Estimation of Firm Performance from a MIMIC Model

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Research Highlights

- Use MIMIC model to estimate latent firm performance with many observable indicators.
- The predicted factor scores are used to rank the firms.
- Estimate stochastic frontier models and obtain efficiency scores.
- Found high correlation between the MIMIC performance scores and the stochastic frontier efficiency scores.

Interfaces with Other Disciplines

Estimation of Firm Performance from a MIMIC Model*

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Abstract

In this paper we propose a new approach (based on the Multiple Indicator Multiple Cause (MIMIC) model of Joreskog and Goldberger (1975)) to assess the performance of firms assuming that the 'true' firm performance is latent but there are many observable indicators of it. In our MIMIC model, the latent firm performance variable is linked with some observed explanatory variables (determinants) like age, size, advertising expenses, debt equity ratio, etc. Since there are many observed indicators (ROE, ROA, Tobin's Q, etc.) of the unobserved latent firm performance, the measurement equations in the MIMIC model link these observed indicators to the latent performance measure. We use firm level data from India during the period 2001 to 2008 to estimate the latent firm performance using the predicted factor scores and rank the firms according to the proposed measure. Finally, we estimate two stochastic frontier models and compute Pearson's correlation between pairs of performance measures. We find high rank correlation between the two measures of firm performance/efficiency, which justifies the use of the MIMIC model as a complementary method of performance measures.

Keywords: Firm Performance; MIMIC Model; Ownership Structure

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1. Introduction

In the efficiency and industrial organization literature the term firm performance is extensively used, although its meaning is not always made very clear. Quite often the term is used as a measure of a firm's overall financial health and is used to compare similar firms across the same industry or to compare industries or sectors. Since there are many ways to measure the financial health of a firm, the firm performance measure should be inclusive of various aspects of financial health such as firm value, return on assets, return on equity, resource use efficiency, etc. The problem lies in choosing a measure that captures more than one performance indicator. No single measure is in itself a comprehensive indicator of the 'true' firm performance.

Our objective, in this paper, is to estimate the 'true' firm performance which is viewed as a latent variable. First, we explain 'true' firm performance in terms of a vector of observed firm specific factors. Second, in estimating the 'true' firm performance we use various indicators of firm performance.[1] Thus the framework fits in to the Multiple Indicator Multiple Cause (MIMIC) model developed by Joreskog and Goldberger (1975). The multiple cause part is where we explain 'true' performance, and the multiple indicators is where we relate the 'true' performance to various indicators[2] (popularly known as the structural equation, although it has no relationship with structural model in economics). Since there are many observed indicators (ROE, ROA, Tobin's Q, etc.) of the latent performance, the measurement equations (in the multiple indicator part of the model) link these observed indicators to the latent performance measure. Note that this modeling exercise is different from aggregating various observed performance indicators into a single aggregate measure which does not take into account possible measurement errors in the observed indicators. Also aggregation, no matter how it is done, involves ad-hoc weighting of individual indicators which might not be even positively related (i.e., a higher value of one indicator might be associated with good performance while it might be opposite for another indicator). This

[1] In the stochastic frontier and data envelopment analysis literature no indicators of firm performance are used. Instead firm performance is estimated from the technology using input and output data. For example, see Ray (2015), Ray and Das (2010), Staub et al. (2010), and Tzeremes (2015) for an application using DEA, and Sun et al. (2015), Zhang et al. (2015), and Dong et al. (2016) for an application using the SF approach. Lampe and Hilgers (2015) have provided an excellent survey on this issue.

[2] The MIMIC model is actually a variant of the linear independent structural relationships (LISREL) model of Joreskog and Sorbom (1999a, 1999b). In LISREL terminology, the multiple cause part is called the structural equation model (SEM), and the multiple indicators part is called the measurement model.

MIMIC model is also different from the multiple-output-multiple-input stochastic frontier (SF) model in the efficiency literature (Kumbhakar, 1996, 2013). First, different indicators are unlikely to be similar to multiple outputs -- the way economists model them in the production possibility function in which outputs are substitutable, given inputs. Second, our indicators are in fact performance measure themselves and estimating efficiency treating the indicators as outputs might go against the principle of the SF models. In spite of these differences, we compare and rank efficiency measures derived from various models to validate our proposed model, viz., the MIMIC model and the two SF models. In the empirical model we find that the performance scores of the SF models are highly correlated with those from the MIMIC model.

Our results (based on data from Indian listed firms) from the MIMIC model show that size has influenced firm performance negatively and significantly but the square of size exerts a positive and significant influence. This reflects a presence of a U-shaped relationship. Age of the firm shares a positive association with firm performance. The advertising expenditure shares a significant relationship with firm performance, but the same is not true with the R&D expenditure and leverage (captured by debt-equity) in our sample. We also find that different ownership structures influence firm performance differently.[3]

The rest of the paper is organized as follows. Section 2 provides a brief review of the literature that uses various indicators as measures of firm performance. Section 3 outlines our MIMIC model. The data and empirical results are presented in Section 4. Section 5 concludes the paper.

2. Indicators of firm performance and it determinants: A brief review

Several indicators, like return on asset (ROA) (Khanna and Palepu, 2000; Huang et al., 2006), return on equity (ROE), Tobin's Q (Habib and Ljungqvist, 2005; Khanna and Palepu, 2000); market to book value ratio (MBVR) (Sarkar and Sarkar, 2000), return on employed capital, operating profit margin, etc., have been used in the existing literature to evaluate firm performance. Indicators like ROA and ROE are accounting-based measures of profitability, whereas indicators such as Tobin's Q and MBVR indicate stock-market based measures. The accounting-based measures reflect the past financial performance, whereas the market based

[3] See Sueyoshi et al. (2010), García-Cestona and Surroca (2008), Gedajlovic and Shapiro (2002) and, for an excellent review on this, Short (1994).

measure the future performance. If ROA were chosen as an indicator of firm performance then it would only explain how effectively the firm has utilized the assets to generate earnings. This, however, is not the only determinant of firm's well-being. Other than utilizing assets, the firm also has to invest in the equity judiciously to generate higher earnings which will make the investors of the firm happy. This can promote the use of return on equity (ROE) as a measure of firm performance. The use of ROE can, however, be problematic. If investors are not careful, it can divert attention from business fundamentals and lead to unpleasant surprises. Companies can resort to financial strategies to artificially maintain a healthy ROE for a while and hide deteriorating performance in business fundamentals. Growing debt leverage and stock buybacks funded through accumulated cash can help to maintain a company's ROE even though operational profitability is eroding. Both ROA and ROE are calculated looking into the balance sheet and other financial statements of the companies and hence, they do not account for the market oriented factors. Also, due to investors' expectations, the balance sheets announcements could influence stock market measures. Low dividends announcements are often depicted in the next day market price. This gets incorporated in market based measures like Tobin's Q, which is a measure of stock valuation. For example, a low Q means that the cost to replace a firm's assets is greater than the value of its stock. This implies that the stock is undervalued. Market to book value ratio (MBVR) is another measure used to find the value of a company by comparing the market value of a firm to its book value. This ratio attempts to identify if the securities are undervalued or overvalued.

