflation factor (VIF) test to check the presence of multicollinearity property. A brief description about these two tests is given below:

I. Pair-wise Correlation Matrix

Estimating pair-wise correlations and presenting them in a correlation matrix is perhaps the simplest way of detecting and presenting the correlations between the set explanatory variables of an empirical study. The purpose of introducing this simple but useful econometric tool is to check the pair-wise correlations among the independent variables. In a pair-wise correlation matrix, if the correlation between any set of explanatory variables is found to be high and statistically significant then this phenomenon is supposed to distort the regression estimation.

The correlation coefficients in a correlation test lie from -1 to +1. Generally a statistically significant correlation coefficient of (-/+) 0.80 to (-/+) 1.00 indicates very strong correlation between the variables and it can't be overlooked. Generally, as a thump rule, a correlation coefficient up to 0.70 is treated as acceptable and avoidable.

II. Variance Inflation Factor (VIF)

Variance inflation factor which is commonly called as VIF test is another useful and reliable econometric test to detect the multicollinearity property among the independent variables. The value of VIF is calculated for each of the explanatory variable in a regression model as below:

- Firstly, the calculation of VIF value for an independent variable includes calculation of R^2 of the respective independent variable where R^2 refers to the proportion of variance for a particular explanatory variable, which can be explained by all the other explanatory variables used in the regression model.

- Now, VIF = 1/ (1 – R^2); where the values of VIF may range from 1 to infinite. In the equation of VIF, (1 – R^2) is known as the level of tolerance. Therefore, VIF is also refereed as 1/tolerance.
- A VIF value 1 indicates the concerned variable is not correlated with other independent variables. As the VIF value of a particular independent variable increases the degree of dependency also increases which implies presence of considerable multicollinearity. However, there is no formally prescribed criterion for determining the bottom line of the tolerance value of VIF but according to Gujarati (2004), explanatory variables can be regarded as highly collinear if the VIF value exceeds ten.

4.3.2 Test of Heteroskedasticity

As a diagnostic test, the test of heteroskedasticity is of equal importance in the classical regression analysis. In simple terms, heteroskedasticity can be defined as a phenomenon in which the variability of a dependent variable under a regression model is found to be unequal across the range of values of a predicting variable. The opposite phenomenon is called homoskedasticity where the variability of the dependent variable is equal across values of an independent variable.

Another way of understanding the problem of heteroskedasticity is that, it s a situation when the error terms of a regression model do not have constant variance.

Now, it is very important to understand the factors that actually cause increase in heteroskedasticity problem in a regression model. Below, we outline a number of reasons as to why the problem of heteroskedasticity arises and increases:

- ❖ The problem of heteroskedasticity may increase with the increase in the value of an independent variable.

- The problem of heteroskedasticity may also become high when as the value of an independent variable become more extreme in either direction i.e. positive or negative.
- Especially in case of primary data, measurement error can cause increase in heteroskedasticity problem.
- The problem of heteroskedasticity sometimes occurs due to sub-population differences or other interaction effects. For example, in establishing the relationship between income level on the consumption, the effect of income level on consumption may differs for people of two different races like whites and blacks.
- Sometimes incorrect model specification can cause the heteroskedasticity problem to arise. For example, sometime a variable needs to be taken in log value or say in its squared tern but if in that cases the variable is taken in its absolute value then the model is called to be misspecified and it may bring in heteroskedasticity.

Therefore, these are the crucial reason which may cause the heteroskedasticity problem in a regression estimation to arise and increase. Notably, we must know that, a regression model with this problem may have many undesirable consequences in an empirical investigation. For instance, in the presence of heteroskedasticity problem the simple regression estimation can't be optimum. This is because with heteroskedasticity the model assigns equal weight to all the observations but in practice observations having larger disturbance variance contain less information in compare to the observations having smaller disturbance variance. Besides, a regression model with heteroskedasticity problem produce biased standard errors which further results into biased test statistics and confidence intervals. Thus,

existence of this problem may exert serious effect on the model estimates and the inference drawn based on the estimations would lose their validity and reliability.

Hence, the present study estimates pair-wise correlation matrix and variance inflation factor for the test multicollinearity property among the independent variables. The study also employs Breusch-Pagan / Cook-Weisberg test for heteroskedasticity (Hettest) and Information Matrix test (Imtest) for heteroskedasticity (White, 1980) for the test of heteroskedasticity problem.

