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Two essays on market efficiency: Tests of idiosyncratic risk: informed trading versus noise and arbitrage risk, and agency costs and the underlying causes of mispricing: information asymmetry versus conflict of interests

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Two Essays on Market Efficiency — Tests of Idiosyncratic Risk: Informed Trading versus Noise and Arbitrage Risk, and Agency Costs and the Underlying Causes of Mispricing: Information Asymmetry versus Conflict of Interests

by

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Two Essays on Market Efficiency — Tests of Idiosyncratic Risk: Informed Trading versus Noise and Arbitrage Risk, and Agency Costs and the Underlying Causes of Mispricing: Information Asymmetry versus Conflict of Interests

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ABSTRACT

I examine the informational efficiency of stock markets by testing the relation between idiosyncratic volatility and equity mispricing. I find that the level of mispricing declines with idiosyncratic volatility consistent with the notion that greater levels of firm-specific risk reflect greater participation of informed traders in the market for the stock. However, I also find that mispricing increases with idiosyncratic volatility for highly volatile stocks, and this is attributed to both noise trading and arbitrage risk.

In addition, I investigate the link between agency costs and equity mispricing, and whether it exists due to information asymmetry or the degree of conflict of interests between managers and shareholders. I provide evidence that the level of agency costs is positively related with mispricing. In contrast to previous studies' claim that the information asymmetry level is a key determinant in the equity mispricing, I find that the conflict of interests is more important than information asymmetry in explaining equity mispricing. Furthermore, the evidence suggests that stock option grants, originally intended to resolve conflicts of interests, actually exaggerate this problem.

Essay 1

Tests of Idiosyncratic Risk: Informed Trading versus Noise and Arbitrage Risk

I. Introduction

What does idiosyncratic volatility mean? In the context of asset pricing, idiosyncratic volatility measures the part of the variation in returns that cannot be explained by the particular asset pricing model used. Other than the stale econometric definition of idiosyncratic volatility, there is little consensus regarding the meaning of idiosyncratic risk in the context of market efficiency. The finance literature has argued that idiosyncratic volatility can reflect the capitalization of private information into prices, noise trading and/or costly arbitrage.[1]

This paper contributes to the finance literature by reconciling the different views on idiosyncratic risk. The goal of this study is to clearly distinguish if and when each of the three aforementioned views of idiosyncratic volatility is more appropriate. In order to achieve my goal, I investigate the relationship between equity mispricing and idiosyncratic risk and develop three hypotheses, one predicting a negative relationship between idiosyncratic volatility and mispricing, and the other two predicting a positive one. On one hand, the *informed trading hypothesis* regards idiosyncratic risk as a sign of active trading by informed arbitrageurs who trace firms' fundamental value, and thus predicts that equity mispricing should be lower for high idiosyncratic risk firms. On the other hand, the *noise trading hypothesis* regards idiosyncratic risk as a sign of

[1] For a description of the different views on idiosyncratic risk, see Roll (1988), Morck, Yeung and Yu (2000), Wurgler and Zhuravskaya (2002), Durnev, Morck and Zarowin (2003), Kelly (2005) and Pontiff (2005), among many others.

uninformed traders' noise trading which causes the stock's price to deviate from fundamental value, and thus predicts a positive relation between idiosyncratic risk and mispricing. The *arbitrage risk hypothesis* proposes that idiosyncratic risk reflects costs of arbitrage, and also predicts a positive relation. I test these hypotheses in an empirical framework that utilizes equity mispricing proxies based on several relative valuation measures, which are constructed as absolute deviations of a firm's equity value from its fundamental value. When I estimate a linear regression model of the relation between mispricing and idiosyncratic volatility, I find that the level of mispricing declines in idiosyncratic risk, consistent with the *informed trading hypothesis*. However, both univariate tests as well as multivariate tests of models that include a second-order idiosyncratic risk term provide strong evidence of a non-linear, U-shaped relationship. Specifically, I find that the level of equity mispricing first decreases until a firm-specific risk ($1 - R^2$) approaches levels in excess of 90%, but then increases thereafter. The number of observations after the inflection point accounts for 10% of total firm-year observations. These findings suggest that in most cases (about 90% of total), idiosyncratic risk implies that informed trading leads to low equity mispricing. Moreover, the results also suggest that at extremely high idiosyncratic risk levels, noise trading and/or arbitrage risk are causing prices to deviate from fundamentals.

To establish if only one of the two or both factors (i.e., noise trading and/or arbitrage risk) are reflected in the right arm of the U-shaped curve that empirically describes the relationship between mispricing and idiosyncratic volatility, I re-examine the relationship for sub-samples constructed by classifying firms on firm-level uncertainty and short-selling constraints measures. Assuming that the proportion of noise traders increases with the firm's informational uncertainty (see Black (1986)), I employ a composite measure of uncertainty to sort firms into sub-samples that are (are not) dominated by noise traders. Furthermore, assuming that, in the absence of constraints to short-sales, informed investors have more and better opportunities to engage in arbitrage, I sort on measures of short-selling constraints to construct sub-samples of firms that are (are not) affected by arbitrage risk. The test results reveal that the non-linear, U-shaped relationship between mispricing and IV remains significant for sub-samples of firms that display low levels of either noise trading or arbitrage risk. The non-linear relationship collapses to a linear one for the sub-sample containing firms that are classified as having both a less uncertain information environment and low short-selling constraints. In this sub-sample, equity mispricing is monotonically decreasing in idiosyncratic volatility. This evidence is consistent with the notion that the increase in mispricing associated with high idiosyncratic risk levels (i.e., highly volatile stocks) reflects *both* noise trading and arbitrage risk.

Therefore, based on my findings, I conclude that idiosyncratic volatility in stock returns may primarily reflect informational market efficiency, but extremely high levels of idiosyncratic risk are associated with noise traders' frenzy and limits to arbitrage (i.e., arbitrage risk).

The rest of the paper is organized as follows. In the next section, I review related literature and prior findings and present the testable hypotheses. Section III describes the data selection process and the measures of idiosyncratic volatility and equity mispricing.

Section IV explains the empirical methodologies, and reports univariate and multivariate test results. Section V contains additional tests and provides a more detailed investigation of the nature of the non-linear relation between idiosyncratic volatility and mispricing. The last section includes a summary and concluding remarks.

II. Literature Review

Roll (1988) points out that U.S. firms display low R-squares for common asset pricing models; the average R-square is about 20% for daily returns' models and about 35% when monthly returns are used. In the conclusion (p. 564) of his article, Roll proposes that this evidence seems to imply the existence of either "private information" or else "occasional frenzy" unrelated to concrete information. Using cross-country data, Morck, Yeung, and Yu (2000) find that stocks in countries with stronger property rights have higher idiosyncratic volatility. They argue that strong property rights promote informed arbitrage, leading to more firm-specific information and thus high idiosyncratic volatility. Durnev, Yeung and Zarowin (2003) find that firms and industries with greater idiosyncratic volatility display greater stock price informativeness. They define informativeness as the amount of information stock prices contain about future earnings, which they estimate from a regression of current stock returns against future earnings changes. They argue that if idiosyncratic volatility reflects the capitalization of private information into prices, high idiosyncratic volatility is a sign of active trading by informed arbitrageurs and implies that the stock price is tracking its fundamental value closely. In addition, Jin and Myers (2006) in a study involving stock returns from 40 countries over the 1990-2001 period test whether limited information (lack of transparency) can affect the division of risk bearing between inside managers and outside investors. They provide evidence consistent with the notion that if a firm is less transparent, insiders will be able to capture more firm-specific risk. Greater opaqueness leads to lower amounts of firm-specific risk absorbed by outside investors and therefore to lower levels of idiosyncratic volatility, i.e. high levels of R-square. In this context, outside investors have limited ability to evaluate changes in cash flows, and consequently their evaluation on equity value will be less accurate.

Based on the above, the *informed trading hypothesis* predicts that idiosyncratic volatility and mispricing are negatively related because high idiosyncratic risk levels are associated with greater trading by informed arbitrageurs who trace firm's fundamental value.

On the other hand, in line with Roll's alternative interpretation of idiosyncratic volatility as "occasional frenzy", idiosyncratic volatility can reflect noise trading. For example, Bhagat, Marr, and Thompson (1985) show that firms with higher equity issuing costs have higher firm-specific daily stock return volatility, which is a proxy for asymmetric information between firm insiders and outsiders. Krishnaswami and Subramaniam (1999) use idiosyncratic volatility as one of measures of information asymmetry and find that firms engage in spin-offs to reduce information asymmetry. Kelly (2005) provides evidence that a low market model R-square (high idiosyncratic volatility) is indicative of a poor information environment with greater impediments to informed trade. If idiosyncratic volatility reflects greater impediments to informed trades and/or informational asymmetry, then it should be associated with noise trading. In this view, named the *noise trading hypothesis*, it is predicted that the relationship of idiosyncratic volatility and mispricing is positive because in the presence of noise trading stock prices will deviate from fundamental value.

In addition to the informed trading and noise trading interpretations of idiosyncratic risk, many authors share the view that idiosyncratic risk reflects risk related to costly arbitrage.[2] For example, Pontiff (2005) points out that arbitrageurs are averse to trading when firms are idiosyncratic. This limit of arbitrage opportunity is also addressed by Shleifer and Vishny (1997), Gromb and Vayanos (2002) and Chen, Hong, and Stein (2002), who provide a possible explanation for persistent mispricing. In particular, Shleifer and Vishny (1997) argue that any systematic mispricing could not be quickly and completely traded away if arbitrage costs exceed arbitrage benefits. Systematic mispricing may epitomize arbitrageurs' limit of opportunity to perfectly hedge fundamental risk in their portfolios. Therefore, the prediction of the *arbitrage risk hypothesis* is that the mispricing of high arbitrage risk stocks should be higher than the mispricing of low arbitrage risk stocks.

In sum, the *informed trading hypothesis* predicts a negative relation between idiosyncratic volatility and equity mispricing, while the other two hypotheses (the *noise trading hypothesis* and the *arbitrage risk hypothesis*) predict a positive relation.

[2] See, for example, (e.g., Wurgler and Zhuravskaya (2002), Ali, Hwang and Trombley (2003), Pontiff and Schill (2003), Mendenhall (2004), and Mashruwala, Rajgopal, and Shelvin (2005)).

III. Data and Measures

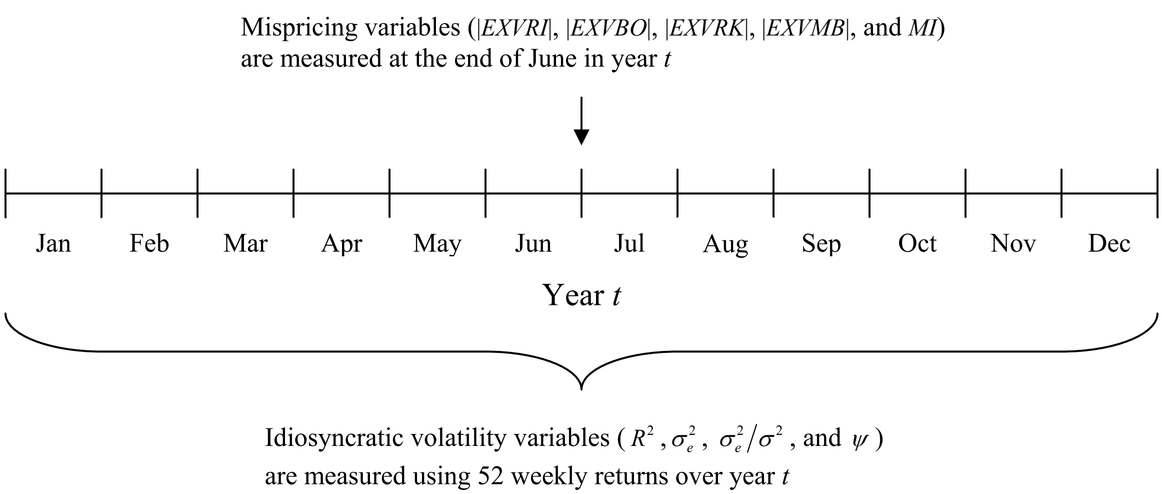
I extract return data from the Center for Research in Securities Prices (*CRSP*) where NYSE, AMEX, and Nasdaq stocks are listed. The initial sample includes all firms in CRSP from 1980 to 2004, omitting financial (SIC 6000-6999) and utility (SIC 4900-4999) firms. I also exclude firms if their industry affiliation is not clear (i.e., SIC codes are missing). For the measure of idiosyncratic volatility, I use weekly stock returns. The choice of a weekly data is a compromise solution to the twin problems associated with a) the relatively low number of monthly observations, and b) the missing observations from non-trading occurrences in daily data (see Conrad and Kaul (1988)). Following Durnev *et al*. (2003 and 2004), I drop firms if they do not have complete return data over 52 weeks in a year to avoid problems associated with firms that experience IPOs, delisting, or trading halts. Accounting and financial data are drawn from *COMPUSTAT*. Firms with market value of equity less than $20 million are excluded in order to avoid cases of firms with distorted valuation multiples used in the construction of the mispricing measures. These requirements result in a final sample that includes 6,956 firms with 44,639 firm-year observations covering the 25 year period from 1980 to 2004.