Researchers in the early years used accounting based measures (Hoskinsson et al., 1999). In the early 1990s, with the rise of shareholder activism, shareholder value maximization became the stated objective of the firms and the use of market-based measures (Tobin's Q, MBVR) had been promoted. Although both accounting and market based indicators are widely accepted, there exists a debate regarding their relationship in the existing literature (Combs et al., 2005; Richard et al., 2009; Rowe and Morrow, 1999). According to Venkatraman and Ramanujam (1986), the accounting-based measures and the market-based measures can be unrelated due to the conflict between achieving short-run and long-run economic goals. Even if they are related, a question still remains, i.e., whether the relationship is high enough that the two measures (accounting and market based measures) can be used interchangeably (Richard et al., 2009). This debate emphasizes that the use of single indicators may not precisely estimate firm's performance.

So far, as determinants of performance are concerned, there exist two schools of thoughts. The structure-conduct-performance (SCP) model emphasizes the degree of concentration in an industry determining firm performance. On the other hand, the firm effect models argue that differences in firm-level characteristics cause differences in performance. Firm specific factors could be the age of the firm, the leverage in a firm, size of the firm, selling expenses, investment in marketing and communication through advertising, investment in R&D, and the shareholding pattern in a firm.[4] The industrial organization literature suggests that older firms are more experienced, enjoy the benefits of learning, and hence turn out to be relatively superior performers compared to the newer firms. Firms' spending on innovation and marketing, as measured by research and development (R&D) and advertising expenses, respectively, is expected to yield positive returns in terms of share price performance. Given resource limitations, firms prioritize the quantum of their investments in R&D and advertising vis-à-vis other investments. Ho et al. (2005) finds that investment in advertising contributes positively to the one-year stock market performances of non-manufacturing firms. Andras and Srinivasan (2003) show that advertising intensity and R&D intensity are positively related to firm profit margins.[5]

A number of earlier studies have incorporated firm size as one of the determinants of firm performance. Larger firms, compared to their smaller counterparts, can monitor their managers

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[4] We are also aware of factors like mergers and acquisitions (Bhaumik and Selarka, 2008), partial privatization (Gupta, 2005), busyness of the board members (Sarkar and Sarkar, 2009), capital structure (Berger and Bonaccorsi di Patti, 2003), affiliation to business group (Khanna and Palepu, 1999; Chacar and Vissa, 2005), as well as compensation to CEO (Core et al., 1999) can influence firm performance. On the other hand, diversification is often looked upon as an option to increase firm performance. Diversification can improve debt capacity, reduce the chances of bankruptcy by going into new products or markets (Higgins and Schall, 1975), and improve asset deployment and profitability (Teece, 1982; Williamson, 1975). Many researchers also argue that it is not the conduct of the management but rather industry structure that governs firm performance (Christensen and Montgomery, 1981; Montgomery, 1985). There are various studies that show empirically that the related diversifiers outperform the unrelated ones (Markides and Williamson, 1994). Simmonds (1990), on the other hand, examines the combined effects of breadth (related versus unrelated) and mode (internal R&D versus mergers and acquisitions) and finds that related diversified firms are better performers and R&D based product development is better than mergers and acquisitions. Although we do not have an explicit control of diversification in our framework, we still think that the use of unobserved heterogeneity at the industry level captures this to some extent.

[5] We denote them with intensity variables since they are expressed as ratios to total sales.

better, improve shareholder value and has the ability to exploit economies of scale and the formalization of procedures. Therefore, size should influence firm performance (Diaz and Sanchez, 2008). We also include the square of the firm size to examine whether the relationship between firm performance and size is monotonic or not.

Corporate governance theory predicts that leverage affects agency costs and thereby influences firm performance. Agency costs represent important problems in corporate governance both in financial and non-financial industries. If the managers maximize their own utility rather than the value of the firm by taking excessive risks, then it could result in free cash-flow (Jensen, 1986). In these circumstances, high debt reduces the agency problems either through the threat of liquidation or through pressure to generate cash flows to service debt. In these situations, debt will have a positive effect on the value of the firm. On the other hand, if there is more debt in a firm, then the agency cost is likely to be higher which can lead to a lower firm value. Also, if a firm is infused with high debt, then the higher interest payment would lower profits and the market value of the firm. Therefore, a high debt-equity ratio might lead to a lower firm performance. We include debt-equity ratio as one of the determinants of firm performance.[6]

The shareholding pattern is also an important variable influencing the firm's performance. All theoretical and empirical research on the relationship between equity ownership and performance is influenced by the separation hypothesis of Berle and Means (1932). The convergence-of-interest or monitoring hypothesis predicts a positive relationship between ownership concentration and firm performance. At the same time, the entrenchment hypothesis proposes a negative relationship. Some authors (Sueyoshi et al., 2010; and García-Cestona and Surroca, 2008) argue that both the effects operate at different levels of shareholding, thus resulting in a non-linear relationship between insider ownership level and performance.