4.3.3 Static Panel Data Analysis

The study first introduces static panel data analysis to establish the relationship among the set of dependent and independent variables. Panel data is the kind of data which contains time series observations of a number of cross-sectional units. Therefore, it is a combination of time series and cross section data. The use of panel data in empirical research has a number of advantages. If we go through the empirical investigations carried out for last three decades we can observe that a considerable research efforts have been carried out pertaining to the theoretical issues and applications of the econometrics of panel data. Some of the notable advantages of using panel data are outlined as below:

- Raj and Baltagi (2012) in their books titled 'Panel Data Analysis' mentioned about the easy availability of panel data and as a result, its increasing contribution to econometric modeling, estimation, hypothesis testing, model evaluation etc.
- According many authors, it allows the researchers to have a large number of observations which leads to improved efficiency of econometric estimates.

- ❖ According to Chamberlain (1984), Hsiao (1986) etc. panel data allows a researcher to undertake in-depth analysis of complex economic hypotheses by controlling for influences corresponding to both individual and time heterogeneities.
- ❖ Again, panel data allows us to control for variables that we cannot observe or measure, for example, variables that represent cultural factors or difference in business practices across firms.
- ❖ According to Hsiao et al. (1995) in compare to cross-sectional data, panel data usually contain more sample variability and degrees of freedom which improves the accuracy of econometric estimation.
- ❖ Unlike cross-section or time series data, use of panel data allows a researcher to capture the complexity in human behavior in a comprehensive way.
- ❖ Moreover, one of the important advantages of using panel data in empirical investigation is that, for panel data estimations a number of sophisticated but easily available software like STATA, SHAZAM, LIMDEP, RATS, etc. are available:

The static panel data analysis includes three regression models namely, ordinary least square model (OLS), fixed effect model (FEM) and random effect model (REM). The analysis also includes the selection of best fit regression model among these three models, because in panel data analysis it largely influences conclusions on the individual coefficients. In panel data, when the number of cross-sectional units is very larger than that of time-series units, as in the present case, the estimates obtained by the FEM and REM differ significantly. Besides, all these three regression models run with different underlying assumptions. The OLS model assumes the intercept as well

as the slope coefficients to be same for all the 91 sample firms taken in the study. The FEM allows the intercepts to vary across the firms to incorporate special characteristics of the cross-sectional units. Finally, the REM assumes the intercept of a particular firm to be a random drawing from a large population which varies non-systematically with a constant mean value. As all these three conditions can't prevail simultaneously, so the study needs to select an appropriate model for regression. The study introduces restricted-F test, Breusch-Pagan Lagrange Multiplier (BP-LM) test suggested by Breusch and Pagan's (1980) and Hausman test suggested by Hausman (1978) to have a judicious selection among the three regression models. The estimated models would be in the following form:

$$ROA_{it} = \alpha + \gamma_1 (CS) + \gamma_2 (ODP) + \gamma_3 (OFP) + \gamma_4 (OIIN) + \gamma_5 (OWN\_CON) + \beta_1 (AGE) + \beta_2 (LQDT) + \beta_3 (AUE) + \beta_4 (FS) + \varepsilon_{it} \ldots\ldots\ldots \text{Equation 1}$$

$$ROE_{it} = \alpha + \gamma_1 (CS) + \gamma_2 (ODP) + \gamma_3 (OFP) + \gamma_4 (OIIN) + \gamma_5 (OWN\_CON) + \beta_1 (AGE) + \beta_2 (LQDT) + \beta_3 (AUE) + \beta_4 (FS) + \varepsilon_{it} \ldots\ldots\ldots \text{Equation 2}$$

$$TQ_{it} = \alpha + \gamma_1 (CS) + \gamma_2 (ODP) + \gamma_3 (OFP) + \gamma_4 (OIIN) + \gamma_5 (OWN\_CON) + \beta_1 (AGE) + \beta_2 (LQDT) + \beta_3 (AUE) + \beta_4 (FS) + \varepsilon_{it} \ldots\ldots\ldots \text{Equation 3}$$

$$MBVR_{it} = \alpha + \gamma_1 (CS) + \gamma_2 (ODP) + \gamma_3 (OFP) + \gamma_4 (OIIN) + \gamma_5 (OWN\_CON) + \beta_1 (AGE) + \beta_2 (LQDT) + \beta_3 (AUE) + \beta_4 (FS) + \varepsilon_{it} \ldots\ldots\ldots \text{Equation 4}$$

Here, ROA_{it} and ROE_{it} represent accounting performance of i_{th} firm at time period t, TQ_{it} and $MBVR_{it}$ refer to market performance of i_{th} firm at time period t, α represents the constant terms in each equation separately, γ_1 to γ_5 represent the coefficients of capital and ownership structure variables respectively, β_1 to β_4 represent the

coefficients of the control variables and ε_{it} represents the error terms in all the three models.