A. Measures of Idiosyncratic Volatility

I estimate R-square and idiosyncratic volatility variables for each stock for each calendar year using weekly data to regress stock returns on the returns of the market index.[3] Figure 1 illustrates how idiosyncratic volatility variables are measured using a time line.

Figure 1
Empirical Design of Time Line for Idiosyncratic Volatility and Equity Mispricing Measurements

The above time line illustrates the methods used to compute idiosyncratic volatility measures and equity mispricing measures. Idiosyncratic volatility measures are computed using 52 weekly returns over each year *t*. Equity mispricing measures are computed at the mid time of each year (i.e., at the end of June in each year t).



The regression model estimated for each stock *i* in year *t* is as follows:

$$r_{i,w,t} = \alpha_{i,t} + \beta_{i,t}\, r_{m,w,t} + e_{i,w,t}, \tag{1}$$

where $r_{i,w,t}$ is the excess return for stock *i* on week *w* in year *t*, and $r_{m,w,t}$ is the value-weighted excess market index return on the week *w* in year *t*. From this regression equation, the idiosyncratic variance is defined as $\sigma^2_{ie,t} = \sigma^2_{i,t} - (\sigma^2_{im,t}/\sigma^2_{m,t})$, where $\sigma^2_{i,t}$ =

[3] In the robustness tests (Table 6), I also use idiosyncratic volatilities obtained from regressions of stock returns on returns of the market index and industry indices, or alternatively, on the three Fama and French factors.

Var($r_{i,w,t}$), $\sigma^2_{m,t}$ = Var($r_{m,w,t}$), and $\sigma_{im,t}$ = Cov($r_{i,w,t}$, $r_{m,w,t}$). I compute each stock's relative idiosyncratic volatility (i.e., the ratio of idiosyncratic volatility to total volatility), $\sigma^2_{ie,t}/\sigma^2_{i,t}$ or equivalently $1 - R^2_{i,t}$, for each year t. The relative idiosyncratic volatility is transformed to a logistic version as follows.

$$\psi_{i,t} = \ln\left(\frac{1-R^2_{i,t}}{R^2_{i,t}}\right) = \ln\left(\frac{\sigma^2_{ie,t}}{\sigma^2_{i,t}-\sigma^2_{ie,t}}\right). \tag{2}$$

Logistic relative idiosyncratic volatility ($\psi_{i,t}$) measures the ratio of unexplained variance to explained variance.[4] Table 1 describes the R-square and idiosyncratic volatility variables, and Table 2 presents descriptive statistics for theses measures over the sample period, 1980 to 2004. I estimate volatility within each sample year t, yielding 44,639 firm-year observations. The average R-square is about 0.152 which is very similar to that shown in other studies (e.g., 0.152 in Kelly (2005)) but lower than the average R-squares of 0.20 and 0.35 computed from daily and monthly returns, respectively, reported in Roll (1988). This relatively low average R-square for my sample is consistent with the increase in idiosyncratic volatility observed over the recent years and reported in Campbell, Lettau, Malkiel, and Xu (2001). In my sample, idiosyncratic volatility on average represents about 85% of total individual stock volatility, in line with Ferreira and Laux (2007) who also report an 85% average relative idiosyncratic volatility.

[4] In addition to logistic relative idiosyncratic volatility ($\psi_{i,t}$ or $\ln\left(\frac{\sigma^2_{ie,t}}{\sigma^2_{i,t}-\sigma^2_{ie,t}}\right)$), I use idiosyncratic volatility ($\sigma^2_{ie,t}$) and relative idiosyncratic volatility ($\sigma^2_{ie,t}/\sigma^2_{i,t}$). All results in univariate and multivariate tests show consistent patterns.

Table 1
Variable Definitions

Variables	Descriptions
Idiosyncratic volatility measures	
R^2	R-square measured using a regression of stock returns on the returns of the market index, $r_{i,w,t} = \alpha_{i,t} + \beta_{i,t}\, r_{m,w,t} + e_{i,w,t}$, where $r_{i,w,t}$ is the excess return for stock i on week w in year t, and $r_{m,w,t}$ is the value-weighted excess market index return on the week w in year t.
σ_e^2	Idiosyncratic volatility. From the regression, $r_{i,w,t} = \alpha_{i,t} + \beta_{i,t}\, r_{m,w,t} + e_{i,w,t}$, idiosyncratic variance is defined as $\sigma^2_{ie,t} = \sigma^2_{i,t} - (\sigma^2_{im,t}/\sigma^2_{m,t})$, where $\sigma^2_{i,t}$ = Var($r_{i,w,t}$), $\sigma^2_{m,t}$ = Var($r_{m,w,t}$), and $\sigma_{im,t}$ = Cov($r_{i,w,t}$, $r_{m,w,t}$).
σ_e^2/σ^2	Relative idiosyncratic volatility which is the ratio of idiosyncratic volatility to total volatility, $\sigma^2_{ie,t}/\sigma^2_{i,t}$ or equivalently $1 - R^2_{i,t}$.
ψ	Logistic relative idiosyncratic volatility. $\psi_{i,t} = \ln\left(\frac{1-R^2_{i,t}}{R^2_{i,t}}\right) = \ln\left(\frac{\sigma^2_{ie,t}}{\sigma^2_{i,t} - \sigma^2_{ie,t}}\right)$.
Mispricing measures	
$\|EXVRI\|$	Absolute value of excess value based on Ohlson's (1995) residual income value approach. $EXVRI_{it} = \ln\left[PRICE_{it}/I(V)_{it}\right]$,where $PRICE_{it}$ is the stock price at the end of June of each year from CRSP, and $I(V)_{it}$ is intrinsic value using the residual income model (Ohlson (1995)) and median values of analysts' forecasts issued in June, as in Frankel and Lee (1998).
$\|EXVBO\|$	Absolute value of excess value based on Berger and Ofek (1995) approach. $EXVBO_{i,t} = [CPTL_{i,t}/I(CPTL)_{i,t}]$, where $CPTL_{i,t}$ is total capital, which is market value of equity plus book value of debt, $I(CPTL_{i,t})$ is the imputed value derived as the product of firm sales and the median capital to size ratio in the firm's industry. The industry classification here is based on the Fama-French 48 sectors. This measure of mispricing is constructed in a similar fashion as the first one ($EXVRI_{i,t}$), but uses firm's total capital instead of price and computes imputed value based on Fama-French 48 industry classification. Thus the intrinsic value here is a size and industry benchmark.
$\|EXVRK\|$	Absolute value of the excess value based on Rhodes-Kropf *et al.* (2005). Fundamental value, V is estimated by decomposing the market-to-book into two components: a measure of price to fundamentals (ln(M/V)), and a measure of fundamentals to book value (ln(V/B)). The first component captures the part of book-to-market associated with mispricing. This component is further decomposed into firm-specific and industry-specific misprising. I use the firm-specific mispricing component based on Model III of Rhodes-Kropf *et al*. (2005) that also accounts for net income and leverage effects. $\ln(M_{i,t}) = \alpha_{0j,t} + \alpha_{1j,t}\ln(B_{i,t}) + \alpha_{2j,t}\ln(NI)^+_{i,t} + \alpha_{3j,t}\, I_{(<0)}\ln(NI)^+_{i,t} + \alpha_{4j,t}\ln(LEV_{i,t}) + \zeta_{i,t}$, where M is firm value, B is book value, NI^+ is absolute value of net income, $I_{(<0)}\ln(NI)^+$ is an indicator function for negative net income observations, and LEV is the leverage ratio.
$\|EXVMB\|$	Absolute value of the industry-adjusted market-to-book ratio. $MBIA_{i,t} = \ln[MB_{i,t}/Med(MB)_{j,t}]$, where, $MB_{i,t}$ is the market to book ratio for firm i at time t, and $Med(MB_{j,t})$ is the j^{th} industry median of MB_t.
MI	Mispricing index which is constructed each year for each observation $i = 1,\ldots,N$ as: $MI_i = (1/N)(1/K)\sum_k^K RANK_k(\|EXV_{i,k}\|)$, where $Rank_k(\|EXV_{i,k}\|)$ is the rank function which assigns a rank for each observation from least misvalued (rank of one) to most misvalued (rank of N). $\|EXV_{i,k}\|$ is the k^{th} measure of mispricing for firm i in my sample, and K represents the dimensions of mispricing measures. The denominator, K, averages the ranks by the number of mispricing values available for each firm in the sample in a particular year. Finally, dividing by N, I scale the MI from 0 (least mispriced) to 1 (most mispriced).

Table 1 (Continued)

Variables	Descriptions
Informativeness measure	
PIN	Annual probability of information-based trading of Easley *et al.* (1996a, 1996b, 1997a, 1997b, 2002, 2005). $PIN = \alpha\mu/(\alpha\mu+\varepsilon_s+\varepsilon_b)$, where α is the probability and information event occurs, μ is the arrival rate of informed trades, , and ε_s and ε_b are the arrival rates of uninformed sells and buys respectively. $\alpha\mu$ is the expected arrive rate of informed trades and $\alpha\mu+\varepsilon_s+\varepsilon_b$ is the arrival rate for all orders.
Uncertainty measures	
EQ1	The first measure of earnings quality. Absolute value of firm-specific residuals from a Fama-French 48 annual industry regression of total accruals on the reciprocal of total assets, sales growth, and fixed assets. $\frac{TACCR_{i,t}}{TA_{i,t-1}} = k_1\frac{1}{TA_{i,t-1}} + k_2\frac{\Delta SALES_i}{TA_{i,t-1}} + k_3\frac{PPE_{i,t}}{TA_{i,t-1}} + \zeta_{i,t}$, where $TACCR_{i,t}$ $= (\Delta CA_{i,t} - \Delta CL_{i,t} - \Delta CASH_{i,t} + \Delta STDEBT_{i,t} - DEPN_{i,t})$ = firm *i*'s total accruals in year *t*, $\Delta CA_{i,t}$ = change in current assets between year *t-1* and year *t*, $\Delta CL_{i,t}$ = change in current liabilities between year *t-1* and year *t*, $\Delta CASH_{i,t}$ = change in cash between year *t-1* and year *t*, $\Delta STDEBT_{i,t}$ = change in debt in current liabilities between year *t-1* and *t*, $DEPN_{i,t}$ = depreciation and amortization expense in year *t*, $\Delta SALES_i$ = change in sales between year *t-1* and *t*, $PPE_{i,t}$ = property, plant, and equipment in year *t*, and $TA_{i,t-1}$ = total assets in year *t-1*.
EQ2	The second measure of earnings quality. Absolute value of firm-specific residuals from a Fama-French 48 annual industry regression of total accruals on lagged, contemporaneous, and leading cash flow from operations. $\frac{TACCR_{i,t}}{TA_i} = k_0 + k_1\frac{CFO_{i,t-1}}{TA_i} + k_2\frac{CFO_{i,t}}{TA_i} + k_3\frac{CFO_{i,t+1}}{TA_i} + \zeta_{i,t}$, where $CFO_{i,t}$ is firm *i*'s cash flow from operations in year *t* and computed as net income before extraordinary items minus total accruals. All variables are scaled by average total assets (TA_i).
AFE	Analyst earnings forecast error. $AFE_{i,t} = \lvert Med(AF)_{i,t} - EPS_{i,t+1}\rvert / \lvert Med(AF)_{i,t}\rvert$, where forecast error, $\lvert Med(AF)_{i,t} - EPS_{i,t+1}\rvert$, is the absolute value of the difference between the median forecast ($Med(AF)_{i,t}$) and the actual earnings per share ($EPS_{i,t+1}$).
AFD	Analyst earnings forecast dispersion. $AFD_{i,t} = Std.Dev.(AF)_{i,t} / \lvert Med(AF)_{i,t}\rvert$, where $Std.Dev.(AF)_{i,t}$ is standard deviation of one year ahead forecasts.
UI	Firm uncertainty index. *UI* is computed each year for each observation $i = 1,\ldots,N$ as: $UI_i = (1/N)(1/K)\sum_k^K RANK_k(UNCER_{i,k})$, where $Rank_k(UNCER_{i,k})$ is the rank function which assigns a rank for each observation from least uncertain (rank of one) to most uncertain (rank of *N*). $UNCER_{i,k}$ is the k^{th} measure of uncertainty for firm *i* in my sample, and *K* represents the dimensions of uncertainty measures (*EQ1*, *EQ2*, *AFE*, and *AFD*). The denominator, *K*, averages the ranks by the number of uncertainty values available for each firm in the sample in a particular year. Finally, dividing by *N*, I scale the *TI* from 0 (least uncertain) to 1 (most uncertain).

