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Corporate Governance and Informational Efficiency in Futures Markets in India's National Stock Exchange*

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Abstract

This paper provides estimates of overall informational efficiency in futures markets on India's National Stock Exchange. We do not examine the price reaction to any public announcement. Instead, we invoke the Hellwig (1980) model, and exploit the property that for futures contracts the terminal value can be treated as observable, to obtain estimates of the overall signal to signal plus noise ratio in markets for single-stock and index futures on India's National Stock Exchange. The variance-covariance parameters governing futures prices and terminal values can be inverted to obtain estimates of the primitive parameters of the Hellwig (1980) model. This lets us identify the MLEs of the precision of private information and the variance of liquidity motivated trades. The signal to signal plus noise ratio – our measure of overall informational efficiency -- is a function of these primitive parameters.

Our primary findings show that there is considerable variation across firms in these parameters despite only large active firms being available for futures trading. Overall informational efficiency varies with variables related to corporate governance – it increases in promoters' and foreign institutional investors' stakeholding, and if the board of directors has a majority that is independent, and decreases if the chairman of the board is also the CEO, and if overall trading activity is fragmented across domestic and international markets. The NIFTY index shows a higher signal to signal plus noise ratio than for any of the firms. This is consistent with the idea that less manipulability is associated with greater informational efficiency.

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This paper estimates parameters governing overall informational efficiency in futures markets in India's National Stock Exchange (NSE). Our contribution is to provide estimates of informational efficiency in an active emerging market. Second, we do so without examining price reactions to public announcements. Our measures are measures of *overall* informational efficiency: how well prices reflect the aggregate of all information in the market, public and private. We also find considerable variation across firms in all these parameters. This is interesting because futures trading is allowed only in large and very active stocks. We also show that cross-sectional variation in informational efficiency in the futures market can be explained by variables related to corporate governance – it increases in promoters' and foreign institutional investors' stakeholding, and if the board of directors has a majority that is independent, and decreases if the chairman of the board is also the CEO, and if overall trading activity is fragmented across domestic and international markets. The NIFTY index shows a higher signal to signal plus noise ratio than for any of the firms. This is consistent with the idea that less manipulability is associated with greater informational efficiency.

Futures contracts have a well-defined maturity date, and the maturity value can be reliably measured using the spot price of the underlying security on maturity date. This allows us to estimate in a simple way the primitive parameters of the Hellwig (1980) model, which views financial markets in a noisy rational expectations setting with perfect competition. We estimate the prior variance of terminal value, the variance of the error term in private signals of market participants, and the variance of supply noise or liquidity trading. We then compute our measure of informational efficiency, the signal to signal plus noise ratio, which is a function of these parameters. We show in an out of sample test that the Hellwig (1980) model cannot be rejected by the data.

India offers a unique setting for estimating overall informational efficiency in a financial market. It is an emerging economy yet there is a long tradition of active participation in financial markets. The Bombay Stock Exchange (BSE) dates back to 1875. The National Stock Exchange

(NSE) that we get our data from was opened only in 1994, but has grown to be about twice as large the BSE for equity volumes, and about two orders of magnitude larger for derivatives volume. In contrast to the BSE which has been largely broker-controlled (though it is making efforts to shed broker control) the NSE was launched as an initiative of various financial institutions, and from the beginning has been the technologically more advanced exchange.

Derivative markets as in the west did not exist till very recently. But as Thomas (2006) points out, because for a long time trading on the spot market for equity allowed weekly or fortnightly settlement, it had the 'risk and difficulties of futures markets, without the gains in price discovery and hedging services that come with a separation of the spot market from the futures market.' In recent years settlement regimes have been steadily tightened, and over the last 5 years we have seen a T+2 settlement regime.

Derivatives of various kinds also existed in informal markets but participation was limited. In June 2000 trading in index futures began on both BSE and NSE, in 31 individual stock options in July 2001, and in 31 individual stock futures in November 2001. Our interest in this paper is limited to futures contracts and we ignore options as option values are bounded from below, and that would seem a gross violation of the distributional assumptions in Hellwig (1980). Single stock futures are traded today in many markets around the world. NSE's futures markets are unusual relative to virtually all other single-stock futures markets in that futures trading in India is very heavy. Trading is in fact heavier in the futures market than in the underlying market for 25 of the 27 futures contracts that constitute our sample. Most futures markets in individual stocks around the world tend to be very thin, at least after a very small initial period. For example in the US such trading resumed in 2002 (first on 2 exchanges, OneChicago and NSLQ, a joint venture between NASDAQ and LIFFE). Trading in single stock futures on these exchanges is very thin: for most futures on most days trading is strictly zero. And NSLQ has since closed down. Open interest is also miniscule relative to the underlying equity stock. This is despite stocks in the US also being chosen based on how active the underlying stock is, and in anticipation of good trading volumes in the futures market. Since the premise of the Hellwig (1980) model is a large competitive market, a setting like India is more appropriate for estimating parameters from futures data.