[6] An anonymous referee pointed out that there could be a potential endogeneity where firm performance can affect capital structure (Margaritis and Psillaki, 2010). We have carried out a panel data fixed/random effects regression (similar to Margaritis and Psillaki, 2010) to examine whether capita structure (as proxied by debt/equity ratio in our paper) is being influenced by firm performance. We did not find any evidence (statistically significant coefficient) to support endogeneity of the capital structure variable. Specifically, we ran the following regression:

$$\begin{aligned}(\text{Debt/equity})_{it} &= \beta_0 + \beta_1 \text{Salesgrowth}_{it-1} + \beta_2 \text{Sales}_{it-1} + \beta_3 \text{F}oreign_{it} + \beta_4 Indian_{it} + \beta_5 Inst_{it} \\ &+ \beta_5 \text{P}erfornmace_{it-1} + e_{it}\end{aligned}$$

where performance is being measured by the obtained scores either from the MIMIC or from the stochastic frontier model. In none of the models is the lagged performance variable was significant.

Institutional shareholders (for example, banks, financial institutions, pension funds, mutual funds, etc.) hold substantial blocks of a company's shares and thereby control a considerable number of voting rights to influence board decisions. They are different from individual shareholders as it is much easier and less expensive for them to play an active role in shareholder meetings, voice their opinion, and ensure that managers need to win their support on matters that require shareholder approval. Shleifer and Vishny (1986) note that large shareholders may have a greater incentive to monitor managers than members of the board of directors, who may have little or no wealth invested in the firm. Cornett et al. (2007) examines the relationship between institutional investor involvement and the operating performance of large firms. They obtain a significant relation between the operating cash flow returns and institutional stock ownership.

Foreign collaborators act as strategic partners for a domestic corporation when they come up with technological expertise. The technological and organizational advantages of foreign firms and their ability to operate internationally bring reputation vis-à-vis domestically owned firms. As foreign firms operate globally, family dominance is less in their firm. Therefore, firms with a foreign collaborator will tend to have a higher market value than completely domestically owned firms.

A promoter is a person or persons who are in over-all control of the company, who are instrumental in the formulation of a plan pursuant to which the securities are offered to the public. In India, the promoter group includes the promoter, an immediate relative, and if the promoter is a company then any subsidiary or other company where the parent company holds more than 10% equity. Insider ownership also reflects the governance problem arising due to variance in the cash flow and control rights such ownership entails. This principal agent problem hugely impacts the performance of a firm. The members of the family are also usually part of the management, thereby resulting in the presence of owner-managers or "promoters" at the highest levels of the firm's management. This gives rise to a situation wherein a group of the principals of the firm are also its agents. In the manager-shareholder relationship, the manager acts as an agent for the shareholders who are considered to be the owners. Shareholders are not in control of the company, since the managers make all pertinent decisions. The separation of ownership and control in a professionally managed firm may result in managers exerting insufficient work effort, indulging in perquisites, choosing inputs or outputs that suit their own preferences, or otherwise failing to maximize firm value. The shareholding pattern could also depict cases of multiple board appointments.

3. Methodology

This section describes the MIMIC model which is a variant of the linear independent structural relationships (LISREL) model of Joreskog and Sorbom (1999a, 1999b). It consists of two sets of equations which, in our case, are:

$$\mathbf{y} = \boldsymbol{\lambda}\eta + \boldsymbol{\varepsilon} \quad (1)$$

$$\eta = \boldsymbol{\gamma}'\mathbf{x} + \zeta \quad (2)$$

where, **y** is a column vector of '*p*' indicators of the single latent variable, η, and **x** is a vector of '*q*' 'causes' of η. In other words, equation (1) is the measurement model for η and equation (2) is the structural equation for the latent variable η. Equation (1) can also be viewed as a confirmatory factor analysis model for the observable '*p*' indicators with a unique factor (η). In the structural model (2) it is assumed that the latent performance is caused by the vector of explanatory variables **x**. Note that $\boldsymbol{\varepsilon}$ refers to a vector of zero mean (p×1) measurement error variables associated with the indicators, while ζ is a zero mean scalar structural error that captures un-modeled variables affecting η and measurement error associated with it. The measurement equations relate each indicator variable to the latent performance and a random measurement error term. It is assumed that ζ and all the elements of $\boldsymbol{\varepsilon}$ are mutually uncorrelated. Further, var(ζ) = ψ, and the variance covariance matrix of $\boldsymbol{\varepsilon} = \Theta_\varepsilon$. The parameter vector $\boldsymbol{\lambda}$ is also known as factor-loadings that need to be estimated along with the $\boldsymbol{\gamma}$ parameters. The factor analysis model assumes that the observed variables (indicators) are different manifestations of one or more underlying unobservable variables called factors. The MIMIC model is a step further in the theoretical explanation of the phenomenon. Here the observed variables are manifestations of a latent performance but there are other exogenous variables that influence the latent factor.

Substituting (2) into (1), the MIMIC model can be conceived as a *p*-equation multivariate (seemingly unrelated) regression model that takes the standard reduced form:

$$\mathbf{y} = \Pi\mathbf{x} + \mathbf{z} \tag{3}$$

where $\Pi = \boldsymbol{\lambda\gamma}'$, $\mathbf{z} = \lambda\zeta + \boldsymbol{\varepsilon}$, and the variance-covariance matrix of $\mathbf{z}$ is: $\text{Var}(\mathbf{z}) = \Omega$ $= E(\mathbf{zz}') = E[(\boldsymbol{\lambda}\xi + \boldsymbol{\varepsilon})(\boldsymbol{\lambda}\xi + \boldsymbol{\varepsilon})'] = \boldsymbol{\lambda\lambda}'\psi + \Theta_\varepsilon$. Using the standard normalization $\psi = E(\xi\xi') = 1$, we get $\Omega = \boldsymbol{\lambda\lambda}' + \Theta_\varepsilon$ where $\Theta_\varepsilon = E(\boldsymbol{\varepsilon\varepsilon}')$. Joreskog and Goldberger (1975) show that the estimator of η is given by: $\hat{\eta} = (1 - \lambda'\Omega^{-1}\lambda)^{-1}(\gamma'\mathbf{x} + \lambda'\Theta_\varepsilon^{-1}\mathrm{y})$. This shows that the MIMIC latent factor estimator is a sum of two terms: the first term is the ‘‘causes’’ term (function of **x**) and the second one can be called the ‘‘indicators’’ term which is nothing but the factor scores of the factor analysis model. Identification of the MIMIC model requires that *p* (the number of **y** variables) is two or more and *q* (the number of **x** variables) is one or more when η is a scalar.