Table 1 (Continued)

Variables	Descriptions
Short-selling constraint measures	
SIZE	Log of total assets.
INSTP	Institutional ownership. Percentage of shares held by institutions.
SI	Short-selling constraint index. *SI* is constructed each year for each observation $i = 1, ..., N$ as: $SI_i = (1/N)(1/K)\sum_k^K RANK_k(SHORT_{i,k})$, where $Rank_k(SHORT_{i,k})$ is the rank function which assigns a rank for each observation from the lowest short-sale constraint (rank of one) to the highest short-sale constraint (rank of *N*). $SHORT_{i,k}$ is the inverse value of k^{th} measure of short-sale constraint for firm *i* in my sample, and *K* represents the dimensions of short-sale constraint measures (*SIZE* and *INSTP*). The denominator, *K*, averages the ranks by the number of short-sale constraint values available for each firm in the sample in a particular year. Finally, dividing by *N*, I scale the *SI* from 0 (lowest short-sale constraint) to 1 (highest short-sale constraint).
Firm characteristics	
LEV	Leverage. The ratio of long-term debt to total assets.
ROA	Return on assets. The ratio of net income to total assets.
AGE	Firm age. *AGE* = ln(1+ *age*), where *age* is the number of years since the stock inclusion in the *CRSP* database.
DIVER	Diversification dummy that equals one if a firm operates in multi-segments and zero otherwise.
DD	Dividend-payer dummy that equals one if a firm pays dividends and zero otherwise.

Table 2
Descriptive Statistics

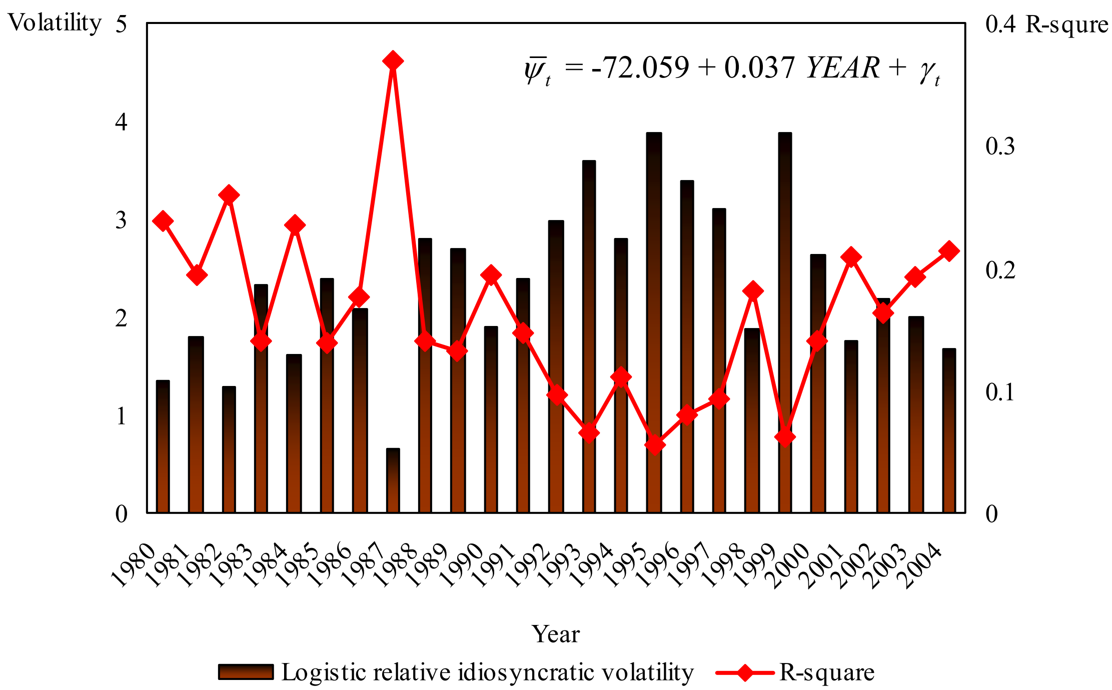
Reported are descriptive statistics for my sample firms. The sample contains 44,639 firm-year observations (6,956 firms) over the period 1980 – 2004. All variables are as defined in Table 1.

Variables	N	Mean	Std.Dev.	5%	Median	95%
Idiosyncratic volatility measures						
R-square (R^2)	44,639	0.152	0.139	0.002	0.113	0.434
Idiosyncratic volatility (σ_e^2)	44,639	0.004	0.013	0.001	0.003	0.013
Relative idiosyncratic volatility (σ_e^2/σ^2)	44,639	0.848	0.139	0.566	0.887	0.998
Logistic relative idiosyncratic volatility (ψ)	44,639	2.476	1.933	0.266	2.059	6.159
Mispricing measures						
Ohlson (1995) approach (|*EXVRI*|)	41,163	0.762	0.863	0.068	0.638	1.853
Berger and Ofek (1995) approach (|*EXVBO*|)	44,433	0.627	0.595	0.035	0.476	1.705
Rhodes-Kropf *et al.* (2005) approach (|*EXVRK*|)	44,637	0.369	0.345	0.024	0.275	1.047
Industry-adjusted market-to-book ratio (|*EXVMB*|)	44,639	0.390	0.370	0.017	0.288	1.125
Mispricing index (*MI*)	44,639	0.502	0.189	0.216	0.485	0.847
Informativeness measure						
Probability of information-based trading (*PIN*)	16,670	0.182	0.059	0.097	0.178	0.286
Uncertainty measures						
Francis *et al*. (2005) (*EQ1*)	33,314	0.332	0.593	0.014	0.166	1.082
Dechow and Dichev (2002) (*EQ2*)	28,879	0.170	0.565	0.012	0.111	0.469
Analyst earnings forecast error (*AFE*)	39,345	0.837	6.120	0.006	0.133	2.637
Analyst earnings forecast dispersion (*AFD*)	38,235	0.228	1.399	0	0.050	0.714
Uncertainty index (*UI*)	43,747	0.503	0.207	0.173	0.494	0.865
Short-selling constraint measures						
Firm size (*SIZE*)	44,639	19.74	1.658	17.36	19.54	22.77
Institutional ownership (*INSTP*)	30,399	0.503	0.244	0.093	0.512	0.892
Short-selling constraint index (*SI*)	44,639	0.507	0.260	0.107	0.496	0.929
Firm characteristics						
Leverage (*LEV*)	44,497	0.169	0.180	0	0.113	0.549
Return on assets (*ROA*)	44,639	0.035	0.115	-0.162	0.052	0.160
Firm age (*AGE*)	44,639	2.362	0.815	1.099	2.398	3.526
Diversification dummy (*DIVER*)	35,729	0.345	0.475	0	0	1
Dividend-payer dummy (*DD*)	42,942	0.432	0.495	0	0	1

Next, to verify what Campbell *et al.* (2001) document as a secular decline in R-squares in the U.S. market from 1960 to 1997, I compute annual average R-square and (logistic transformed) idiosyncratic volatility ($\overline{\psi}_t$) and analyze the time trend by plotting them by year. Figure 2 shows clearly that annual average idiosyncratic volatility increases and equivalently annual average R-square declines. To verify this trend statistically, I run the simple regression of annual average $\overline{\psi}_t$ on year, and find that the coefficient of *YEAR* is 0.037 with t-statistic of 1.70. Abnormally high average R-square observed for 1987 can be attributed to the market crash in October 1987.

Figure 2
Time-series of Idiosyncratic Volatility and R-square

This figure presents averages of annualized logistic relative idiosyncratic volatility ($\bar{\psi}_t$) and R-square for the period from 1980 to 2004. The time-series relation is computed as the regression of $\bar{\psi}_t$ on calendar year. The coefficient of *YEAR* is 0.037 with t-statistic of 1.70.



B. Measures of Mispricing

Firm mispricing is measured as the deviation of a firm's equity value from its intrinsic or fundamental value. I employ five alternative mispricing measures. The first four measures employ alternative techniques in estimating intrinsic value benchmarks, while the last one is an index that combines all individual measures. The mispricing measures are:

1) $|EXVRI_{i,t}|$, the absolute value of the natural logarithm of the ratio between the stock price and its intrinsic value obtained from Ohlson's (1995) residual income valuation model. *EXVRI* is computed at the end of June of each year.

$$EXVRI_{i,t} = \ln\left[\frac{PRICE_{i,t}}{I(V)_{i,t}}\right], \tag{3}$$

where $PRICE_{i,t}$ is the CRSP stock price at the end of June of each year, and $I(V)_{i,t}$ is the intrinsic value using the residual income model (Ohlson (1995)) with median values of analysts' forecasts issued in June, as was done in Frankel and Lee (1998). There is strong empirical evidence in support of the residual income valuation ratio, V/P, as an indicator of mispricing.[5]

2) $|EXVBO_{i,t}|$, the absolute excess value computed at the end of June of each year as the natural logarithm of the ratio between a firm's capital and its imputed value, based on the Berger and Ofek (1995) approach.

$$EXVBO_{i,t} = \ln\left[\frac{CPTL_{i,t}}{I(CPTL)_{i,t}}\right], \tag{4}$$

where $CPTL_{i,t}$ is total capital, which is market value of equity plus book value of debt, $I(CPTL_{i,t})$ is the imputed value derived as the product of firm sales and the

[5] Lee, Myers and Swaminathan (1999) report that V/P predicts one-month-ahead returns on the Dow 30 stocks better than aggregate book-to-market. Frankel and Lee (1998) also show that the residual income value is a better predictor than book value of the cross-section of contemporaneous stock prices, and that V/P is a predictor of the one-year-ahead cross-section of returns. In addition, Ali *et al.* (2003) show that after controlling for several possible risk factors, V/P continues to significantly predict future returns. D'Mello and Shroff (2000) apply V/P to measure mispricing of equity repurchases, and Dong, Hirshleifer, Richardson, and Teoh (2006) to takeovers.

median capital to sales ratio in the firm's primary industry. The industry classification here is based on the Fama-French 48 sectors. This measure of mispricing is constructed in a similar fashion as the first one ($EXVRI_{i,t}$), but uses firm's total capital instead of price and computes imputed value based on Fama-French 48 industry classification.

3) $|EXVRK_{i,t}|$, the absolute value of the firm-specific component of the difference between market value and fundamental value, based on the procedure outlined in Rhodes-Kropf, Robinson, and Viswanathan (2005). This procedure differs from the residual income valuation approach in the sense that it does not rely on analysts' earnings forecasts. According to Rhodes-Kropf *et al*. (2005), fundamental value, V is estimated by decomposing the market-to-book into two components: a measure of price to fundamentals (ln(M/V)), and a measure of fundamentals to book value (ln(V/B)). The first component captures the part of book-to-market associated with mispricing. In extreme cases where markets perfectly price stocks, this component would be equal to zero, otherwise positive (over-valuation) or negative (under-valuation). This component is further decomposed into firm-specific and industry-specific misprising. In my tests, I use the firm-specific mispricing component based on Model III of Rhodes-Kropf *et al*. (2005) that also accounts for net income and leverage effects.

$$\ln(M_{i,t}) = \alpha_{0j,t} + \alpha_{1j,t}\ln(B_{i,t}) + \alpha_{2j,t}\ln(NI)^{+}_{i,t} + \alpha_{3j,t}\, I_{(<0)}\ln(NI)^{+}_{i,t} + \alpha_{4j,t}\ln(LEV_{i,t}) + \zeta_{i,t} \quad (5)$$

where M is firm value, B is book value, NI^{+} is absolute value of net income, $I_{(<0)}\ln(NI)^{+}$ is an indicator function for negative net income observations, and LEV is the leverage ratio.

4) $|MBIA_{i,t}|$, the absolute value of the industry-adjusted market-to-book ratio.

$$MBIA_{i,t} = \ln\left[\frac{MB_{i,t}}{Med(MB)_{j,t}}\right], \tag{6}$$

where, $MB_{i,t}$ is the market to book ratio for firm i at time t, and $Med(MB_{j,t})$ is the j^{th} industry median of MB_t. Several empirical studies have utilized MB as a mispricing measure (see, among others, Walkling and Edmister (1985), Rau and Vermaelen (1998) and Ikenberry, Lakonishok and Vermaelen (1995)). However, as Rhodes-Kropf *et al.* (2005) point out, the market to book ratio can be viewed as not only a proxy for misvaluation but also as a measure of future growth opportunities and managerial ability.