4.3.4 Dynamic Panel Data Estimation

Considering the dynamism of the relationship and bias caused by potential endogeneity of the explanatory variables, the study introduces Arellano-Bond (1991) dynamic panel estimation technique that determines the joint effects of the explanatory variables on the explained variable while controlling for potential bias due to endogeneity of the explanatory variables including the lagged dependent variable. The dynamic panel data model is mostly preferred when the number of cross-section units is larger than that of time series units, as in the present case. This is because of the fact that, the estimation methods don't require larger time periods to obtain consistent parameter estimates (Mishra, 2008). The dynamic panel data regression model includes lagged dependent variable as one of the independent variable with the supposition that, the lagged dependent variable is correlated with the random disturbance term of the model and inclusion of it in the model accounts for the dynamic effects (Wintoki et al., 2012; Altaf and Shah, 2018). Notably, in such a situation when the lagged dependent variable is likely to be correlated with the error term of the model, the static panel data models like OLS and FEM become biased and thereby produce inconsistent estimates as these models largely ignore unobserved time-variant effects and the endogeneity of dependent variable.

Therefore, following the previous literatures we also take one year lagged dependent variables as one of the independent variable to consider the dynamism of relationship and to take into account the effect of some unobservable historical factors on the current dependent variable (Wooldridge, 2009).

Although, some of the previous literatures have considered instrumental variable in estimating dynamic panel data model (Anderson and Hsiao, 1981; Bhargava and Sargan, 1983) but following Mishra (2008) we adopt Arellano-Bond (1991) dynamic panel model which is based on Generalised Method of Moments (GMM). Besides, according to Ahn and Schmidt (1995) GMM estimator is likely to convey more information on data during the course of estimation than the method of instrumental variables. In GMM method we control the potential bias due to endogeneity of independent variables by taking one year lagged value of the lagged dependent variable and other independent variables as instruments (Basant and Mishra, 2013). Additionally, the study introduces Arellano-Bond test for autocorrelation and Sargan (1958) test of over-identification to check the presence of autocorrelation and validity of the instruments used in the model respectively.

Notably, there are two versions of Arellano-Bond estimator namely one step and two step estimator. The asymptotic standard errors of one step estimator are unbiased and more reliable to draw inferences on the individual coefficients but at the same time, under this estimation the Sargan test over-rejects the null-hypothesis of over-identification restriction in the presence of heteroskedasticty. Moreover, the robust standard error under one-step estimation can largely control the problem of heteroskedasticity but it can't produce the Sargan statistic. Therefore, the researcher executes both the estimations wherein the researcher considers the individual coefficients of one-step estimation with robust standard error to draw inferences and the statistics of two-step estimation like Sargan statistic, Wald–Chi^2 statistic to check the over-identification restriction and overall significance of the model respectively. In nutshell, recognising the dynamism of the relationship and the issue of endogeneity the researcher chooses to extend our analysis from static approach to dynamic

approach which would ultimately lead us to most robust estimates and thereby strong inferences.

4.4. Scheme of Investigation

This sub-section provides a brief description on the overall procedures followed by the researcher of this empirical study to arrive at the research outcomes. The study first constructs a moderately balanced panel data taking a sample of 91 manufacturing companies listed and traded on BSE 200 index of Bombay Stock Exchange (BSE) of India for the period of 2009 to 2016. The study sets a range of $\bar{x} \pm 2\sigma$ (where $\bar{x}$ and σ stand for the sample mean and standard deviation of each variable respectively) to eliminate the outliers from the panel dataset to avoid distortion in results. For the purpose of analysis of the collected data, the study employs both descriptive and inferential statistics. Under descriptive statistics the researcher tries to understand the basic property of the variables by estimating measures of central tendency like mean, median and measures of dispersion like standard deviation, minimum and maximum value. Now, before going to the mainstream data analysis, the study checks the presence of multicollinearity property and heteroskedasticity problem. To test the presence of multicollinearity property the study uses pair-wise correlation matrix and variance inflation factor whereas to detect the heteroskedasticity problem the study employs Breusch-Pagan / Cook-Weisberg test (Hettest) and Information Matrix test (Imtest) for heteroskedasticity.

The study employs two versions of panel data regression analysis. Firstly, it introduces static panel data approach under which results of Ordinary Least Square Model, Fixed Effect Model and Random Effect Model are estimated. The study further employs Restricted F Test, Breusch-Pagan Lagrange Multiplier test and

Hausman test to make a judicious selection among these three regression models. Besides, considering the dynamism of the relationship and the bias caused by potential endogeneity of the explanatory variables the researcher estimates the Arellano-Bond (1991) dynamic panel estimation technique which is based on Generalised Methods of Moments. Under dynamic panel data analysis the researcher gets one step and two step estimator and executes both the estimations wherein the researcher considers the individual coefficients of one-step estimation with robust standard error for the purpose of drawing inferences. The researcher uses the statistics of two-step estimation like Sargan statistic, Wald–Chi2 statistic to check the over-identification restriction and overall significance of the model