The model is fitted by minimizing the discrepancy function where the discrepancy is defined as the difference between the sample and model implied covariance. The closer this difference is to zero, the better is the evaluated fit (Schermelleh-Engel et al., 2003). The estimator of the conditional mean of η is used as an estimator η given the values of the **y** and **x** variables. Following Joreskog (2000), we obtain the latent variable scores η_{j} for each firm $j = 1, 2, \ldots, J$ (in a cross-sectional model). However, the MIMIC model can only yield an ordinal index for the latent variables (firm performance).[7] While both the MIMIC and the seemingly unrelated regression (SUR) models use the information in all the available *p* indicators, the SUR model assigns equal weight across the available *p* indicators. An advantage of the MIMIC model is that in addition to estimating the factor loading parameters for each indicator in the *p*-equations model, we can also estimate the parameters of the structural equation.

In this study we assume the unobserved firm performance is manifested through various accounting and market-based indicators. We use return on assets (ROA) and Tobin’s Q as indicators of firm performance (**y**).[8] There are two indicator variables in our model, i.e., $p = 2$.[9] We include age, the square of age, size, size squared, debt equity ratio, advertising intensity,

[7] The MIMIC model is widely used for the measurement of a hidden economy. See, for example, Frey and Week-Hannemann (1984) and Aigner et al. (1988) for an early application of the MIMIC model. Chaudhuri et al. (2006) uses the MIMIC methodology for the estimation of a hidden economy for Indian States. On the other hand, Parikh and Allen (1982) use the MIMIC model approach to study the relationship between unemployment and vacancies in the United Kingdom.

[8] Our measure of Tobin’s Q takes into account the future prospects of the firm and therefore measures the management’s ability to generate a certain income stream from an asset base (Short and Keasey, 1999).

[9] As a robustness test, we also considered a model with four indicators but the results were found to be qualitatively similar. Details are available from the authors upon request.

R&D intensity, and the shareholding pattern of Indian promoters, foreign promoters, and institutional shareholders as the vector of exogenous causal variables denoted as the vector of exogenous causal variables as $\boldsymbol{x}$ in equation (2).[10]

Table 1 summarizes all the causal and indicator variables used in our analysis along with their descriptions. To control for the unobserved heterogeneity both at the industry and year level, we have included industry and year dummies.

Table 1: Causal and Indicator variables

Variable	**Description**
Indicators	
Return on assets	Net profit/(total assets – intangible assets)
Tobin's Q	(Market value of equity + Book value of assets – Book value of Equity)/ Book value of Assets
Causal Variables	
Age	Number of years from the incorporation year
Size	Natural logarithm of gross sales
Debt equity ratio	Ratio of debt to equity
Advertising intensity	Advertisement, selling and distribution expenses divided by total sales
R&D intensity	R&D expenses divided by total sales
Indian promoters	Percentage of shares held in a firm by the Indian owner-managers
Foreign promoters	Percentage of shares held in a firm by foreign promoters
Institutional shareholding	Percentage of shares held in a firm by institutions such as banks, etc.

4. Data and Empirical Results

[10] We are thankful to an anonymous referee for pointing out the paper by Hansen and Wernerfelt (1989) who have shown that organizational factors (such as the employee's perception of how concerned the organization is with his welfare, work conditions, etc., and the employee's perception of relative emphasis on achieving aggressive goals or objectives) explain about twice more variance than economic factors. However, we do not have information on these variables in our dataset.

4.1 Data

The data set for the study consists of annual observations from 2001 – 2008 for all the firms that are listed in either the National Stock Exchange (NSE), the Bombay Stock Exchange (BSE), or both. We use the Indian data for several reasons. First, the Indian corporate sector has a large number of corporate firms and the contribution of the industrial and manufacturing sectors is close to that of several advanced economies (Khanna and Palepu, 2000). Moreover, our study includes all the firms that are listed in either the National Stock Exchange (NSE) or in the Bombay Stock Exchange (BSE). The BSE has the second largest number of domestic quoted companies on any stock exchange in the world after the New Work Stock Exchange (NYSE).

Second, corporate governance affects the development and functioning of capital markets and exerts a strong influence on resource allocation and therefore the behavior and performance of firms. India actually has one of the best corporate governance laws with a shareholder rights index of 5 (out of a maximum possible of 6) (La Porta et al., 1998). According to the World Bank's Doing Business 2008 report, India gets an investor protection score of 6, ahead of all the other BRIC countries. An extremely important aspect of investor protection in any country is securities markets regulation. Using the framework of La Porta et al. (2006), which focuses on disclosure and liability requirements, as well as the quality of public enforcement of the regulations controlling securities markets, India scores an impressive 0.92 in the index of disclosure requirements, which is the third highest after the United States and Singapore. As for liability standards, India's score of 0.66 is again high, being the fifth highest, while the sample mean is only 0.47. In terms of the quality of public enforcement, or the nature and powers of the supervisory authority, the Securities and Exchanges Board of India earns a score of 0.67. Numerous initiatives have been taken by the Stock Exchange Board of India to enhance corporate governance practice. Third, the accounting system in India is well established and accounting standards are similar to those followed in most of the advanced economies (Khanna and Palepu, 2000).

The variables used in our study are divided into two major categories: (1) data on the indicator variables (ROA and Tobin's Q) and (2) data on the causal variables. The source of our data is the electronic database Capitaline.[11] It contains detailed time series information on the financial performance of various companies along with company specific information including

[11] http://www.capitaline.com

the digitalized formats of annual reports filed by the companies. Data on firm performance measures like ROA and Tobin's Q was obtained from the annual income and balance sheet statements of each company available in the database. The database also has information on the firm characteristics used in the model. Data on the sales or revenue of each company was obtained from the profit and loss statement for the corresponding financial year. The extent of the institutional, Indian, and foreign promoter shareholding in the company has been obtained from the shareholding pattern report that companies have disclosed in their annual reports. The final dataset consists of pooled data for the years 2001 to 2008 with a total of 5,960 observations.

4.2 Results

This Section is divided into four parts: Section 4.2.1 reports the descriptive statistics. Section 4.2.2 reports the results for the MIMIC model, and the robustness results are reported in Section 4.2.3. In Section 4.2.4, we analyze the obtained firm performance from our estimated model.