5) $MI_{i,t}$, a mispricing index (MI) that combines all four mispricing measures described above.[6] The mispricing index (MI) is constructed each year for each observation $i = 1,\ldots,N$ as:

$$MI_i = \frac{1}{N}\frac{1}{K}\sum_{k}^{K} RANK_k(|\,EXV_{i,k}\,|)\,, \tag{7}$$

where $Rank_k(|EXV_{i,k}|)$ is the rank function which assigns a rank for each observation from least misvalued (rank of one) to most misvalued (rank of N). $|EXV_{i,k}|$ is the k^{th} measure of mispricing for firm i in the sample, and K represents the dimensions of

[6] In constructing MI, I employ the methodology outlined in Butler, Grullon, and Weston (2005). In their paper, they create a liquidity index that aggregates the rankings of six different liquidity measures.

mispricing measures. The denominator, K, averages the ranks by the number of mispricing values available for each firm in the sample in a particular year. For example, the sum of the $Rank_k(|EXV_{i,k}|)$ values of a firm that has only three mispricing measures is divided by K=3. Finally, dividing by N, I scale the *MI* from zero (least mispriced) to one (most mispriced). I argue that, since it is computed as the average of all available ranks from four different mispricing measures, *MI* provides a more complete picture of mispricing.

Variable definitions and summary statistics for all measures are reported in Table 1 and Table 2, respectively. Table 3 shows the coefficients of correlations between the different mispricing measures. As expected, all measures are positively correlated. The correlations are significant at the one percent level or better, despite the fact that these valuation measures are based on widely different theoretical concepts, measurement constructions and accounting/financial variables. I also find that generally individual mispricing measures are more significantly correlated with the mispricing index (*MI*) than with the other individual measures. This suggests that *MI* balances out the effects and shortcomings of the individual mispricing measures, while aggregating their informativeness. Therefore, *MI* is an appropriate aggregate measure of mispricing for use in the tests. For the most part, in this paper I present results based on *MI* for the sake of brevity. However, results obtained using the individual mispricing measures are qualitatively similar to those using *MI*.

Table 3
Correlations Coefficients between Mispricing Measures

This table shows the correlations coefficients between the mispricing measures, |*EXVRI*|, |*EXVBO*|, |*EXVRK*|, |*MBIA*|, and *MI*. The corresponding p-values are reported in brackets. All variables are as defined in Table 1. *** indicates significance at the 1%-level.

	Mispricing index (*MI*)	Ohlson (1995) approach (|*EXVRI*|)	Berger and Ofek (1995) approach (|*EXVBO*|)	Rhodes-Kropf *et al.* (2005) approach (|*EXVRK*|)
Ohlson (1995) approach (|*EXVRI*|)	0.319*** [0.000]			
Berger and Ofek (1995) approach (|*EXVBO*|)	0.523*** [0.000]	0.083*** [0.000]		
Rhodes-Kropf *et al.* (2005) approach (|*EXVRK*|)	0.713*** [0.000]	0.174*** [0.000]	0.252*** [0.000]	
Industry-adjusted market-to-book ratio (|*EXVMB*|)	0.736*** [0.000]	0.141*** [0.000]	0.300*** [0.000]	0.746*** [0.000]

IV. Idiosyncratic Volatility and Equity Mispricing

This section contains univariate analyses, a description of how I designed the empirical methodology, and regression evidence on the relation between idiosyncratic volatility and equity mispricing.

A. Univariate Analyses

Table 4 illustrates how high idiosyncratic risk firms differ from low idiosyncratic risk firms in terms of firm characteristics. It reports mean values of all variables used in the study for the quartile groups classified on the level of idiosyncratic volatility (ψ). Also reported are the mean differences between the two extreme groups (highest ψ versus lowest ψ quartiles) and the corresponding t-statistics for the mean difference tests. The pattern of mean *MI* values across ψ quartiles is not consistent with a monotonic relation between *MI* and ψ. Average *MI* decreases in the first three sub-samples, Q1 through Q3, but finally increases in the quartile consisting of the highest idiosyncratic risk firms, Q4. This non-linear, U-shape relation is also shown in Figure 3.

The evidence from the remaining variables is consistent with prior studies examining the relationship of firm characteristics and idiosyncratic risk. High idiosyncratic volatility firms are associated with high probability of information-based trading and greater uncertainty. In addition, high ψ firms have greater leverage and lower ROA, are younger, less diversified and less likely to pay dividends than low ψ firms. Moreover, idiosyncratic volatility is higher when short-selling constraints become more binding, consistent with the notion that idiosyncratic volatility captures arbitrage risk.

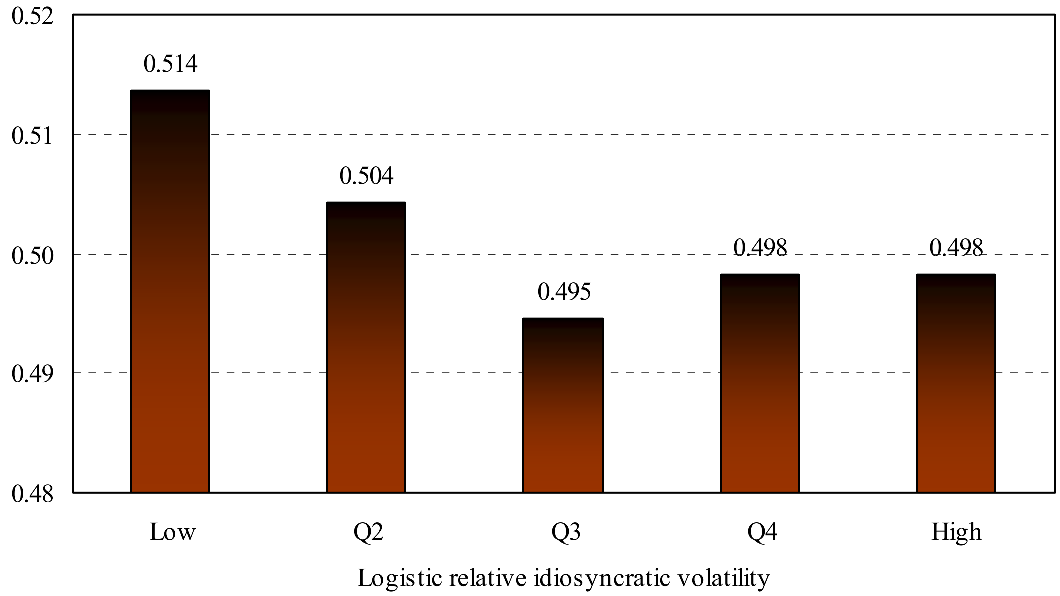
Table 4
Univariate Tests

Reported are mean values of variables for the quartile sub-samples sorted on the logistic relative idiosyncratic volatility (ψ). Also reported are the differences in mean values between high- and low-ψ firms and the corresponding t-statistics. All variables are as defined in Table 1. *** indicates significance at the 1%-level.

	Sorted on the logistic relative idiosyncratic volatility (ψ)					
	Low Q1	Q2	Q3	High Q4	Mean diff.: High - Low	t-stat: Diff.=0
Mispricing measures						
Ohlson (1995) approach (|*EXVRI*|)	0.785	0.749	0.744	0.770	-0.015	-1.16
Berger and Ofek (1995) approach (|*EXVBO*|)	0.636	0.621	0.619	0.631	-0.004	-0.55
Rhodes-Kropf *et al.* (2005) approach (|*EXVRK*|)	0.403	0.369	0.352	0.352	-0.051***	-10.72
Industry-adjusted market-to-book ratio (|*EXVMB*|)	0.416	0.391	0.376	0.376	-0.040***	-7.85
Mispricing index (*MI*)	0.513	0.499	0.495	0.499	-0.014***	-5.55
Informativeness measure						
Probability of information-based trading (*PIN*)	0.163	0.183	0.192	0.204	0.041***	32.98
Uncertainty measures						
Francis *et al*. (2005) (*EQ1*)	0.323	0.340	0.344	0.323	-0.0002	-0.02
Dechow and Dichev (2002) (*EQ2*)	0.175	0.175	0.165	0.165	-0.010	-0.83
Analyst earnings forecast error (*AFE*)	0.500	0.683	0.862	1.322	0.822***	7.57
Analyst earnings forecast dispersion (*AFD*)	0.147	0.208	0.258	0.319	0.172***	8.15
Uncertainty index (*UI*)	0.464	0.499	0.515	0.535	0.071***	25.64
Short-selling constraint measures						
Firm size (*SIZE*)	20.67	19.82	19.40	19.06	-1.608***	-76.39
Institutional ownership (*INSTP*)	0.579	0.527	0.473	0.422	-0.156***	-41.66
Short-selling constraint index (*SI*)	0.368	0.482	0.556	0.624	0.256***	80.50
Firm characteristics						
Leverage (*LEV*)	0.146	0.161	0.176	0.192	0.046***	19.19
Return on assets (*ROA*)	0.054	0.039	0.028	0.020	-0.035***	-23.82
Firm age (*AGE*)	2.602	2.381	2.268	2.196	-0.406***	-38.12
Diversification dummy (*DIVER*)	0.416	0.343	0.321	0.301	-0.114***	-16.00
Dividend-payer dummy (*DD*)	0.556	0.442	0.389	0.338	-0.218***	-32.92

Figure 3
Equity Mispricing by Idiosyncratic Volatility

This figure presents averages of mispricing index (*MI*) for the quintile sub-samples sorted on the logistic relative idiosyncratic volatility (ψ).



B. Multivariate Analyses

Univariate tests can only provide limited, preliminary evidence on whether equity mispricing has truly a non-linear relationship with idiosyncratic volatility because a pattern could disappear after controlling for other factors that affect idiosyncratic volatility. Therefore, more tests in a multivariate setting are necessary to uncover the true relationship between mispricing and idiosyncratic volatility. I use the time-series average of cross-sectional annual regressions as outlined in Fama and MacBeth (1973) and estimate the following model:[7]

$$MI_{it} = \beta_0 + \beta_1\, \psi_{it} + \beta_2\, SIZE_{it} + \beta_3\, LEV_{it} + \beta_4\, ROA_{it} + \beta_5\, AGE_{it} + \beta_6\, DIVER_{it} + \beta_7\, DD_{it} + \mu_{it}, \tag{8}$$

where i indexes firms, t is a yearly time index, and ψ_{it} is a logistic transformation of relative idiosyncratic volatility. The control variables are market capitalization (*SIZE*), leverage (*LEV*), profitability (*ROA*), firm age (*AGE*), a diversification dummy (*DIVER*), and a dividend-payer dummy (*DD*). Descriptions of all variables can be found in Table 1 and descriptive statistics in Table 2.

To examine whether there is a non-linear relation between idiosyncratic risk and mispricing, I include the second-order idiosyncratic volatility (ψ_{it}^2) in the model, resulting in the following equation.

$$MI_{it} = \beta_0 + \beta_1\, \psi_{it} + \beta_2\, \psi_{it}^2 + \beta_3\, SIZE_{it} + \beta_4\, LEV_{it} + \beta_5\, ROA_{it} + \beta_6\, AGE_{it} + \beta_7\, DIVER_{it} + \beta_8\, DD_{it} + \mu_{it}. \tag{9}$$

If the pattern observed in the univariate tests persists, the regression will show the significantly negative sign for the coefficient of first-order idiosyncratic volatility, β_1, and positive sign for the coefficient of second-order, β_2. If I find that β_1 is significant and negative but β_2 is insignificant, then my tests would lend support to the *informed trading* hypothesis only.

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[7] Following Fama and MacBeth (1973), I estimate separate annual regressions and calculate t-statistics as follows. $t(\overline{\hat{\beta}_j}) = \dfrac{\overline{\hat{\beta}_j}}{s(\hat{\beta}_j)/\sqrt{n-1}}$, where $\overline{\hat{\beta}_j}$ is the mean coefficient over the sample years, $s(\hat{\beta}_j)$ is the standard deviation of the yearly estimates, and n is the number of years.

The results of the multivariate tests appear in Table 5. In Panel A, I report results of regressions using the mispricing index (*MI*, columns [1] and [2]) and the logistic-transformed mispricing index (columns [3] and[4]) as dependent variables.[8] In Panel B, I show regression results using the four individual mispricing measures as dependent variables. The results in Panel A show a significant negative relation between idiosyncratic risk and mispricing, suggesting that higher idiosyncratic volatility is strongly associated with lower level of equity mispricing. In column [1], for example, the estimated coefficient of idiosyncratic volatility is -0.004 with t-statistic of -3.36. However, more importantly, the coefficients of second-order idiosyncratic volatility in columns [2] and [4] are significantly positive (e.g., 0.002 with t-statistic of 6.01 in column [2]) without reducing the significance in the first-order ψ coefficient. The evidence in Panel B based on the individual mispricing measures is qualitatively similar to that using the mispricing index. The ψ and ψ^2 coefficients are always negative and positive, respectively, and significant in almost all cases.