The noisy rational expectations literature has emphasized that observable market prices serve at least two important roles. Firstly, they help define the opportunity sets of agents. They large the BSE for equity volumes, and about two orders of magnitude larger for derivatives volume. In contrast to the BSE which has been largely broker-controlled (though it is making efforts to shed broker control) the NSE was launched as an initiative of various financial institutions, and from the beginning has been the technologically more advanced exchange.

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The noisy rational expectations literature has emphasized that observable market prices serve at least two important roles. Firstly, they help define the opportunity sets of agents. They also act as potentially informative signals, conveying information about relevant unobservable variables. There is considerable understanding of the empirical significance of the first role of prices. There is much less work in assessing the empirical significance of the role of prices as signals. This paper takes a small step towards redressing this imbalance. Cho and Krishnan (2000) have estimated the Hellwig (1980) model in the S&P 500 index futures market. To the best of our knowledge no such estimates exist at the level of individual firms in any country.

In accounting and finance there is a literature estimating informational efficiency by examining price reactions to news releases, e.g. earnings announcements or takeovers. Such exercises are useful in assessing informational efficiency with respect to public announcements, though they are subject to the caveat that such statements are conditional on the underlying asset pricing model. Our assessment of informational efficiency in this paper examines how well prices reflect the aggregate of all, not just public, information.

Note that in our approach once terminal value and prices are observable, we can uncover the Hellwig (1980) model parameters from these two series alone. No other data relating to announcements or volume or anything else is needed. This implies both a cost and a benefit. The cost is that to obtain estimates we must invoke a particular asset pricing model (though we also separately test the model). The benefit is that we minimize measurement errors arising from other variables, and can make a more general statement about informational efficiency. By assumption the market is efficient in that agents behave rationally. But to the extent that there is noise the price will reflect less of the overall information in the economy. We also implement an out of sample test of the Hellwig (1980) model and show that it cannot be rejected in our sample. So our results can be interpreted as more than a conditional statement of informational efficiency.

Because our estimates of informational efficiency show significant cross-sectional variation we also study the impact of some potential cross-sectional determinants. We show that cross-sectional variation in informational efficiency in the futures market can be explained by variables related to corporate governance – it increases in promoters' and foreign institutional investors' stakeholding, and if the board of directors has a majority that is independent, and decreases if the chairman of the board is also the CEO, and if overall trading activity is fragmented across domestic and international markets. The NIFTY index shows a higher signal to signal plus noise ratio than for any of the firms.

We assume that a noisy rational expectations model under perfect competition (a la Grossman and Stiglitz (1980) and Hellwig (1980)) provides a reasonable description of the active futures markets in NSE that we study. In this setting the value of prices as costlessly observable signals depends on several parameters: the prior variance of terminal value, i.e. the spot price at maturity, the variance of the error term in agents' private signals, the variance of liquidity motivated trades, and the level of risk aversion. If agents have very good priors and the prior variance of terminal value is small, the potential benefit from any additional information, be it a private signal or a publicly observable price, would be small. If the precision of private signals that agents have is small, then the quality of even the aggregate information that could be reflected in the market price would be low, so that even a noiseless price would be of limited informational value. If noise provided by liquidity motivated trades is large, then again market prices would be of limited value as public signals. Finally, if risk aversion is large, agents would react very cautiously to their private information, causing less of the information to be incorporated into prices. Thus, for prices to be significant sources of information about asset value, we must have priors that are not too good, private information of sufficiently high precision, supply noise sufficiently small, and sufficiently small risk aversion.

The primary purpose of this paper is to take a step towards formally *quantifying* such parameters. This would allow us to assess the numerical impact of at least some parameters on the informativeness of prices, which is of some interest in itself given the paucity of available parameter estimates, and may help decide if conditioning on prices is indeed an empirically important assumption. The availability of parameter estimates may also enable us to ask further questions pertaining to the information structure: are parameters stable, are they correlated with other fundamental variables, which may give further clues to the nature of the market for information.

The starting point for our work is a version of the Hellwig (1980) model with common unit risk aversion across all agents, which, because of the assumptions of linearity, normality, CARA utility, a single asset, a large market and symmetry across all agents, may be regarded as the simplest among the class of perfect competition noisy rational expectations models: it has the fewest exogenous parameters. The equilibrium in this model defines the parameters of the bivariate distribution of price and terminal value, as functions of primitive parameters such as the variance of liquidity motivated trades, the variance of errors in private signals and the prior variance of terminal value. We first present theoretical results from Hellwig (1980) and Cho and Krishnan (2000) that are the basis of our empirical work. We show that the functional relationship between these primitive parameters and the parameters of the variance-covariance matrix between price and terminal value can be inverted to obtain the values of the primitive parameters as functions of the variance-covariance parameters. Invoking the invariance principle of maximum likelihood estimation we can use this inverse relationship to easily obtain the MLE's of our primitive parameters conditional on values of the risk aversion coefficient. This allows us to make a limited assessment of ancillary quantities which are functions of primitive parameters, like the signal to signal plus noise ratio, the coefficients of the linear price conjecture, and the weights agents place on different sources of information in forming their expectations of terminal value.

The plan of the paper is as follows. In Section 1 we summarize the model of Hellwig (1980), and present the theoretical results that underlie the empirical work in this paper. Section 2 presents different sets of primitive parameter estimates and estimates of ancillary quantities. Section 3 makes some concluding remarks.