4.2.1 Descriptive Statistics

In Table 2, the summary statistics for the causal and indicator variable are reported. Among the indicator variables the mean ROA and the mean Tobin's Q have not increased significantly over the 2005-2008 period in comparison with the 2001-2004 period.[12] Among the causal variables, the mean age and size of the firms have not changed much over the years and are also close to the overall sample mean. The mean R&D and advertising intensity figures are the same for both time periods and there is almost no variations in them. The mean debt equity ratio declined over the years (from 3.79 in 2001-2004 to 1.53 in 2005-2008) indicating that during the post 2005 period most of the activities of the businesses have been financed through equity and not by debt. This is justified as the number of initial public offerings (IPOs) in the period 2005-2008 has been about 277 reflecting the preference of equity to debt. There is an increase in the mean shareholding of Indian promoters from 42.52 in 2001-2004 to 43.75 in 2005-2008; however, the variations decreased from 22.3 to 21.87. This highlights the increase in the prevalence of family owned businesses in the Indian corporate sector which is one of the

[12] The unconditional correlation (without controlling for the causal variables) for the overall sample (combining firms and years) between the two observed indicators, namely ROA and Tobin's Q, takes a value of 0.146 and is significant, whereas that between ROA and MBVR is 0.036.

most striking features. On the other hand, the mean foreign promoter and institutional shareholding declined over the years. This could be due to the increase in insider ownership.

Table 2: Descriptive Statistics

	Mean (2001-2004)	Mean (2005-2008)	Standard Deviation (2001-2004)	Standard Deviation (2005-2008)	Mean (2001-2008)	Standard Deviation (2001-2008)
Indicator Variables						
ROA	0.09	0.12	0.24	0.62	0.11	0.49
Tobin's Q	1.58	2.58	1.31	3.28	2.14	2.66
Causal Variables						
Age	33.57	36.46	21.45	21.41	35.21	21.47
Size	5.26	5.45	1.71	1.84	5.34	1.79
Advertising	0.03	0.03	0.04	0.04	0.03	0.04
R&D	0.01	0.01	0.01	0.02	0.01	0.02
Debt equity ratio	3.79	1.53	101.12	8.97	2.51	66.84
Foreign promoter	8.43	8.01	18.90	19.10	8.19	19.01
Indian promoter	42.52	43.75	22.37	21.87	43.22	22.09
Institutional holding	11.61	10.81	12.83	12.92	11.15	12.88

Note: For the definition of both the indicator and the causal variables, see Table 1.

4.2.2 Results from the MIMIC Model

Table 3 presents the estimates from the MIMIC model. Results from three models are presented. In Model A, we do not include the squares of the share-holding pattern. Model B includes the square of the shareholdings for different stakeholders. In Model C we exclude the causal variables from Model B that were not statistically significant. Each model includes both industry and year dummies. The unobserved heterogeneity is controlled by industry-specific dummies at the industry level whereas the impact of aggregate (macroeconomic) shocks is captured by the year dummies.

Table 3: Results from the Estimated MIMIC Model

Variables	Model A	Model B	Model C
	Indicators		
ROA	1.00	1.00	1.00
Tobin's Q	6.582 (0.000)***	6.792 (0.000)***	6.815 (0.000)***
	Causes		
Age	0.177 (0.002)***	0.161 (0.001)***	0.161 (0.001)***
Square of Age	-0.091 (0.019)**	-0.080 (0.036)**	-0.080 (0.036)**
Size	-0.179 (0.020)**	-0.155 (0.029)**	-0.155 (-0.030)**
Square of Size	0.320 (0.000)***	0.278 (0.004)***	0.278 (0.005)***
Advertising intensity	0.025 (0.113)	0.024 (0.116)	0.024 (0.116)
R&D intensity	0.010 (0.280)	0.009 (0.341)	-
Debt equity ratio	-0.005 (0.242)	-0.004 (0.284)	-
Foreign promoter	0.269 (0.000)***	0.205 (0.001)***	0.201 (0.000)***
Indian promoter	0.113 (0.000)***	-0.208 (0.026)**	-0.208 (0.025)**
Institutional holding	0.050 (0.002)***	0.094 (0.007)***	0.096 (0.006)***
Square of Foreign promoter	-	-0.004 (0.927)	-
Square of Indian promoter	-	0.297 (0.003)***	0.296 (0.003)***
Square of Institutional holding	-	-0.049 (0.039)**	-0.050 (0.038)**
Residual Variances			
ROA	0.978	0.978	0.978
Tobin's Q	0.041	0.011	0.008
Factor 1	0.889	0.886	0.887
Industry dummies	Yes	Yes	Yes

Year dummies	Yes	Yes	Yes
No of observations	5960	5960	5960

Note: The numbers in the parenthesis denote the p-values of the associated t-statistics which we obtain using robust standard error. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The results indicate that all the causal variables have the expected signs. Except for the debt equity ratio and R&D intensity, the rest of the variables are almost significant. In Model A, all the indicator variables are individually statistically significant. Age of the firm shares an inverted U-shaped relationship with firm performance, whereas the size of the firm confirms a U-shaped relationship. The coefficient associated with the advertising intensity is not significant. The coefficients associated with the Indian, foreign, and institutional shareholders are significant and positive.

In Model B, we include the squares of the shareholding pattern to account for the non-monotonic nature of each of these variables with firm performance. Our results show that as the stake held by the Indian promoters in a firm increases, they are able to monitor the managers and induce them to not only maximize their own wealth but also that of the shareholders. This implies that at lower levels of shareholding the entrenchment hypothesis dominates and at higher levels of shareholding the monitoring hypothesis dominates. The square of the foreign ownership is insignificant. On the other hand, the institutional shareholders have an inverted U-shaped relationship, i.e., at lower levels of shareholding the firm performance increases but at higher levels it decreases. Model C omits those causal variables from Model B that were not significant. The results remain qualitatively the same with Model B.

Table 4 reports the diagnostic statistics of the estimated MIMIC models. A necessary condition for model identification is: $(p \times q + 1/2(p)(p+1) - 2p - q) \geq 0$ where p denotes the number of indicator variables and q is the number of causal variables. In our case, the necessary condition for identification is always satisfied, as our models are over-identified. We do provide a test for over-identification.