This evidence provides room for two important interpretations. First, consistent with the *informed trading hypothesis*, the significant and negative sign for the first-order relation supports the notion that higher levels of idiosyncratic volatility signal more information-laden stock prices. Second, the significant positive sign for the second-order coefficient combined with the significant negative sign for the first-order coefficient implies that the *informed trading hypothesis* view of idiosyncratic volatility does not hold

[8] This transformation is to guard against a possibility that mispricing index (*MI*) which takes value from 0 to 1 can lead to erroneous interpretation of results. I find that the results are, as shown, very similar to ones obtained from the original regressions.

for firms with very high levels of idiosyncratic risk. The positive relation between mispricing and idiosyncratic volatility beyond a certain point could be driven by the predominance of uninformed noise traders and/or by the inability of arbitrageurs to find close substitutes for high idiosyncratic volatility firms when they want to hedge fundamental risk. Both of these two effects are consistent with increases in mispricing for high levels of idiosyncratic volatility.

Table 5
Idiosyncratic Volatility and Equity Mispricing

This table shows time-series average of cross-sectional regressions of mispricing on idiosyncratic volatility and other firm characteristics. Panel A reports results of regressions using mispricing index (*MI*) or logistic mispricing index as dependent variable, while Panel B reports results of regressions using individual mispricing measure as dependent variable. All variables are as defined in Table 1. *, **, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Panel A: Dependent variable is mispricing index (*MI*) or logistic mispricing index.				
	Dep. var. = *MI*		Dep. var. = ln(1+*MI*)	
	[1] Linear	[2] Non-linear	[3] Linear	[4] Non-linear
Intercept	0.652***	0.704***	0.497***	0.530***
	(19.74)	(21.58)	(22.69)	(24.15)
Logistic relative idiosyncratic volatility (ψ)	-0.004***	-0.017***	-0.003***	-0.011***
	(-3.36)	(-7.45)	(-2.95)	(-6.86)
ψ^2		0.002***		0.001***
		(6.01)		(5.72)
Log of total assets (*SIZE*)	-0.002	-0.003*	-0.001	-0.002*
	(-0.91)	(-2.04)	(-0.93)	(-1.99)
Leverage (*LEV*)	-0.211***	-0.205***	-0.136***	-0.133***
	(-11.10)	(-10.93)	(-10.75)	(-10.56)
Return on assets (*ROA*)	0.111*	0.105*	0.069	0.063
	(1.80)	(1.74)	(1.68)	(1.59)
Log of firm age (*AGE*)	-0.025***	-0.025***	-0.016***	-0.016***
	(-9.89)	(-9.89)	(-9.63)	(-9.65)
Diversification dummy (*DIVER*)	-0.030***	-0.030***	-0.019***	-0.019***
	(-11.22)	(-11.17)	(-10.55)	(-10.49)
Dividend-payer dummy (*DD*)	-0.038***	-0.205***	-0.025***	-0.024***
	(-10.13)	(-10.93)	(-10.19)	(-10.29)
N	34,471	34,471	34,471	34,471
Average R^2	11.96%	12.27%	11.50%	11.79%

Table 5 (Continued)

Panel B: Dependent variable is individual mispricing measure.								
	Dep. var. = |*EXVRI*|		Dep. var. = |*EXVBO*|		Dep. var. = |*EXVRK*|		Dep. var. = |*EXVMB*|	
	[1] Linear	[2] Non-linear	[3] Linear	[4] Non-linear	[5] Linear	[6] Non-linear	[7] Linear	[8] Non-linear
Intercept	0.689***	0.756***	0.595***	0.650***	0.586***	0.682***	0.851***	0.959***
	(4.60)	(4.28)	(14.01)	(12.86)	(14.37)	(14.89)	(19.46)	(20.30)
ψ	-0.003	-0.025	-0.006*	-0.020**	-0.008***	-0.031***	-0.012***	-0.037***
	(-0.45)	(-1.62)	(-1.78)	(-2.33)	(-4.94)	(-6.66)	(-5.89)	(-7.43)
ψ^2		0.003**		0.002		0.003***		0.003***
		(2.18)		(1.30)		(4.64)		(5.77)
SIZE	0.015**	0.013*	0.013***	0.011***	-0.001	-0.005**	-0.013***	-0.017***
	(2.40)	(1.92)	(6.05)	(4.86)	(-0.66)	(-2.48)	(-6.10)	(-7.95)
LEV	-0.389***	-0.378***	-0.252***	-0.246***	-0.392***	-0.382***	-0.317***	-0.305***
	(-5.15)	(-5.15)	(-4.82)	(-4.77)	(-10.49)	(-10.55)	(-9.72)	(-9.71)
ROA	-1.550***	-1.556***	-0.013	-0.021	0.306***	0.295***	0.815***	0.804***
	(-5.97)	(-6.00)	(-0.09)	(-0.14)	(4.32)	(4.18)	(6.45)	(6.38)
AGE	-0.028	-0.027	-0.068***	-0.068***	-0.037***	-0.037***	-0.053***	-0.054***
	(-1.38)	(-1.37)	(-10.93)	(-10.91)	(-13.92)	(-13.50)	(-13.12)	(-13.00)
DIVER	-0.030***	-0.029***	-0.045***	-0.045***	-0.037***	-0.037***	-0.052***	-0.052***
	(-3.26)	(-3.21)	(-5.61)	(-5.76)	(-9.25)	(-9.43)	(-17.91)	(-17.58)
DD	-0.078***	-0.075***	-0.063***	-0.061***	-0.076***	-0.074***	-0.060***	-0.058***
	(-5.46)	(-5.39)	(-8.42)	(-8.37)	(-12.41)	(-12.74)	(-8.43)	(-8.47)
N	31,420	31,420	33,707	33,707	33,751	33,751	33,751	33,751
Average R^2	7.01%	7.27%	5.18%	5.37%	12.02%	12.37%	15.05%	15.37%

In order to better identify the size and composition of the group of firms belonging to the right-hand of the U-shape curve, I compute the inflection point using the coefficients of first- and second-order terms of volatility obtained from estimating the non-linear regression models. I find that the inflection point is far to the right of the ψ distribution, indicating that mispricing declines with ψ for most of firms. For example, the relation between *MI* and ψ is inflected at a ψ of 4.930 (equivalently, idiosyncratic volatility ($1 - R^2$) of 99.28%) in regression model [2]. Even though idiosyncratic risk of that magnitude is extremely high, the number of observations with ψ values greater than the inflection point is not negligible. The total number of firms residing on the right-hand side of the U-shape curve accounts for about 10% of the total firm-year observations (i.e., 3,388 out of 34,471).

Overall the evidence from Table 5 suggests that in most cases (about 90%), higher idiosyncratic risk implies that the activity of informed traders leads to lower equity mispricing, but that in the presence of extremely high idiosyncratic risk levels the effects of noise and/or arbitrage risk cause higher mispricing.

C. Robustness Tests

In this sub-section I conduct several robustness checks, which aim at determining whether or not the findings in Table 5 are due to the particular model of returns used to estimate idiosyncratic volatility or to the estimation methodology used.

I start my robustness tests by using alternative idiosyncratic volatility measures. First, I re-estimate idiosyncratic volatility by adding each firm's industry returns into the market model (equation (1)) as was suggested by other authors (e.g., Durnev *et al*. (2003 and 2004) and Kelly (2005)). The Fama-French 48 industry SIC classification code is used to define the industry. Second, I use idiosyncratic volatility estimates from the Fama-French three-factor model of returns. Fama and French (1992, 1993, 1995, and 1996) suggest that a three-factor model explains the time-series of stock returns. The three Fama-French factors are the excess return on the value-weighted market portfolio, R_m, the return on a zero investment portfolio measured as the difference between the return on a large firm portfolio and the return on a small firm portfolio, *SMB*, and the return on a zero investment portfolio estimated as the return on a portfolio of high book-to-market minus the return on a portfolio of low book-to-market stocks, *HML*. Third, in order to solve the problem that arises with cross-sectional time series models when differences between firms are regarded as parametric shifts of the regression function, I use a fixed-effects model to control for possible differences across firms. Fourth, I compute difference-in-differences estimates by including year fixed-effects as well as firm fixed-effects. Fifth, I compute statistical significances using White's (1980) standard errors which are robust to heteroskedasticity. Finally, I estimate a model using only the first-year observation of each firm. This check with the test that uses first-year data only allows me to see whether previous results are not driven by multiple observations on the same firms.

Table 6
Robustness Checks of Regression of Equity Mispricing on Idiosyncratic Volatility

This table reports robustness checks of regressions of mispricing on idiosyncratic volatility and other firm characteristics. Reported are the coefficients and t-statistics of regression models [3] and [4] in Table V which use log-transformed mispricing index, ln(1+*MI*), as a dependent variable. Columns [1] and [2] report results using idiosyncratic volatility estimates from a model controlling market returns and industry returns according to the Fama-French 48 industry SIC classification. Columns [3] and [4] report results using idiosyncratic volatility estimates from Fama-French three-factor model of returns. Columns [5] and [6] report results using panel regressions. Columns [7] and [8] report results of regressions computing difference-in-difference estimates (i.e., including firm fixed-effects and year fixed-effects). Columns [9] and [10] report results using White's (1980) heteroskedasticity correction model. Columns [11] and [12] report results only using the first-year data of each firm. All variables are as defined in Table 1. *, **, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	Industry model		Fama-French model		Panel regression model		Difference-in-differences		White (1980) model		First-year regression	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear
Intercept	0.539***	0.591***	0.508***	0.530***	0.770***	0.780***	0.823***	0.838***	0.530***	0.549***	0.525***	0.557***
	(22.81)	(24.60)	(23.51)	(24.30)	(34.79)	(35.11)	(31.77)	(32.14)	(28.90)	(29.67)	(18.61)	(19.19)
ψ	-0.006***	-0.019***	-0.006***	-0.019***	-0.001***	-0.004***	-0.001***	-0.005***	-0.004***	-0.010***	-0.007***	-0.016***
	(-6.27)	(-9.89)	(-4.61)	(-6.07)	(-3.03)	(-5.70)	(-2.65)	(-5.59)	(-9.75)	(-9.35)	(-8.12)	(-7.56)
ψ^2		0.003***		0.004***		0.0004***		0.0004***		0.001***		0.001***
		(7.99)		(4.36)		(4.86)		(4.93)		(6.20)		(4.55)
SIZE	-0.003**	-0.005***	-0.001	-0.002*	-0.017***	-0.017***	-0.019***	-0.019***	-0.002**	-0.003***	-0.002	-0.003**
	(-2.55)	(-4.26)	(-1.34)	(-1.99)	(-12.81)	(-13.04)	(-12.77)	(-13.14)	(-2.39)	(-3.00)	(-1.39)	(-2.02)
LEV	-0.132***	-0.126***	-0.135***	-0.133***	-0.055***	-0.054***	-0.057***	-0.055***	-0.162***	-0.160***	-0.187***	-0.183***
	(-10.46)	(-9.99)	(-10.56)	(-10.35)	(-8.90)	(-8.73)	(-8.92)	(-8.58)	(-24.47)	(-24.17)	(-18.20)	(-17.68)
ROA	0.062	0.059	0.065	0.064	-0.009	-0.010	-0.012	-0.014*	-0.047***	-0.048***	-0.071***	-0.072***
	(1.58)	(1.51)	(1.63)	(1.60)	(-1.25)	(-1.39)	(-1.63)	(-1.81)	(-5.42)	(-5.47)	(-5.70)	(-5.75)
AGE	-0.016***	-0.016***	-0.016***	-0.016***	-0.013***	-0.013***	-0.018***	-0.018***	-0.014***	-0.014***	-0.005*	-0.006**
	(-9.98)	(-10.26)	(-9.73)	(-9.61)	(-6.25)	(-6.11)	(-6.62)	(-6.58)	(-8.94)	(-9.01)	(-1.80)	(-2.20)
DIVER	-0.019***	-0.019***	-0.019***	-0.019***	0.001	0.00004	-0.003	-0.003	-0.017***	-0.018***	-0.022***	-0.023***
	(-10.31)	(-10.11)	(-10.50)	(-10.42)	(0.27)	(0.02)	(-1.29)	(-1.40)	(-6.60)	(-6.74)	(-5.04)	(-5.21)
DD	-0.024***	-0.024***	-0.025***	-0.024***	-0.003	-0.003	-0.002	-0.003	-0.018***	-0.018***	-0.011**	-0.012***
	(-9.67)	(-9.50)	(-9.99)	(-9.92)	(-0.99)	(-1.07)	(-0.80)	(-0.85)	(-6.19)	(-6.26)	(-2.43)	(-2.57)
N	34,468	34,468	34,471	34,471	34,471	34,471	34,471	34,471	34,471	34,471	5,284	5,284
R^2	11.63%	12.12%	11.54%	11.80%	5.74%	5.90%	5.81%	5.93%	10.08%	10.23%	11.40%	11.75%

The results of these robustness checks are reported in Table 6. To save space, Table 6 only reports the results of regression models [3] and [4] in Table 5, which use log-transformed msipricing index, ln(1+*MI*), as a dependent variable.[9] I find that all regressions show a consistent pattern of coefficients on the estimates of idiosyncratic volatility. The first- and second-order coefficients remain significantly negative and positive, respectively. Therefore, the previous results are confirmed by these various robustness checks.