1. Theory

For the reader's convenience we first summarize the development in Hellwig (1980). Assume that there exists a perfectly competitive market for trading in an asset with risky return $\tilde{v}$. Assume a large market, in which there is a continuum of agents on the unit interval, each of whom gets a signal of identical quality but with idiosyncratic error, where each agent's signal is given by $\tilde{\theta}_i = \tilde{v} + \tilde{\varepsilon}_i$, $i \in [0,1]$ where $\tilde{v}$ and $\tilde{\varepsilon}_i$ are independent, and $\tilde{v}$ is distributed normally with mean μ_v and variance σ_v^2; $\tilde{\varepsilon}_i$ with mean zero and variance σ_ε^2. There is also a riskless asset which serves as the numeraire, and which earns zero interest. Agents' preferences are described by a CARA utility function with identical unit risk aversion parameter. Agents decide on how much of the risky asset to buy after observing their private signal, and by learning whatever they can from the realized price where this equilibrium price random variable is assumed to be a function of the average information of all agents, and liquidity motivated trades

$\tilde{S}_x$, which is normally distributed with zero mean and variance σ_s^2. Equilibrium is defined in this market by

(a) agents' optimization taking the realized price as given

(b) market clearing, and

(c) the requirement that agents' conjectures about the relationship between the price random variable and both aggregate private information and liquidity motivated trades be confirmed.

Using the main result in Hellwig (1980), we get

Proposition 1: Let the price random variable $\tilde{P}$ be defined as a linear function of aggregate private information and supply noise

$$\tilde{P} = \alpha\mu_v + \beta\int \tilde{\theta}_i di - \gamma\tilde{S}_x \tag{1}$$

Then in equilibrium, the coefficients are given by

$$\alpha = \frac{\left(\sigma_\varepsilon^2\right)^2 \sigma_s^2}{\left(\sigma_\varepsilon^2\sigma_s^2 + 1\right)\sigma_v^2 + \left(\sigma_\varepsilon^2\right)^2 \sigma_s^2} \tag{2}$$

$$\beta = \frac{\left(\sigma_\varepsilon^2\sigma_s^2 + 1\right)\sigma_v^2}{\left(\sigma_\varepsilon^2\sigma_s^2 + 1\right)\sigma_v^2 + \left(\sigma_\varepsilon^2\right)^2 \sigma_s^2} \tag{3}$$

$$\gamma = \frac{\left(\left(\sigma_\varepsilon^2\right)^2 \sigma_s^2 + \sigma_\varepsilon^2\right)\sigma_v^2}{\left(\sigma_\varepsilon^2\sigma_s^2 + 1\right)\sigma_v^2 + \left(\sigma_\varepsilon^2\right)^2 \sigma_s^2} \tag{4}$$

We can interpret the Hellwig (1980) equilibrium as defining the parameters of the distribution of a bivariate normal random variable, $(\tilde{P}, \tilde{v})$. This is relevant in the context of the subsequent empirical work as the terminal value is treated as observable. In particular we get

$$Z_1 \equiv Cov\left(\tilde{P}, \tilde{v}\right) = \frac{\left(\sigma_\varepsilon^2 \sigma_s^2 + 1\right)\left(\sigma_v^2\right)^2}{\left(\sigma_\varepsilon^2 \sigma_s^2 + 1\right)\sigma_v^2 + \left(\sigma_\varepsilon^2\right)^2 \sigma_s^2} \quad \textbf{(5)}$$

$$Z_2 \equiv Var\left(\tilde{P}\right) = \frac{\left(\sigma_\varepsilon^2 \sigma_s^2 + 1\right)^2 \left(\sigma_v^2\right)^2 \left(\sigma_v^2 + \left(\sigma_\varepsilon^2\right)^2 \sigma_s^2\right)}{\left(\sigma_\varepsilon^2 \sigma_s^2 + 1\right)\sigma_v^2 + \left(\sigma_\varepsilon^2\right)^2 \sigma_s^2} \quad \textbf{(6)}$$

$$Z_3 \equiv Var(\tilde{v}) = \sigma_v^2 \quad \textbf{(7)}$$

Note that when both prices and terminal values are observable the above parameters can be easily estimated using sample moments. But what is of greater interest is whether we can obtain estimates of the *primitive parameters*, especially σ_s^2, governing noise produced by liquidity-motivated trading, and σ_ε^2, governing the precision of private information. The following result, which is the basis for the empirical work in this paper, helps provide an answer to this question. By adapting a result in Cho and Krishnan (2000) we get

Proposition 2: The above relations (5)-(7) can be inverted to obtain

$$\hat{\sigma}_\varepsilon^2 = \frac{(Z_3 - Z_1)(Z_2 Z_3 - Z_1^2)}{Z_1(Z_2 - Z_1)} \quad \textbf{(8)}$$

$$\hat{\sigma}_s^2 = \frac{(Z_2 - Z_1)^2 Z_3}{(Z_3 - Z_1)^2 \left(Z_2 Z_3 - Z_1{}^2\right)} \quad \textbf{(9)}$$

It is important to note that the estimators obtained by transforming the sample moments by using Proposition 2 are the maximum likelihood estimators (hereafter MLE's). This is because given a Gaussian likelihood, the sample moments of the $(\tilde{P},\tilde{v})$ distribution are MLE's, and any one-to-one transformation of MLE's will yield MLE's by the Invariance Principle of maximum likelihood estimation. Equation (8) suggests that estimates of σ_ε^2 can potentially be negative. In practice we find that this hardly ever occurs. The problem is analagous to the problem that arises when obtaining negative estimates of a variance with a jackknife estimator. In the jackknife literature the estimator is abandoned only when negative estimates occur so frequently that it is not possible to interpret the estimates of the variance. Because we never obtain a negative estimate in our samples, as a practical matter this is of no significance.