Following Joreskog and Goldberger (1975) and Spanos (1984), the over-identification test can be expressed as follows: the joint null hypothesis is $\Pi = \boldsymbol{\lambda}\boldsymbol{\gamma}'$ and $\Omega = \boldsymbol{\lambda}\boldsymbol{\lambda}' + \Theta_{\varepsilon}$ whereas the alternative hypothesis is that the null is not true. This test statistic (under the null hypothesis) is distributed as a χ^2 with $q(p\text{-}1)+\frac{1}{2}p(p\text{-}3)$ degrees of freedom. The first row of Table 4 reports the results from the over-identification test. Rejection of the null hypothesis would suggest the estimated model is miss-specified. Our results, as stated in row 1 of Table 4 clearly indicate that the estimated model is not mis-specified. Given this evidence, we then provide a series of model fit diagnostics to render the estimated model statistically adequate. We use four different statistics: the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square of approximation (RMSEA), and the standardized root mean square of residual (SRMR). All these statistics indicate a measure of overall good-fit of our estimated model.

Table 4: Diagnostic statistics of the estimated MIMIC models

Diagnostic Statistics	Model A	Model B	Model C
Chi-Square Test of Model Fit p-value for Model Fit	31.14 [0.223]	37.370 [0.167]	34.384 [0.155]
RMSEA	0.006	0.006	0.007
p-value that RMSEA is less than or equal to 0.05	1.000	1.000	1.000
CFI	0.993	0.991	0.991
TLI	0.986	0.982	0.982
SRMR	0.004	0.006	0.004

4.2.3 Robustness check

Since almost 62% of the sample consists of firms from the manufacturing industry, we estimated a MIMIC model by excluding firms belonging to the manufacturing industries. Table 5 depicts the results of this model. The sign of all the variables remain qualitatively the same in Model B for the entire sample. However the square of the foreign ownership becomes significant and the obtained coefficients show that at the lower levels of foreign-shareholding the firm performance increases but at higher levels it decreases.

Table 5: MIMIC model results excluding "Manufacturing Industries"

Variables	**Coefficient and p-value**
Indicators	
Return on assets	1.000
Tobin's Q	1.930 (0.000)***
Causes	
Age	0.155 (0.014)**
Square of Age	-0.081 (0.127)
Size	-0.096 (0.254)
Square of Size	0.309 (0.007)***
Advertising intensity	0.060 (0.034)**
R&D intensity	-0.027 (0.190)
Debt equity ratio	-0.047 (0.173)
Foreign promoter	0.488 (0.000)***
Indian promoter	-0.538 (0.006)***
Institutional holding	0.239 (0.000)***
Square of Foreign promoter	-0.208 (0.030)**
Square of Indian promoter	0.679 (0.001)***
Square of Institutional holding	-0.177 (0.000)***
Diagnostic Statistics	
Chi-Square Test of Model Fit	48.663 [0.006]
RMSEA	0.019
p-value that RMSEA is less than or equal to 0.05	1.000
CFI	0.956
TLI	0.907
SRMR	0.007
No of observations	2260

Note: The numbers in the parenthesis denote the p-values of the associated t-statistics which we obtain using robust standard error. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.2.4 Stochastic Frontier Model

We noted before that the efficiency measures in the frontier models estimate shortfall in either output/revenue/profit or increase in cost. Although ROA and Tobin's Q are already measures of efficiency, estimating stochastic frontier models on them will give us an idea of whether ROA and Tobin's Q could have increased, ceteris paribus. With multiple outputs and multiple inputs, the stochastic output distance function (ODF) is another way to measure efficiency and productivity. However, in an ODF formulation, the outputs are always substitutable (given by the production possibility function), given the inputs. This is not the case with ROA and Tobin's Q. That is, given other factors, one cannot always argue that an increase in ROA will lead to a decrease in Tobin's Q the way it is argued in production theory (more guns means less butter, given the resources). Further, the ODF is homogeneous of degree one in outputs which helps to express it in natural logarithms. In our case, given that ROA is negative for some firms, we could not estimate the ODF. So we do not find any theoretical and/or practical reason for using an ODF to estimate ROA and Tobin's Q efficiency. Rather we estimate two stochastic frontier models where we use ROA and Tobin's Q as the output variables. That is, we have estimated the following stochastic frontier models (Habib and Ljungqvist, 2005; Lozano-Vivas et al., 2011):

$$\begin{aligned} y_{it} &= \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \text{Age}_{it}^2 + \beta_3 \text{Sales}_{it} + \beta_4 \text{Sales}_{it}^2 + \beta_5 \text{Advertising Intensity}_{it} \\ &\quad + \beta_6 \text{R\&DIntensity}_{it} + \beta_7 (\text{Debt/equity})_{it} + \sum_{j=1}^{\text{J-1}} \theta_{\text{j}} D_j + \sum_{t=1}^{\text{T-1}} \lambda_{\text{t}} D_t + v_{it} - u_{it} \end{aligned} \tag{4}$$

where y_{it} is either ROA or Tobin's Q, D_j are the industry dummies, and D_{Tt} are the year dummies. All other variables are as described before. We assume that v_{it} are random variables and distributed as $N(0, \sigma_v^2)$, and u_{it} are technical inefficiency and distributed as half-normal with pre-truncated mean zero and variance σ_u^2. Further, we assume that both σ_u^2 and σ_v^2 are functions of ownership variables, industry dummies, and a trend. Presence of these variables in σ_u^2 can be viewed as determinants of technical inefficiency, while presence in σ_v^2 indicates heteroscedasticity (see Kumbhakar and Lovell (2000) and Kumbhakar et al. (2015) for details). The firm-specific estimate of the technical efficiency and the marginal effects of determinants of inefficiency are obtained from the conditional mean of u and derivatives of E(u) (see Kumbhakar et al. (2015) for details). Table 6 reports the results. In comparison with the MIMIC model results, we observe that advertising intensity is significant when we use Tobin's Q as the output, whereas the R&D intensity variable exerts a significant impact when ROA is used as the output variable. The age and sales is no longer significant in case of Tobin's Q. The debt-Equity ratio becomes significant when we use Tobin's Q as the output measure.