The univariate and multivariate tests on the relation between idiosyncratic volatility and equity mispricing have provided evidence that idiosyncratic volatility can imply informed trading as well as noise trading and/or arbitrageurs' risk. This evidence can be confirmed by focusing on "information flow" and examining whether the probability of information-based trading (*PIN*) is strongly related to idiosyncratic volatility. Recent research has utilized the probability of information-based trading (*PIN*) to proxy private information flow. According to Easley *et al.* (1996a, 1996b, 1997a, 1997b, 2002, and 2005), the *PIN* is estimated as the ratio of expected informed order flow to total order flow:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_s + \varepsilon_b}, \tag{10}$$

where α is the probability that an information event occurs, μ is the arrival rate of informed trades, and ε_s and ε_b are the arrival rates of uninformed sells and buys respectively. $\alpha\mu$ is the expected arrive rate of informed trades and $\alpha\mu + \varepsilon_s + \varepsilon_b$ is the

[9] I obtain similar results to the ones presented here when I repeat the tests using the individual mispricing measures. These results are available upon request.

arrival rate for all orders. Consequently, the ratio is the fraction of orders that arise from informed traders or the probability that the opening trade is information based.[10]

PIN is expected to be related to idiosyncratic volatility according to three hypotheses established for the relation between idiosyncratic volatility and equity mispricing. The *informed trading hypothesis* regards idiosyncratic risk as a sign of active trading by informed traders, and thus predicts that probability of information-based trading (*PIN*) should be higher for high idiosyncratic volatility firm (i.e., positive relation between *PIN* and idiosyncratic volatility). *The noise trading hypothesis* regards idiosyncratic volatility as a sign of uninformed traders' noise trading, and thus predicts the negative relation between *PIN* and idiosyncratic volatility. *The arbitrage risk hypothesis* regards idiosyncratic volatility as a sign of limited opportunities for informed traders to arbitrage, and thus predicts the negative relation between *PIN* and idiosyncratic volatility. If the evidence of U-shape relation between mispricing and idiosyncratic volatility from Table 5 is true and supported by the analysis using *PIN*, the relation between *PIN* and idiosyncratic volatility is expected to be non-linear, i.e., have a concave shape.

To test the above predictions, I estimate the following regression equation using the private information flow proxy (*PIN*) as dependent variable:

$$PIN_{it} = \beta_0 + \beta_1\, \psi_{it} + \beta_2\, SIZE_{it} + \beta_3\, LEV_{it} + \beta_4\, ROA_{it} + \beta_5\, AGE_{it} + \beta_6\, DIVER_{it} + \beta_7\, DD_{it} + \mu_{it}, \tag{11}$$

$$PIN_{it} = \beta_0 + \beta_1\, \psi_{it} + \beta_2\, \psi_{it}^2 + \beta_3\, SIZE_{it} + \beta_4\, LEV_{it} + \beta_5\, ROA_{it} + \beta_6\, AGE_{it}$$

[10] The yearly *PIN* estimates are available on Soeren Hvidkjaer's web site: http://www.smith.umd.edu/faculty/hvidkjaer/data.htm

$$+ \beta_7\, DIVER_{it} + \beta_8\, DD_{it} + \mu_{it}. \qquad (12)$$

I report these regression results in Table 7. Columns [1] and [2] display the results of models using the raw *PIN* as dependent variable, while columns [3] and [4] show results when a log-transformed version, ln(1+*PIN*), is used. *PIN* is found to be positively related to the idiosyncratic volatility, which supports the *informed trading hypothesis* that high idiosyncratic risk is caused by informed arbitrageurs who trade in stocks using private information to trace fundamental firm value. The conjecture is that high idiosyncratic volatility stocks are associated with high private information-based trading. This evidence is in line with the findings of other authors. For example, Kelly (2005) finds that *PIN* is higher for low R-square (i.e., high idiosyncratic risk) firms. Ferreira and Laux (2007) show that *PIN* is negatively correlated with the governance index which, in turn, is negatively correlated with idiosyncratic volatility. Their findings also imply a positive relation between *PIN* and idiosyncratic volatility.

Regression results for models that include the second-order idiosyncratic volatility also reveal a non-linear relation between *PIN* and volatility. Thus, while the coefficient of ψ is positive, the coefficient of ψ^2 is negative. Moreover, both coefficients are significant. This finding is in line with the evidence that mispricing increases beyond a certain high level of idiosyncratic volatility. Accordingly, the non-linear relation is inflected at the idiosyncratic volatility ($1 - R^2$) of 99.75%, and the number of observations after the inflection point accounts for 568 firms (about 5%) of firm-year observations used in the regression (11,741 firms). The inflection point is similar to the one on the relation between idiosyncratic volatility and mispricing in Table 5. The U-shape was inflected at the idiosyncratic volatility ($1 - R^2$) of 99.28% and about 10% of observations were included in the right side of U-shape curve.

Table 7
Idiosyncratic Volatility and Information-based Trading

This table shows time-series average of cross-sectional regressions of probability of information-based trading on idiosyncratic volatility and other firm characteristics. All variables are as defined in Table 1. *, **, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	Dep. var. = *PIN*		Dep. var. = ln(1+*PIN*)	
	[1] Linear	[2] Non-linear	[3] Linear	[4] Non-linear
Intercept	0.219***	0.210***	0.198***	0.190***
	(52.28)	(53.52)	(57.16)	(59.24)
Logistic relative idiosyncratic volatility (ψ)	0.007***	0.012***	0.006***	0.010***
	(8.30)	(11.76)	(8.53)	(11.97)
ψ^2		-0.001**		-0.001***
		(-2.67)		(-3.08)
Log of total assets (*SIZE*)	-0.023***	-0.027***	-0.019***	-0.019***
	(-27.43)	(-27.90)	(-27.19)	(-27.54)
Leverage (*LEV*)	0.012***	0.011***	0.010***	0.009***
	(3.91)	(3.66)	(3.89)	(3.64)
Return on assets (*ROA*)	-0.045***	-0.041***	-0.038***	-0.035***
	(-5.31)	(-5.01)	(-5.38)	(-5.07)
Log of firm age (*AGE*)	-0.013***	-0.012***	-0.011***	-0.010***
	(-10.53)	(-10.27)	(-10.37)	(-10.13)
Diversification dummy (*DIVER*)	-0.010***	-0.010***	-0.009***	-0.008***
	(-8.42)	(-7.89)	(-8.51)	(-7.97)
Dividend-payer dummy (*DD*)	-0.004	-0.003	-0.003*	-0.003
	(-1.62)	(-1.51)	(-1.71)	(-1.60)
N	11,741	11,471	11,741	11,741
Average R^2	38.67%	39.30%	39.48%	40.14%

However, the results from Table 7 do not provide us with a clear answer to the question of why the level of equity mispricing increases for very high volatility firms. It could be because uninformed noise traders dominate trading for highly volatile firms, or because high ψ firms are associated with arbitrage risk. Consequently, in order to further investigate the above question I will repeat the multivariate tests using different sub-samples where noise trading and/or arbitrage risk are more (or less) likely. This analysis is conducted in the coming section.

V. Interpretations on the Non-linear Relationship

To answer to the question of why mispricing rises with idiosyncratic volatility for high volatility stocks, I create sub-samples consisting of stocks classified based on whether they are more or less likely to have noise trading as well as whether they are more or less likely to display arbitrage risk. First, I use uncertainty[11] as a measure of probability of low/high noise trading, by assuming that if a firm's information environment is less uncertain, the market participants for these stocks are better informed and thus there are relatively fewer noise traders compared to other stocks. Second, I use short-sale constraints as a measure of the extent of arbitrage risk. The use of the short-selling constraints as a proxy for the likelihood of arbitrage risk relies on the assumption that informed traders have a better opportunity to engage into arbitrage when short-selling constraints are less binding. In the following sub-sections, I describe how I computed aggregate measures of firm uncertainty and short-selling constraints from a number of proxies.

A. Measures of Firm's Uncertainty

To measure uncertainty, I focus on the measures of earnings quality, captured by the absolute size of abnormal accruals, and on measures of the quality of security

[11] Black (1986) argues that noise caused by uncertainty makes it difficult for either practitioners or academic researchers to understand how financial or economic markets work.

analysts' forecasts. Abnormal accruals (i.e., accruals larger or smaller than expected) reflect poor earnings quality, which is likely to occur in the presence of uncertainty. I use two measures based on Francis, LaFond, Olsson, and Schipper (2005) and Dechow and Dichev (2002). The first measure of earnings quality (*EQ1*) is defined as the absolute value of firm-specific residuals from an industry regression of total accruals on the reciprocal of total assets, sales growth, and fixed assets.

$$\frac{TACCR_{i,t}}{TA_{i,t\text{-}1}} = k_1 \frac{1}{TA_{i,t\text{-}1}} + k_2 \frac{\Delta SALES_i}{TA_{i,t\text{-}1}} + k_3 \frac{PPE_{i,t}}{TA_{i,t\text{-}1}} + \zeta_{i,t}\,, \tag{13}$$

where $TACCR_{i,t} = (\Delta CA_{i,t} - \Delta CL_{i,t} - \Delta CASH_{i,t} + \Delta STDEBT_{i,t} - DEPN_{i,t})$ = firm *i*'s total accruals in year *t*, $\Delta CA_{i,t}$ = change in current assets between year *t-1* and year *t*, $\Delta CL_{i,t}$ = change in current liabilities between year *t-1* and year *t*, $\Delta CASH_{i,t}$ = change in cash between year *t-1* and year *t*, $\Delta STDEBT_{i,t}$ = change in debt in current liabilities between year *t-1* and *t*, $DEPN_{i,t}$ = depreciation and amortization expense in year *t*, $\Delta SALES_i$ = change in sales between year *t-1* and *t*, $PPE_{i,t}$ = property, plant, and equipment in year *t*, and $TA_{i,t\text{-}1}$ = total assets in year *t-1*.

Following Dechow and Dichev (2002) I also create an alternative earnings quality (*EQ2*) measure, which is the absolute value of firm-specific residuals from the regression of total accruals on lagged, contemporaneous, and leading cash flow from operations.

$$\frac{TACCR_{i,t}}{TA_i} = k_0 + k_1 \frac{CFO_{i,t\text{-}1}}{TA_i} + k_2 \frac{CFO_{i,t}}{TA_i} + k_3 \frac{CFO_{i,t+1}}{TA_i} + \zeta_{i,t}\,, \tag{14}$$

where $CFO_{i,t}$ is firm *i*'s cash flow from operations in year *t* and computed as net income before extraordinary items minus total accruals. All variables are scaled by average total assets (TA_i).

I also use two variables constructed from non-stale security analyst one fiscal year-ahead forecasts, issued every June and extracted from *I/B/E/S* Detail History Database. These are the absolute value of the analyst forecast error (*AFE*) and the dispersion of analyst forecasts (*AFD*). The forecast error captures forecasting ability of security analysts covering the firm. The absolute value of the forecast error has been also used by several studies as a proxy of information asymmetry (e.g., see Atiase and Bamber (1994), and Christie (1987)). If there is less uncertainty, a considerable amount of information about future earnings is available to market participants, and so analysts should be in better position to make accurate earnings forecasts. Barron, Kim, Lim and Stevens (1998) show that analyst forecast dispersion reflects both diversity of analyst beliefs and the uncertainty (lack of precision) in analyst forecasts. Prior studies have used the dispersion of analyst forecasts as an information uncertainty proxy (e.g., see Zhang (2005)), as well as an information asymmetry proxy (e.g., see Krisnhnaswami and Subramaniam (1999)). Therefore, I expect analyst forecast error and dispersion will increase with uncertainty. *AFE* and *AFD* are computed as follows:

$$AFE_{i,t} = \frac{|\,Med(AF)_{i,t} - EPS_{i,t+1}\,|}{|\,Med(AF)_{i,t}\,|}, \tag{15}$$

$$AFD_{i,t} = \frac{Std.Dev.(AF)_{i,t}}{|\,Med(AF)_{i,t}\,|}, \tag{16}$$

where forecast error, $|Med(AF)_{i,t} - EPS_{i,t+1}|$, is the absolute value of the difference between the median analyst forecast ($Med(AF)_{i,t}$) and the actual earnings per share ($EPS_{i,t+1}$), while $Std.Dev.(AF)_{i,t}$ is standard deviation of one year ahead analyst forecasts.