Once the primitive parameters, σ_v^2, σ_ε^2 and σ_s^2, are estinated, several important ancillary quantities are also estimated. First, note that the agent *i*'s expectation of the terminal value conditional on the prior, μ_v , his private signal, θ_i, and market price, *P*, is given by

$$E\left(\tilde{v}|\,\theta_i, P\right) = h_0\mu_v + h_1\theta_i + h_2 P$$

where

$$h_0 = \frac{(\sigma_s^2)^2\left(\sigma_\varepsilon^2\right)^3}{(\sigma_s^2\sigma_\varepsilon^2+1)(\sigma_s^2\sigma_\varepsilon^2\sigma_v^2+\sigma_v^2+\sigma_s^2\left(\sigma_\varepsilon^2\right)^2)} \qquad \textbf{(10)}$$

$$h_1 = \frac{\sigma_s^2\sigma_\varepsilon^2\sigma_v^2}{\sigma_s^2\sigma_\varepsilon^2\sigma_v^2+\sigma_v^2+\sigma_s^2\left(\sigma_\varepsilon^2\right)^2} \qquad \textbf{(11)}$$

$$h_2 = \frac{1}{\sigma_s^2\sigma_\varepsilon^2+1}\,. \qquad \textbf{(12)}$$

Second, we look at the signal-to-signal-plus-noise (hereafter SSN) ratio, defined as $(1/\sigma_\varepsilon^2)$ / $(1/\sigma_\varepsilon^2 + \sigma_s^2)$. As it can be seen from equation (12), the coefficient h_2 is exactly this ratio. This suggests that in general a higher SSN ratio will result in a more informative price, and hence greater reliance on the price by market participants. Finally, we estimate the coefficients in the price conjecture (greek parameters in equation (1)). The results will help us understand the relative importance of the factors in determining the equilibrium price.

2. Empirical Implementation

2.1 Data

Our empirical work is primarily focused on primitive parameter estimation. This exercise is similar in spirit to recent examples in the context of asset pricing models under imperfect competition, such as Foster and Viswanathan (1995) and Easley, Kiefer and O'Hara (1996, 1997). While some papers (e.g. Foster and Viswanathan (1995)) explicitly also test overidentifying restrictions of the model, most (e.g. Easley, Kiefer, O'Hara (1996, 1997)) interpret parameter estimates *assuming* that the postulated model is correct. Our approach in this paper is to estimate parameters taking the Hellwig (1980) model as a maintained assumption, and to then examine the validity of the Hellwig (1980) model with an out of sample test. The closest example in previous work to this approach is in Cho and Krishnan (2000) who estimated the Hellwig (1980) model based on S&P 500 index futures data. Single-stock futures did not exist in their sample period either in the US or in India.

Our data comes from NSE's Futures and Options daily summary database (referred to in India as the "bhavcopy") and the equity daily summary database, covering the period from January 2002 to December 2005 (48 months). The futures contracts are all quarterly contracts, with a new contract arising every month, so for each firm and index we have 12 contracts each year. The maturity date is typically the last Thursday of each month, though sometimes (say, because of a holiday) it is the next day. Our proxy for terminal value, v, was given by spot price on the maturity date, whereas our proxy for price, P, was given by the futures price obtained at a fixed weekly interval before maturity. We measure the futures price at three weeks from maturity in the work we report in this paper.

Measuring the futures price at a fixed horizon from maturity date is important because the Hellwig (1980) model is a static single-period model. We ignore prices very close to maturity because previous work suggests there are expiration day and expiration week effects in most cases. Thomas (2006) documents these for the NSE Nifty index (full name = S&P CNX Nifty) futures market. We did examine a variety of different distance from the maturity date in preliminary work. It turns out that at least between 3 weeks and 8 weeks from maturity each horizon yields approximately the same conclusions.

When we examine single-stock futures we first scale by the market index (Nifty equity index) to adjust for possible market-wide factors that our model is silent about but which may be important in practice. To adjust for possible non-stationarity we divide the resulting price and terminal value numbers by the futures price 10 weeks before maturity. For the index futures data only the second adjustment is made. To ensure fewer small numbers and resulting numerical instability we multiply every number in each series by 10. We further employed an outlier screen dropping upto two extreme observations for a firm if the values of either the adjusted price or the adjusted terminal value was away from the mean by more than 3 standard deviations. This caused us to lose one observation for Mahindra and Mahindra and two observations for Ranbaxy.