Table 6: Results from the SF Model

Variables	**Coefficient and p-value**	**Coefficient and p-value**
Indicators	ROA	**Tobin's Q**
Causes		
Age	-0.002 (0.000)***	0.003 (0.103)
Square of Age	0.00002 (0.000)***	-0.000004 (0.807)
Size	-0.002 (0.785)	0.051 (0.190)
Square of Size	0.002 (0.005)***	0.005 (0.150)
Advertising intensity	0.091 (0.428)	3.362 (0.007)***
R&D intensity	0.459 (0.080)*	0.100 (0.718)
Debt equity ratio	-0.00002 (0.347)	-0.0002 (0.030)**
Log(σ^2_u)		
Foreign promoter	0.171 (0.075)*	0.112 (0.122)
Indian promoter	0.011 (0.668)	0.012 (0.335)
Institutional holding	-0.008 (0.573)	-0.014 (0.236)
Square of Foreign promoter	-0.013 (0.087)*	-0.009 (0.073)*
Square of Indian promoter	-0.00001 (0.959)	-0.0003 (0.064)*
Square of Institutional holding	0.0004 (0.105)	0.00002 (0.923)
Log(σ^2_v)		
Foreign promoter	0.032 (0.507)	0.054 (0.000)***
Indian promoter	-0.021 (0.417)	-0.032 (0.016)**
Institutional holding	0.049 (0.301)	0.019 (0.245)
Square of Foreign promoter	-0.001 (0.141)	-0.0004 (0.006)***
Square of Indian promoter	-0.0001 (0.685)	0.0005 (0.000)***
Square of Institutional holding	-0.002 (0.069)*	-0.0001 (0.482)
Log-Likelihood	-2193.464	-11422.922
Industry dummies	Yes	Yes
Year dummies	Yes	Yes
No of observations	5960	5960

Note: The numbers in the parenthesis denote the p-values of the associated t-statistics which we obtain using robust standard error. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.2.5 Ranking of Firms: Comparison between MIMIC and SF Model

The MIMIC model can only yield an ordinal time series index for the latent variables (firm performance). Given the formulation of our model, the predicted factor scores can take negative values and has zero mean across all firms. We construct a cardinal measure of performance, which we call the performance measure (P_c). To construct P_c, we take the logistic transformation of the obtained factor scores.[13] In Table 7, we report the results for each year by taking the yearly averages of each firm's score over the years. From Table 7, results can be summarized as follows: a) performance measures in both models are found to vary over time; b) the Pearson correlation coefficient shows that the MIMIC model can be an alternative to the SF model, c) 95% limits of agreements from Bland and Altman (1986) show that the average difference is always within the confidence band.

In Tables 8a and 8b, we report the mean efficiency scores obtained from the MIMIC model (as reported in Table 3, Model B) and the two SF models (as reported in Table 6) for industries across years. Our results show varied patterns of technical efficiency scores across industries and years.

[13] See Fayers and Hand (2002) for details on this.

Table 7: Year-wise Mean Performance Measure (MIMIC and SF model)

Year	MIMIC Model Mean (SD)	SF Model Mean (SD) Using ROA as the output	Pearson Corr. Coeff. b/w MIMIC and SF using ROA as the output	Average Difference and 95% Limits of Agreement b/w MIMIC and SF using ROA as the output	SF Model Mean (SD) Using Tobin's Q as the output	Pearson Corr. Coeff. b/w MIMIC and SF using Tobin's Q as the output	Average Difference and 95% Limits of Agreement b/w MIMIC and SF using Tobin's Q as the output	No. of Obs.
2001	0.888 (0.008)	0.933 (0.039)	0.347	-0.045 [-0.116, 0.027]	0.658 (0.163)	0.465	0.230 [-0.082, 0.542]	342
2002	0.888 (0.006)	0.939 (0.036)	0.310	-0.045 [-0.116, 0.027]	0.749 (0.123)	0.459	0.139 [-0.098, 0.375]	620
2003	0.890 (0.008)	0.944 (0.030)	0.315	-0.055 [-0.110, -0.000]	0.841 (0.080)	0.477	-0.049 [-0.102, 0.200]	783
2004	0.891 (0.008)	0.949 (0.025)	0.362	-0.058 [-0.104, -0.012]	0.898 (0.049)	0.459	-0.007 [-0.097, -0.083]	832
2005	0.894 (0.013)	0.954 (0.023)	0.324	-0.059 [-0.103, -0.015]	0.937 (0.030)	0.403	-0.042 [-0.092, 0.012]	866
2006	0.896 (0.014)	0.959 (0.021)	0.250	-0.063 [-0.106, -0.020]	0.961 (0.019)	0.319	-0.066 [-0.104, -0.027]	880
2007	0.900 (0.017)	0.962 (0.019)	0.197	-0.062 [-0.106, -0.018]	0.976 (0.012)	0.265	-0.076 [-0.111, -0.041]	883
2008	0.892 (0.011)	0.964 (0.016)	0.150	-0.072 [-0.107, -0.038]	0.985 (0.007)	0.209	-0.093 [-0.116, -0.071]	754
Overall	0.893 (0.012)	0.952 (0.027)	0.302	-0.060 [-0.111, -0.008]	0.899 (0.115)	0.329	-0.006 [-0.225, 0.213]	5960

Note: The 95% limits of agreements is for Bland and Altman's (1986) procedure, a data-scale assessment of the degree of agreement, is a complementary approach to the relationship-scale approach of Lin (1989, 2000).

Table 8a: Mean Efficiency measure by Year and Industry (MIMIC Model)

INDUSTRY	Mean Efficiency							
	2001	2002	2003	2004	2005	2006	2007	2008
Agriculture	0.886	0.886	0.889	0.890	0.892	0.893	0.898	0.890
Construction	0.886	0.885	0.886	0.886	0.888	0.898	0.902	0.889
Electricity	0.888	0.888	0.893	0.892	0.894	0.895	0.908	0.894
Finance	0.885	0.885	0.888	0.888	0.891	0.890	0.898	0.889
Hotel	0.886	0.886	0.888	0.891	0.893	0.895	0.902	0.893
Manufacturing	0.887	0.887	0.889	0.891	0.894	0.895	0.899	0.891
Others	0.893	0.892	0.893	0.894	0.899	0.901	0.907	0.895
Realty	0.885	0.885	0.886	0.887	0.895	0.899	0.905	0.891
Trading	0.887	0.888	0.891	0.892	0.897	0.898	0.901	0.894
Transport	0.887	0.887	0.890	0.890	0.892	0.892	0.895	0.889
Overall	0.888	0.888	0.890	0.891	0.894	0.896	0.900	0.892

Note: According to NIC-1 classification, in our case Agriculture: Agriculture, Hunting and Forestry, Construction: Construction, Electricity: Electricity, Gas and Water Supply, Finance: Financial Intermediation, Hotel: Hotels and Restaurants, Manufacturing: Manufacturing, Realty: Real Estate, Renting and Business Activities, Trading: Wholesale and Retail Trade; Repair Of Motor Vehicles, Motorcycles and Personal and Household Goods, Transport: Transport, Storage and Communications and Others not mentioned elsewhere. Overall denotes the mean across all industries over the years.