All four aforementioned variables (*EQ1*, *EQ2*, *AFE*, and *AFD*) are positively related to uncertainty. Thus, I construct an uncertainty index (*UI*) for each firm by combining the inverse ranks of the four variables. The methodology used to construct *UI* is the same as the one used for the mispricing index (*MI*). *UI* is computed each year for each observation $i = 1,\dots,N$ as:

$$UI_i = \frac{1}{N}\frac{1}{K}\sum_{k}^{K} RANK_k(UNCER_{i,k}), \tag{17}$$

where $Rank_k(UNCER_{i,k})$ is the rank function which assigns a rank for each observation from least uncertain (rank of one) to most uncertain (rank of N). $UNCER_{i,k}$ is the k^{th} measure of uncertainty for firm i in my sample, and K represents the dimensions of uncertainty measures (*EQ1*, *EQ2*, *AFE*, and *AFD*). The denominator, K, averages the ranks by the number of uncertainty values available for each firm in the sample in a particular year. Finally, dividing by N, I scale the *UI* from 0 (least uncertain) to 1 (most uncertain). Table 1 provides detail descriptions of uncertainty measures and Table 2 documents descriptive statistics.

B. Measures of Short-selling Constraints

I control for the effects of short-sale constraints using two alternative proxies: size (*SIZE*), and institutional ownership (*IO*). I also construct an aggregate measure, a short-sale costs index (*SI*). Previous research suggests firm size as a short-selling characteristic (see Chen *et al.* (2002), and Diether, Malloy, and Scherbina (2002) among others). The supply of shortable shares for small firms is generally low because small capitalization stocks tend to be held primarily by individual investors who rarely lend their shares. Furthermore, outstanding shares of small firms are not necessarily floated since insiders may hold a considerable portion of the shares outstanding. Large capitalization firms, however, are held more widely, and so finding a lender of shares should be less difficult. Shares of small firms are also less likely to be "on special" than those of large firms (Reed (2003)). Finally, search and bargaining costs involved in short-selling are more likely to be higher in small firms than in large ones. Therefore, based on the above arguments, the cost of borrowing and shorting small capitalization stocks is expected to be higher than in large capitalization stocks.

As a second proxy for short-selling constraints, I use institutional ownership (*INSTP*). D'Avolio (2002) shows that institutional ownership is the major determinant of the quantity of shares supplied to the market. Therefore, the cost of short-selling should be less (more) expensive for stocks with high (low) institutional ownership. Gompers and Metrick (2001) report a strong relationship between institutional ownership and liquidity. This suggests that the cost of trading large quantities of shares for stocks with high institutional ownership should be low. The search and bargaining cost for stocks with high institutional ownership is also expected to be low. Indeed, if several institutional investors are lending many shares, it should be less costly to locate them and competition should lower the cost of direct borrowing. Finally, derivative instruments, and in particular put options, an alternative method of creating short positions, are likely to be more often available for stocks with high levels of institutional shareholdings.[12] Therefore, stocks with low institutional ownership are subject to a higher short-selling cost.

Finally, a short-selling constraints index (*SI*) is constructed using the inverse of both firm size and institutional ownership (see also Doukas, Kim, and Pantzalis (2006)). *SI* is computed each year for each observation $i = 1,\ldots,N$ as:

$$SI_i = \frac{1}{N}\frac{1}{K}\sum_{k}^{K} RANK_k(SHORT_{i,k}), \tag{18}$$

where $Rank_k(SHORT_{i,k})$ is the rank function which assigns a rank for each observation from the lowest short-sale constraint (rank of one) to the highest short-sale constraint (rank of N). $SHORT_{i,k}$ is the inverse value of k^{th} measure of short-sale constraint for firm i in my sample, and K represents the dimensions of short-sale constraint measures (*SIZE* and *INSTP*). The denominator, K, averages the ranks by the number of short-sale constraint values available for each firm in the sample in a particular year. Finally, dividing by N, I scale the *SI* from 0 (lowest short-sale constraint) to 1 (highest short-sale constraint). Details of all short-selling variables are provided in Table 1 and summary statistics are documented in Table 2.

[12] Ofek, Richardson and Whitelaw (2004) show that the violation of the put-call parity is strongly related to lending fees. Lending fees, however, are related to institutional ownership.

C. Analysis of Non-linear Relation

I begin my analysis of the non-linear relationship by comparing the mean values of uncertainty and short-selling constraint measures across firms that belong to the left-hand side and the right-hand side of the U-shape relationship between MI and ψ. The comparison is presented in Table 8. In the left half of the table I present evidence based on the sample used in the main multivariate test presented in Table 5, which had 34,471 observations. The results for model [2] showed a non-linear (U-shape) relation between *MI* and ψ. A firm that lies on the right side of the U-shape curve (i.e., one with very high idiosyncratic volatility) is a firm whose idiosyncratic volatility (ψ) is greater than the inflection point (which was at $\psi = 4.930$). 3,388 firms (about 10% of the total sample) are included in the high-volatility group. Alternatively, in the right half of Table 8, I use all sample observations (N=44,639) and sort firm into high-volatility group if its volatility is ranked within top 10%. The results reported in Table 8 show that firms with high volatility display greater levels of uncertainty and are subject to higher short-sale constraints than firms with low idiosyncratic volatility. The mean differences are significant in most cases. Since uncertainty is more likely to be associated with noise trading and more binding short-sale constraints with more arbitrage risk, this evidence is also consistent with the notion that firms with high idiosyncratic volatility will be characterized by both more noise trades and higher arbitrage risk, compared to firms with normal levels of idiosyncratic volatility.

Table 8
Firms with Very High Idiosyncratic Volatility

This table reports mean values of firm uncertainty measures and short-selling constraint measures for firms with very high idiosyncratic volatility (ψ) and for the other firms. Columns [1] and [2] test 34,471 observations used in the regression [2] of Table 5. The relation is inflected at the point where ψ is at 4.930. Firms with very high idiosyncratic volatility are included in column [1] if ψ is greater than 4.930. Columns [3] and [4] test all sample observations. Firms with very high idiosyncratic volatility are included in column [3] if ψ is ranked within top 10%. All variables are as defined in Table 1. * and *** indicate significance at the 10%- and 1%-levels, respectively.

	Observations used in the regression [2] of Table 5 (N = 34,471)				All sample observations (N = 44,639)			
	[1] Firms with very high ψ (N=3,388)	[2] The other firms (N=31,083)	Mean diff.: [1] – [2]	t-statistics: difference =0	[3] Firms with very high ψ (N=4,475)	[4] The other firms (N=40,164)	Mean diff.: [3] – [4]	t-statistics: difference =0
Uncertainty measures								
Francis *et al*. (2005) (*EQ1*)	0.302	0.339	-0.037***	-3.15	0.317	0.334	-0.017	-1.55
Dechow and Dichev (2002) (*EQ2*)	0.158	0.173	-0.015	-1.27	0.161	0.171	-0.010	-0.91
Analyst earnings forecast error (*AFE*)	1.191	0.727	0.465***	4.03	1.415	0.775	0.640***	6.14
Analyst earnings forecast dispersion (*AFD*)	0.232	0.192	0.040*	1.71	0.317	0.220	0.096***	3.72
Uncertainty index (*UI*)	0.519	0.496	0.023***	6.32	0.541	0.499	0.042***	12.75
Short-selling constraint measures								
Firm size (*SIZE*)	18.94	19.69	-0.751***	-27.03	18.93	19.83	-0.898***	-34.85
Institutional ownership (*INSTP*)	0.406	0.516	-0.110***	-21.19	0.400	0.513	-0.114***	-23.69
Short-selling constraint index (*SI*)	0.634	0.512	0.122***	27.12	0.649	0.492	0.158***	39.27

Next, I classify firms into different sub-samples after independently sorting on both on the uncertainty and short-selling constraint measures and re-test the regressions for all sub-samples in order to establish which of the two effects (i.e., noise trades and/or arbitrage risk) is reflected in the right side of the U-shaped curve. Table 9 documents the coefficients of the first- and second-order terms of idiosyncratic volatility and the inflection point obtained from estimating the regression. If any one of the two effects that can cause the positive relation between mispricing and firm-specific risk for high idiosyncratic volatility stocks dominates, the non-linearity should disappear only in the sub-sample where the possibility of that effect is restricted. For instance, I construct a group which contains only firms with low uncertainty, i.e., a sub-sample of firms with few noise traders. If the U-shaped relationship is not significant for this sub-sample, it is possible that the increase of mispricing for high volatility firms is attributed to noise traders. Similarly, if the non-linearity becomes insignificant only for firms with low short-selling constraints, the positive relation between *MI* and ψ for high volatility firms could be associated with arbitrage risk.

Table 9
Coefficient of Idiosyncratic Volatility and Inflection Point for Sub-samples

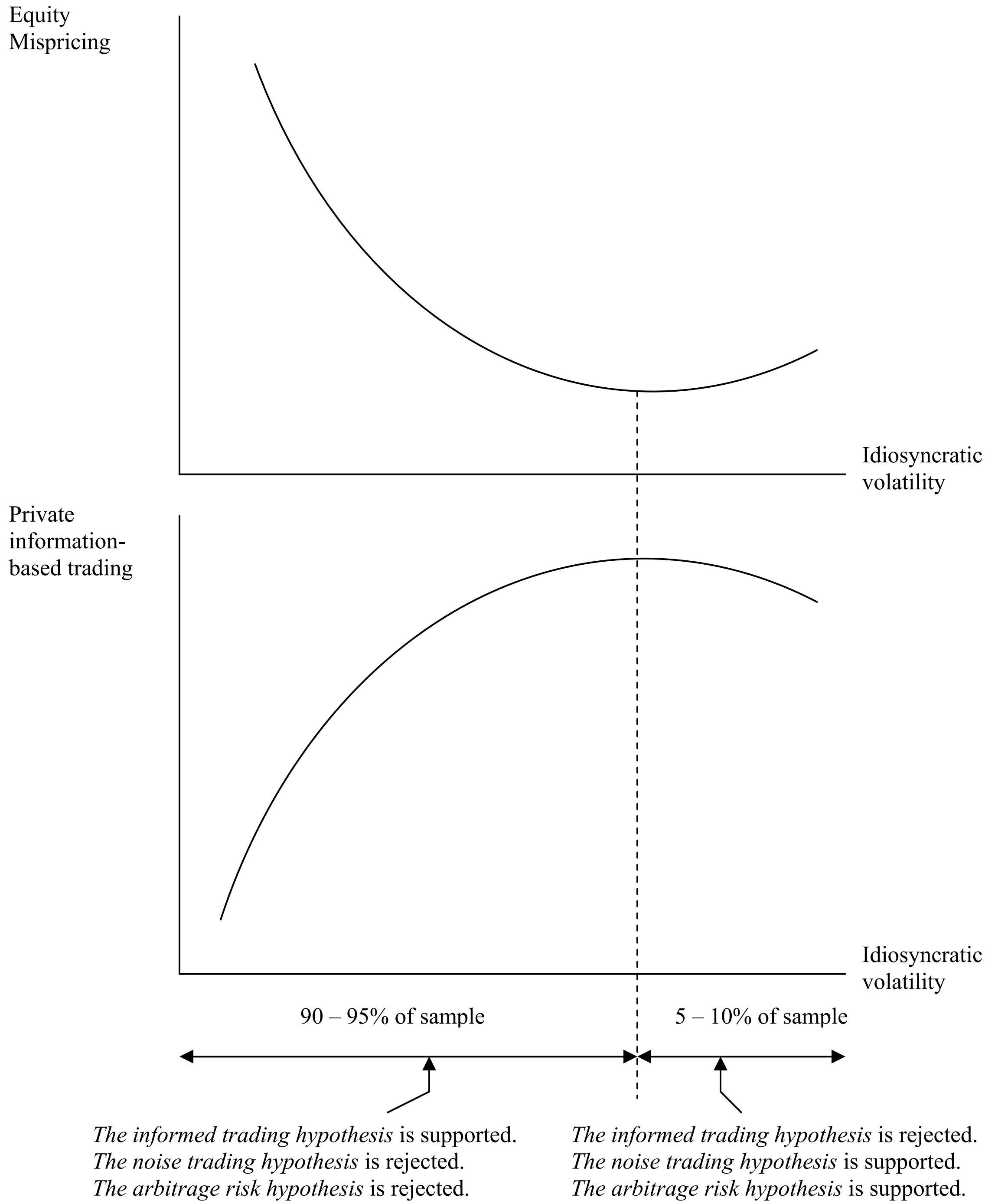
This table shows the coefficient of idiosyncratic volatility and inflection point in the time-series average of cross-sectional regressions of Table V. Sub-samples are classified on firm uncertainty and short-selling constraint. All variables are as defined in Table 1. *, **, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