The corporate governance related variables were constructed from Corporate Governance reports available in the ISI Emerging Markets database. (An initial pilot analysis was completed using data provided by Jayati and Subrata Sarkar using the data they had used in Sarkar, Sarkar and Sen (2006)).

Since our estimates of primitive parameters would be meaningful only if we can assert that the Hellwig (1980) model is a valid candidate description of the market, we check the plausibility of the model. First, for our variance estimators in Proposition 2 to be meaningful, they must be positive. This imposes constraints on the MLE's of the $(\tilde{P}, \tilde{v})$ variance-covariance matrix. Since the estimators are undefined when these constraints are binding, we can use them to assess the a priori reasonableness or plausibility of the Hellwig (1980) model as a description of the markets from which the data are drawn. For the S & P futures contract data we use, these constraints were all met.

Second, we test the assumption that the data are drawn from a normal sample, using the Bera-Jarque (1982) statistic, which uses information from the third and fourth moments. For each of the six series (spot prices on maturity date, and futures prices at each of the five weekly intervals before maturity), we computed the Bera-Jarque statistic, which is distributed asymptotically as a chi-square with 2 degrees of freedom, and compared it to the critical values (9.21 for 1%; 5.991 for 5%). The Bera-Jarque statistics show a lot of variation, and we decided to also implement an out of sample test to assess the overall goodness of fit of the model.

For this we used the data from 2002 to 2004 as the in-sample or estimation sample, and the remaining period, 2005, as the out or test sample. To ensure that we have adequate data for estimating parameters we required that a firm have at least 25 contracts in the estimation period. This created a sample of 27 firms. For purposes of comparison we also used the NIFTY index in addition to these firms.

2.2 Parameter Estimates

Please insert Table 1 approximately here.

Please insert Table 2 approximately here.

Please insert Table 3 approximately here.

Table 1 provides descriptive statistics about the futures markets we study. The primary message in this table is that even the single-stock futures markets are very active (whether measured in terms of average daily volume or open interest), in contrast to futures markets elsewhere. In fact for 25 of the 27 single-stock futures contracts listed we find the futures market trading volume exceeds the trading volume in the underlying equity. Thomas (2006) points out that that at least in the index market that he studies a large fraction of all futures contracts are settled for cash, and not by actually delivering the underlying equity. This is what allows the futures market trading volume to be larger than the underlying equity market trading volume.

Table 2 presents the sample moments of the $(\tilde{P}, \tilde{v})$ distribution, while Table 3 provides estimates of the primitive parameters. We also summarize the results across all firms, and compare this with the corresponding estimates based on the NIFTY index. The most graphic implication of the estimates in Table 3 is that our estimates for σ_s^2 are larger than our estimates of σ_ε^2 by at least two orders of magnitude in all cases. Overall, these numbers suggest that noise in the price due to the noise in agents' private information is much smaller than due to the liquidity motivated trades. This is not true of the NIFTY index, in which case the supply noise is less than the noise in agents' private signals. Our NIFTY numbers are consistent with the finding in Cho and Krishnan (2000) who found that liquidity noise was much smaller than the noise in agents' private information in the case of the S&P index. At the aggregate or index level supply noise seems considerably less.

Please insert Table 4 approximately here.

We provide, in Table 4, estimates of the coefficients in each agents' expectation function, and coefficients in the rational expectations price conjecture. The coefficients in the agents' expectation function suggest considerable variation across firms in forming the expectation about the liquidating value. Sometimes the agents in general put less weight on the private signal than on the market price; sometimes they weight the private signal more. So the average across firms shows roughly equal weight being placed on the private signal and the price. The prior in all cases is weighted the least.

The coefficients in the price conjecture tell us how the market aggregates all of the private information in the economy. The market also does not put much weight on the prior, and weights the aggregate information heavily. Note that under our large market assumption the market will filter out the errors in agents' private signals, though what the price reveals is limited by supply noise. Given the large magnitude of supply noise, and the substantial weight on it in the price conjecture it is not suprising that agents do not rely on it more heavily.

In the case of the NIFTY index the results resemble those obtained for the S&P 500 index in Cho and Krishnan (2000). Agents do rely heavily on the price in forming their own expectations. We find that in the price conjecture now there is almost 28 percent weight on the prior. While the coeffiicient on supply noise is much larger than on the prior or on the average information in the market, note that the level of supply noise in index futures is very low, so the extent to which noise contaminates what prices reveal is less in the case of the index.

This is consistent with the market participants being better informed about overall market prospects than the prospects of any single firm. Greater manipulability is associated with lower informational efficiency, though in general causation would run in both directions. When futures trading in individual stocks was banned in the 80s an argument given was that single stock futures were much more easily manipulable than index futures. Given the negative association between manipulability and informational efficiency, Table 4 would seem to bear that argument out. A more complete assessment would involve examining also the effects on the underlying equity and index. For some work in that direction see Thomas (2006).