Table 8b: Mean Efficiency measure by Year and Industry (SF Model)

INDUSTRY	Mean Efficiency using ROA as the Output							
	2001	2002	2003	2004	2005	2006	2007	2008
Agriculture	0.950	0.965	0.969	0.971	0.974	0.976	0.978	0.979
Construction	0.921	0.926	0.941	0.948	0.962	0.967	0.973	0.971
Electricity	0.925	0.926	0.930	0.931	0.937	0.940	0.939	0.944
Finance	0.878	0.881	0.903	0.921	0.924	0.926	0.934	0.934
Hotel	0.945	0.915	0.942	0.951	0.959	0.963	0.969	0.971
Manufacturing	0.932	0.938	0.941	0.946	0.951	0.957	0.960	0.962
Others	0.934	0.937	0.945	0.949	0.954	0.958	0.962	0.964
Realty	0.982	0.973	0.974	0.975	0.976	0.978	0.980	0.979
Trading	0.957	0.961	0.967	0.968	0.969	0.972	0.975	0.975
Transport	0.910	0.932	0.936	0.939	0.940	0.951	0.956	0.954
Overall	0.933	0.939	0.944	0.949	0.954	0.959	0.962	0.964
INDUSTRY	Mean Efficiency using Tobin's Q as the Output							
	2001	2002	2003	2004	2005	2006	2007	2008
Agriculture	0.579	0.724	0.842	0.901	0.935	0.960	0.975	0.984
Construction	0.747	0.803	0.881	0.929	0.960	0.975	0.985	0.991
Electricity	0.647	0.708	0.850	0.903	0.942	0.964	0.978	0.986
Finance	0.623	0.642	0.797	0.867	0.918	0.949	0.969	0.981
Hotel	0.502	0.524	0.667	0.784	0.855	0.909	0.945	0.964
Manufacturing	0.679	0.766	0.851	0.906	0.941	0.964	0.978	0.986
Others	0.600	0.690	0.799	0.870	0.922	0.952	0.971	0.982
Realty	0.667	0.733	0.826	0.898	0.943	0.964	0.979	0.987
Trading	0.696	0.797	0.870	0.916	0.946	0.967	0.979	0.987
Transport	0.644	0.736	0.825	0.879	0.929	0.958	0.975	0.983
Overall	0.658	0.749	0.841	0.898	0.937	0.961	0.976	0.985

Note: According to NIC-1 classification, in our case Agriculture: Agriculture, Hunting and Forestry, Construction: Construction, Electricity: Electricity, Gas and Water Supply, Finance: Financial Intermediation, Hotel: Hotels and Restaurants, Manufacturing: Manufacturing, Realty: Real Estate, Renting and Business Activities, Trading: Wholesale and Retail Trade; Repair Of Motor Vehicles, Motorcycles and Personal and Household Goods, Transport: Transport, Storage and Communications and Others not mentioned elsewhere. Overall denotes the mean across all industries over the years.

5. Conclusion

The definition of economic performance in the empirical literature of firm performance includes either various productivity measures such as production costs, productivity growth, or profitability measures like return on equity, return on assets, and market to book value ratio. All of these measures are imperfect indicators of a variable that is inherently unobservable, namely performance. We use a latent variable approach to model firm-performance which is manifested through various indicators. We use firm level data from India for the period 2001-2008 to demonstrate the usefulness of the MIMIC model. We derive performance scores from the estimated model and examined performance pattern across industries over the years. To validate our proposed model, we also estimate two SF models. Our results show that the two obtained performance scores are highly correlated. The average difference between the rankings obtained using MIMIC and the two SF models always lies in the confidence band of the 95% limits of agreement according to the procedure developed by Bland and Altman (1986). Thus we claim that the MIMIC model can be used as a complimentary approach in evaluating firm performance along with the SF model.

The results from the MIMIC model show that size and age exert significant influence on firm performance. We also obtain a positive and significant impact of advertising and R&D expenditure (in some cases) on firm performance. The debt-equity ratio does not seem to be a significant determinant except when we use Tobin's Q as the output variable in the case of the SF model. The result also show different shareholders influence firm performance differently. Using the MIMIC model, the relationship turned out to be U-shaped for the Indian promoter while for institutional investors the relationship was that of an inverted U. Although our model has been applied to the Indian data, we believe that it is equally applicable in similar issues using data from other countries.

The MIMIC model has some advantages over the SF model, especially when there are multiple indicators but a single performance measure. The SF model makes distributional assumptions and the payoff from it is that it can deliver an absolute measure of efficiency and a ranking of firms. On the other hand, the MIMIC model does not make any distributional assumptions, but the downside is that it can deliver only relative measures of efficiency. So there is no real winner, one can complement the other in real applications.

Since the MIMIC model can accommodate multiple indicators of a single (or multiple) unobserved causal variable, perhaps one can think of combining this feature to a SF model in future applications. For example, banking studies often examine profit and cost efficiency separately using SF models and then use them to examine financial health or stability (Schaech and Cihak, 2014). In the MIMIC framework, one can view stability (financial health) as a latent variable (η) which might be related to some observed bank characteristics (**x**) as in (2). Different observed indicators (such as competition, returns to outlay (the ratio of revenue to cost), etc.) can be related to the latent stability variable η as in (1) which allows measurement errors ($\boldsymbol{\varepsilon}$) in the indicator variables (**y**). The challenge might be to add one-sided errors (as in SF models) and separate them from the measurement error vector ε in the measurement equation (1).

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