Our work has relied heavily on one particular version of the model in Hellwig (1980) which imposes strong symmetry assumptions. Our primary justification for this in empirical work is that it helps keep the number of parameters that we need to estimate small. But it is natural to ask if the underlying Hellwig (1980) model is in fact a good representation of the world generating our data. To assess this we implemented an out of sample test. We plugged in our in-sample estimates of the primitive parameters into the price conjecture to obtain predicted out of sample prices, which we compared with actual prices. Since different firms could have different underlying parameters we standardize each firm's out of sample price differences by its in-sample standard deviation of price differences. We then pool all the standardized out of sample price differences and test if the mean is zero. Under the null that Hellwig (1980) is a good representation the mean difference should be close to zero. This is exactly what we find. We are unable to reject the null with the t, sign or signed-rank tests, for which the respective p-values are 0.95, 0.84 and 0.73 respectively.

Please insert Table 5 approximately here.

Finally, given the enormous variation across firms in informational efficiency we identify some of its cross-sectional determinants. We focus on variables related to corporate governance. Informational efficiency as defined in this paper is a function of not only public but also private information. We looked at the percentage of the promoters' shareholding (and in an alternate specification, the sum of promoters' and foreign institutional investors' shareholding). If promoters seek greater perquisite consumption, they will not favor transparency. On the other hand if firms actively seek to raise resources in the capital markets (as per an argument made formally in Fishman and Hagerty (1989)) then they have a stake in increasing informational efficiency. Because firms selected for futures trading are large firms that have been in expansion mode we expect the second effect to dominate. If the board of directors has a majority of independent directors, and the if the chairman of the board is not also the CEO we expect better monitoring to lead to greater informational efficiency. If a firm is cross-listed on an international exchange, it is possible that additional listing requirements contribute to greater informational efficiency. On the other hand it is well-known that US GAAP is itself not particularly stringent, and with overall trading activity fragmented across multiple markets (activity of Indian equity in US markets also takes place through American depository receipts) the information conveyed through trading can be diluted, and overall informational efficiency can be less. What Table 5 shows is that informational efficiency is increasing in the promoters' stake and if the board of directors has a majority of independent directors, and decreasing if the chairman is also the CEO and if the firm's shares are traded also on an international exchange.

3. Concluding Remarks

We have tried in this paper to demonstrate one approach to measure overall informational efficiency in a futures market. We provide estimates of the precision of private information, and other related quantities, including the signal to signal plus noise ratio. This is an alternative to measuring informational efficiency relative to a public announcement such as earnings or a takeover. Not needing to condition on a specific public announcement arguably reduces the potential for measurement error. On the other hand in order to do this we do need to estimate a particular variant of Hellwig (1980). Because in out of sample tests the model performs remarkably well we feel the tradeoff seems appropriate.

While for a long time financial markets were considered the best real-world example of textbook perfect competition, the plethora of imperfect competition models of the financial market in the last decade has disturbed that conventional wisdom. This would make an empirical contest between perfect and imperfect competition interesting. Given that quantities (trading volumes or order flows) can be treated as observable, in addition to prices and terminal values, it could perhaps suggest a way of setting up an empirical contest between a perfect competition model and an imperfect competition model. This is an important target that we leave for future research.

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Table 1: descriptive statistics

Table 1 provides descriptive statistics about the futures markets we study.

	Open Interest		Trading Volume (Futures)		Trading Volume (Equity)	
symbol	**mean**	**stddev**	**mean**	**stddev**	**mean**	**stddev**
ACC	4008674	2639607	4036099	4022820	1526735	1404970
BAJAJAUTO	339271	162260	199693	160672	140984	101721
BHEL	1069223	422412	942138	657883	558908	443138
BPCL	1693925	858085	1431386	1269988	1053582	1131011
BSES	485373	581698	480822	740000	234641	318940
CIPLA	987458	1504919	612660	1085310	288515	401497
DIGITALEQP	535346	219078	956685	630859	2510926	1860781
DRREDDY	570111	382471	278870	263370	192980	169201
GRASIM	798239	397164	406317	392685	204319	199355
GUJAMBCEM	4435478	5717503	2820873	4416094	1077456	1645340
HDFC	280035	250362	158618	174833	259310	326632
HINDALC0	1913973	4398626	836892	2206271	401054	968854
HINDLEVER	6194471	5059240	3103899	3289111	1903566	1334766
HINDPETRO	3729170	1689610	2950396	2590982	1786747	1813150
INFOSYSTCH	940446	796535	909142	702217	809511	469539
ITC	2528354	6602951	1559437	4506297	1030458	2567771
L&T	1646794	682658	1305312	995887	976984	740434
M&M	2467548	985552	2909547	2806282	977667	823015
MTNL	6244536	4874450	3110431	3204527	1537685	1430944
RANBAXY	1872185	1904280	1037763	1150474	627203	665280
RELIANCE	9388205	6234633	8343852	6228159	5396491	3908835
SATYAMCOMP	5378181	1667767	10939339	4644697	9891999	6520092
SBIN	5360377	2842782	5887534	4251685	2744835	2002929
TATAPOWER	2609463	1708586	2458654	2723175	962127	1059541
TATATEA	929140	528341	505258	512286	205151	203862
TELCO	5096675	2381204	8490972	8379285	2592993	2253686
TISCO	13363289	8247872	12635446	9326531	5179093	3970822
Average Across Firms	3143183	2360765	**2937335**	2641940	**1669330**	1434671
NIFTY	3222828	5828091	4188244	7549967		

TABLE 2: Summary Statistics of (P,ν) Series and Estimates of Endogenous Parameters

This table provides the summary statistics of the innovations for the futures price. The futures price is given by the futures price 3 weeks before maturity. The maturity value is given by the spot price on maturity date. In each case the price defined was divided by the equity market index to adjust for market factors. Then, following Cho and Krishnan (2000), we divided by the market-adjusted price of the futures contract 9 weeks before maturity to control for possible non-stationarity. We use innovations rather than raw prices in order to avoid the problems arising from the apparent non-stationarity of raw price series. The innovation in spot price is our measure for the terminal value, ν, and that in the futures price is our measure for the market price, P. The data are obtained from all the future contracts starting from Jan. 2002 to Dec. 2004. There were originally 133 firms during this period, but 27 remained after we restricted each firm in sample must have at least 25 full-length contracts. Z parameters are the elements in the variance-covariance matrix of (P, ν). The Z parameter estimates will be inverted to obtain the estimates of the primitive parameters.

			Cov (*v*, *P*)	**Var(*P*)**	**Var(*v*)**
Symbol	**Spot (*v*)**	***P***	**z1**	**z2**	**z3**
ACC	1.459	1.475	0.005	0.008	0.009
BAJAJAUTO	5.121	5.022	0.280	0.301	0.350
BHEL	2.486	2.462	0.505	0.508	0.537
BPCL	2.313	2.345	0.060	0.085	0.082
BSES	2.305	2.270	0.083	0.096	0.091
CIPLA	6.388	6.605	7.588	7.922	8.380
DIGITALEQP	5.072	5.162	0.716	0.867	0.860
DRREDDY	7.358	7.443	3.396	3.504	3.496
GRASIM	4.574	4.539	2.216	2.313	2.233
GUJAMBCEM	1.738	1.765	0.015	0.019	0.020
HDFC	4.095	4.122	0.981	1.173	1.182
HINDALC0	6.502	6.513	0.414	0.565	0.488
HINDLEVER	1.278	1.290	0.164	0.167	0.165
HINDPETRO	2.431	2.497	0.134	0.166	0.166
INFOSYSTCH	29.414	29.457	100.093	105.507	102.073
ITC	6.178	6.179	0.147	0.163	0.199
L&T	2.129	2.098	0.210	0.215	0.226
M&M	1.654	1.635	0.508	0.512	0.519
MTNL	0.943	0.960	0.038	0.042	0.040
RANBAXY	6.449	6.428	0.703	0.736	0.850
RELIANCE	2.820	2.827	0.032	0.043	0.036
SATYAMCOMP	2.067	2.071	0.058	0.070	0.067
SBIN	2.815	2.806	0.188	0.200	0.202
TATAPOWER	1.404	1.406	0.125	0.129	0.127
TATATEA	1.887	1.902	0.095	0.106	0.105
TELCO	1.667	1.649	0.155	0.158	0.160
TISCO	1.634	1.629	0.160	0.193	0.173
Average Across Firms	4.229	4.243	4.410	4.658	4.549
NIFTY	10.430	10.441	0.892	0.908	1.251
S&P 500 (Cho-Krishnan, 2000)	6.190	4.190	76.190	94.160	121.230

TABLE 3: Estimates of Primitive Parameters

This table provides the estimates of the primitve parameters of the model: the variance of prior, σ_ν^2, the variance of each agent's private signal, σ_ε^2, and the variance of liquidity motivated trades, σ_s^2. These estimates are obtained by using Proposition 2 together with the estimates of variance-covariance matrix of (P, ν) given in Table 2.

Symbol	sigmaE	sigmaS	sigmaV
ACC	0.012	94.025	0.009
BAJAJAUTO	0.320	1.181	0.350
BHEL	0.496	0.147	0.537
BPCL	0.051	30.741	0.082
BSES	0.013	145.231	0.091
CIPLA	2.748	0.170	8.380
DIGITALEQP	0.310	4.075	0.860
DRREDDY	0.195	5.717	3.496
GRASIM	0.020	301.964	2.233
GUJAMBCEM	0.014	77.701	0.020
HDFC	0.453	2.542	1.182
HINDALC0	0.123	19.594	0.488
HINDLEVER	0.001	9766.231	0.165
HINDPETRO	0.071	17.502	0.166
INFOSYSTCH	2.743	1.017	102.073
ITC	0.235	1.802	0.199
L&T	0.071	4.502	0.226
M&M	0.040	9.947	0.519
MTNL	0.005	341.430	0.040
RANBAXY	0.831	0.329	0.850
RELIANCE	0.006	483.369	0.036
SATYAMCOMP	0.017	96.193	0.067
SBIN	0.029	31.171	0.202
TATAPOWER	0.004	450.133	0.127
TATATEA	0.021	54.499	0.105
TELCO	0.010	75.523	0.160
TISCO	0.019	140.402	0.173
Average across firms	0.328	450.264	4.549
Std error across firms	0.139	359.300	3.765
NIFTY	8.477	0.007	1.251
S&P 500 (Cho-Krishnan)	184.510	0.003	121.230

TABLE 4: Estimates of Coefficients in Agents' Expectation Function and the Price Conjecture

This table provides the estimates of the coefficients in agents' expectation function, $E\left(\tilde{v}|\theta_i, P\right) = h_0\mu_v + h_1\theta_i + h_2P$, where μ_v is the prior mean of risky terminal value, θ_i , the i^{th} agent's private information, and P, the price of futures contract. These estimates are obtained by using equations (10)-(12) together with the estimates of primitive parameter given in Table 2. This table also provides the estimates of the coefficients in the price conjecture, $\tilde{P} = \alpha\mu_v + \beta\int\tilde{\theta}_i d_i - \gamma\tilde{S}_x$ where μ_v is the prior mean of risky terminal value, θ_i , the i^{th} agent's private information, $\tilde{S}_x$, the liquidity-motivated trades, and P, the price of futures contract. These estimates are obtained by using equations (2)-(4) together with the estimates of primitive parameter given in Table 3. The parameter h2 is the signal to signal plus noise ratio and is our measure of overall informational efficiency in the market.

	Coefficients in agents' expectation functions on			Coefficients in the market's price conjecture on		
Symbol	prior h0	signal h1	price h2	prior alpha	signals beta	noise gamma
ACC	0.221	0.312	0.467	0.414	0.586	0.007
BAJAJAUTO	0.055	0.219	0.726	0.200	0.800	0.256
BHEL	0.004	0.064	0.932	0.059	0.941	0.467
BPCL	0.166	0.443	0.392	0.273	0.727	0.037
BSES	0.053	0.593	0.354	0.082	0.918	0.012
CIPLA	0.030	0.288	0.682	0.094	0.906	2.489
DIGITALEQP	0.094	0.465	0.442	0.168	0.832	0.258
DRREDDY	0.015	0.512	0.473	0.029	0.971	0.189
GRASIM	0.006	0.849	0.145	0.007	0.993	0.019
GUJAMBCEM	0.139	0.383	0.478	0.266	0.734	0.010
HDFC	0.091	0.444	0.465	0.170	0.830	0.376
HINDALC0	0.107	0.600	0.294	0.151	0.849	0.104
HINDLEVER	0.003	0.847	0.150	0.003	0.997	0.001
HINDPETRO	0.106	0.448	0.447	0.191	0.809	0.057
INFOSYSTCH	0.014	0.722	0.264	0.019	0.981	2.689
ITC	0.078	0.220	0.702	0.261	0.739	0.174
L&T	0.017	0.225	0.757	0.071	0.929	0.066
M&M	0.006	0.280	0.713	0.022	0.978	0.039
MTNL	0.041	0.574	0.386	0.066	0.934	0.004
RANBAXY	0.037	0.178	0.785	0.174	0.826	0.687
RELIANCE	0.087	0.665	0.247	0.116	0.884	0.006
SATYAMCOMP	0.083	0.534	0.382	0.135	0.865	0.015
SBIN	0.031	0.447	0.522	0.065	0.935	0.027
TATAPOWER	0.014	0.638	0.348	0.021	0.979	0.004
TATATEA	0.053	0.485	0.462	0.098	0.902	0.019
TELCO	0.011	0.417	0.572	0.026	0.974	0.010
TISCO	0.055	0.676	0.269	0.076	0.924	0.018
Average across firms	0.060	0.464	0.476	0.067	0.933	0.310
NIFTY	0.017	0.042	0.941	0.287	0.713	6.043
S&P 500 (CK, 2000)	0.144	0.244	0.612	0.478	0.522	44.100

TABLE 5: Regression of Signal-to-Signal-Plus-Noise Ratio on Corporate Governance Related Variables

This table presents the estimates of the regression of signal-to-signal-plus-noise ratio on corporate governance related variables. Panel A summarizes the regression estimates of the two models we choose. Panel B summarizes the descriptive statistics of the numerical variables. Panel C summarizes the descriptive statistics of the binary variables.

Panel A

Dependent variable = signal-to-signal-plus-noise ratio (h2)		
	Model 1	**Model 2**
Variable	**Coefficient (t-statistic)**	**Coefficient (t-statistic)**
Promoters' stake (P)		0.708
		(3.09)
Promoters' and foreign institutional investors' stake (P + FII)	0.627	
	(2.69)	
Board of directors with independent majority? (1=yes) (MIB)	0.122	0.161
	(1.89)	(2.49)
Chairman of the board also the CEO? (1= yes) (CMD)	-0.129	-0.189
	(-1.60)	(-2.22)
Also listed in the US? (1= yes) (USE)	-0.231	-0.177
	(-2.36)	(-2.02)
Adjusted R-squared	0.235	0.299

Panel B

Variable	n	mean	stddev	min	p10	median	p90	max
h2	27	0.476	0.201	0.145	0.247	0.462	0.757	0.932
P	27	0.243	0.201	0.000	0.000	0.262	0.562	0.677
FI	27	0.191	0.109	0.093	0.101	0.161	0.385	0.553

Panel C

Variable	n	n: =0	n:=1
MIB	27	15	12
CMD	25	17	8
USE	27	22	5