		Dep. var. = *MI*					Dep. var. = ln(1+*MI*)				
Sub-samples		[1] Linear	[2] Non-linear	ψ at infl. point	$1-R^2$ at infl. point	% of obs. after infl. point	[3] Linear	[4] Non-linear	ψ at infl. point	$1-R^2$ at infl. point	% of obs. after infl. point
[1] Less uncertain (low *UI*) firms (= few noise traders)	ψ	-0.006*** (-2.82)	-0.021*** (-3.42)	4.850	99.22%	8.85%	-0.004** (-2.60)	-0.013*** (-3.30)	4.861	99.23%	8.82%
	ψ^2		0.002** (2.43)					0.001** (2.36)			
[2] Low short-selling cost (low *SI*) firms (= low arbitrage risk)	ψ	-0.005** (-2.23)	-0.027*** (-4.45)	2.800	94.27%	18.11%	-0.003* (-1.87)	-0.017*** (-4.19)	2.752	94.00%	18.79%
	ψ^2		0.005*** (3.56)					0.003*** (3.39)			
[3] Low *UI* & low *SI* firms (= few noise traders & low arbitrage risk)	ψ	-0.016** (-2.49)	-0.029* (-2.00)	N/A†	N/A	N/A	-0.011** (-2.38)	-0.019* (2.02)	N/A	N/A	N/A
	ψ^2		0.007 (1.21)					0.004 (1.27)			
[4] Low *UI* & non-low *SI* firms (= few noise traders & arbitrage risk)	ψ	-0.005** (-2.68)	-0.018*** (-3.04)	4.465	98.86%	13.44%	-0.003** (-2.47)	-0.011*** (-2.89)	4.414	98.80%	13.92%
	ψ^2		0.002** (2.16)					0.001** (2.08)			
[5] Non-low *UI* & low *SI* firms (= noise traders & low arbitrage risk)	ψ	-0.005 (-1.63)	-0.026*** (-2.96)	3.163	95.94%	13.36%	-0.003 (-1.37)	-0.017*** (-2.75)	3.132	95.82%	13.79%
	ψ^2		0.004** (2.46)					0.003** (2.24)			
[6] Non-low *UI* & non-low *SI* firms (= noise traders & arbitrage risk)	ψ	-0.005** (-2.27)	-0.016*** (-6.46)	5.511	99.60%	8.38%	-0.003** (-2.08)	-0.010*** (-5.90)	5.410	99.55%	8.86%
	ψ^2		0.001*** (5.68)					0.001*** (5.71)			

† Not available due to the insignificance of non-linear relation.

Figure 4
Tests of Three Hypotheses and Evidence

This figure describes the empirical evidence of non-linear relationships among idiosyncratic volatility, equity mispricing, and private information-based trading. Based on the findings, tested are three hypotheses; 1) the *noise trading hypothesis*, 2) the *informed trading hypothesis*, and 3) the *arbitrage risk hypothesis*.



In Table 9, results show that the non-linear relation remains significant both for low uncertainty firms (sub-sample [1]) and for firms with low short-selling constraints (sub-sample [2]). The non-linear relationship collapses to a linear one only for the sub-sample containing firms that have both low uncertainty and low short-selling constraints (sub-sample [3]). In this sub-sample, while the negative linear relationship remains strong, the non-linear relation becomes insignificant. These results indicate that the increase in mispricing for highly volatile stocks cannot be attributed to only one effect. The results indicate that both noise trading and arbitrage risk contribute to an increase in *MI* when ψ is very high. Consistent with the previous evidence in Table 5, firm-specific risk ($1 - R^2$) at the inflection point is very high, ranging from 90% to 99%. The percentage of total observations in the range to the right of the inflection point is somewhere between 8% and 19%.

In summary, all test results in this paper provide evidence that idiosyncratic volatility in stock returns primarily reflects informational market efficiency. Moreover, extremely high volatility implies the possibility of both noise traders' frenzy and limits of informed arbitrage. To clarify the relation between idiosyncratic volatility and equity mispricing based on three hypotheses, I sketch the main results in Figure 4.

VI. Summary and Conclusions

In this paper, I revisit three alternative interpretations of idiosyncratic volatility found in past studies and attempt to provide an answer as to if and when each view is suited for describing idiosyncratic risk. Past studies have argued that idiosyncratic volatility may reflect informed arbitrageurs' trading, uninformed noise traders' frenzy without concrete information about a firm, and/or limits to arbitrage opportunities. I test three hypotheses of the relation between idiosyncratic volatility and equity mispricing corresponding to each of the aforementioned views. The *informed trading hypothesis* proposes that idiosyncratic volatility is a sign of active trading by informed arbitrageurs who trace the firm's fundamental value, and thus predicts that equity mispricing should be lower for high idiosyncratic volatility firm. On the contrary, *the noise trading hypothesis* regards idiosyncratic volatility as a sign of uninformed investors' noise trading which causes deviation from the stock's fundamental value, and thus predicts that equity mispricing should be higher for high idiosyncratic volatility firm. *The arbitrage risk hypothesis* predicts that arbitrage activity is impeded when idiosyncratic risk is high because arbitrageurs cannot hedge their positions successfully. Systematic mispricing may epitomize arbitrageurs' limit of opportunity to perfectly hedge fundamental risk in their portfolios. Therefore, the prediction of *the arbitrage risk hypothesis* is that the equity mispricing of high arbitrage risk stocks should be higher than one of low arbitrage risk stocks.

I test the three hypotheses by employing several mispricing measures as well as an aggregated measure, the mispricing index (*MI*). I find that the level of mispricing declines in volatility, consistent with the *informed trading hypothesis*. However, I also find a strong non-linear, U-shape relation; the level of equity mispricing decreases first with idiosyncratic risk but then increases for high levels of idiosyncratic risk. Regressions for sub-samples created after sorting on uncertainty and short-selling constraints indicate that high volatility reflects both noise trades and arbitrage risk, thereby inducing a positive relation with equity mispricing.

Recently, the finance literature has emphasized the importance of idiosyncratic volatility but provided different ways to interpret it. The contribution of this paper is to reconcile the different views of several areas of finance research, and, specifically, to produce evidence on the link between idiosyncratic volatility and stock mispricing, which allows a clearer understanding of idiosyncratic volatility.

In summary, the findings in this paper are consistent with the Roll's (1988) former view that idiosyncratic volatility is associated with information-laden stock prices and efficient markets. For extremely high volatility, however, we should not ignore the possibility of noise traders' frenzy as well as limits of informed arbitrages.

Essay 2

Agency Costs and the Underlying Causes of Mispricing: Information Asymmetry versus Conflict of Interests

I. Introduction

Both theory and empirical evidence support the notion that equity mispricing has an impact on managers' investment and financing decisions. For example, misvaluation can drive firms' takeover behavior.[13] Furthermore, there is evidence that the levels of firms' investment are affected by inefficient market valuations[14] and that firms try to time equity issues to take advantage of misevaluation.[15]

There are several possible reasons why equity mispricing exists. These are related to market imperfections such as information asymmetry, transactions costs, unsophisticated market participants or unequal access to prices. According to the proponents of the efficient markets hypothesis and rational asset pricing, stock mispricing, i.e., the deviation from intrinsic (fundamental) value can be either a short-term temporary phenomenon quickly exploitable by arbitrageurs (Friedman (1953)), or a rational compensation for risks that are not accounted for in asset pricing models (see, for example, Fama and French (1993 and 1996)). On the other hand, advocates of behavioral finance regard persistent mispricing as the result of the existence of an irrational (behavioral) component to asset prices. In this study, unlike previous studies that link

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[13] Shleifer and Vishny (2003), Dong, Hirshleifer, Richardson, and Teoh (2006), Rhodes-Kropf and Viswanathan (2004), and Rhodes-Kropf, Robinson, and Viswanathan (2005).
[14] Polk and Sapienza (2003) and Baker, and Stein and Wurgler (2003).
[15] Ritter (1991), Loughran and Ritter (1995), Rajan and Servaes (1997), and Baker and Wurgler (2002).

market inefficiency to equity mispricing, my focus is on providing evidence on whether agency theory can reliably explain equity mispricing.

Agency theory defines agency costs as the costs associated with divergent objectives between agents (management) and owners (shareholders). These conflicts of interest cause problems that are exacerbated in the presence of information asymmetry where agents discriminately have better/more information than owners. I hypothesize that a sizeable component of stock mispricing is due to the lack of transparency at the corporate level.[16] The term "lack of transparency" in this context refers to the opacity caused by information asymmetry and conflict of interests between managers and shareholders. However, while most prior studies have focused on the linkage between information asymmetry and stock misvaluation,[17] there is little direct evidence in the literature on the potentially important effect of conflict of interests between managers and outside shareholders on equity mispricing.

Suppose, for instance, that there are large differences in the quality and availability of information between managers and outside investors of a particular firm. Then, one may expect that the firm's stock is likely to be mispriced because ambiguity about future cash flows leads to stock mispricing (see, for example, Kumar (2005) and Zhang (2006)). The question that I want to examine is what happens to the size of mispricing if the firm attempts to reduce managerial disincentives, e.g., if the board of directors provides an incentive-laden compensation package to managers. In this case,

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[16] Alternatively, mispricing can exist due to 1) high transactions costs (Ali, Hwang, and Trombley (2003)), 2) lack of investor sophistication, 3) noise trading (Roll (1988)) etc.
[17] See, among others, Nanda and Narayanan (1999), and Healey and Palepu (2001).

even if investors have difficulty obtaining true, reliable information about the firm's future cash flows, they may credibly rely on inference from observing managers' decisions, and thereby the ambiguity that causes misvaluation could be mitigated. Thus, if my conjecture is correct, the level of mispricing should be related to components of managerial compensation packages which are intended to resolve the conflict of interests (or, incentive conflicts).

Using ten agency conflict proxy variables, I identify the firms which are most likely to have agency problems. However, it is unclear whether these variables measure the level of information asymmetry or incentive conflicts. In fact, they could represent one or the other, or even both. This is because information asymmetry and incentive conflicts are highly correlated. In order to identify which component of agency conflict (i.e., information asymmetry or conflict of interests) drives mispricing, I employ managerial compensation data and investigate whether and how mispricing is affected by equity-based compensation, which is known as the tool that can align managerial interests with those of shareholders but not necessarily as a tool suited for resolving information asymmetry. Previous studies suggesting stock-based compensation is an efficient agency problem resolution mechanism typically do not differentiate among different stock-based incentives and relate them to both lowered agency costs and enhanced firm stock value.[18] In light of the recent public skepticism about the effectiveness of equity-based compensation fueled from financial scandals (i.e., Enron

[18] For a detailed discussion about equity-based compensation, see Bhagat, Brickley, and Lease (1985), Jensen and Murphy (1990a and 1990b), DeFusco, Johnson, and Zorn (1990), Mehran (1995), Core and Guay (2001), Datta, Iskandar-Datta, and Raman (2001), Loughran and Vijh (1997), Frye (2004), Core and Larcker (2002), and Nam, Tang, Thornton, and Wynne (2006).

and WorldCom) and academic evidence (e.g., Bergstresser and Philippon (2006)), in my analysis I consider separately both major equity-based compensation components, i.e. stock options and restricted stock grants. While options have been shown to induce managerial myopia (i.e., shorter-term orientation), restricted stock grants have been shown to induce managers to become less myopic (i.e., longer-term orientated).[19]

My results show a significant positive relation between agency problems and equity mispricing. Furthermore, using CEO compensation data, I find that, contrary to previous studies' argument that information asymmetry is a key determinant in equity mispricing, information asymmetry is not a powerful explanatory variable of mispricing. When I interact agency costs proxies with variables that capture managerial compensation components intended to resolve the interests' conflict between CEO and owners, the models explain a significant proportion of mispricing. My findings obtained from several univariate and multivariate tests support the notion that the positive relation of agency costs with mispricing is mainly driven by stock options' awards to the CEO. The empirical evidence also suggests that the use of restricted stock grants that are known to not be associated with managerial myopia is a better choice in terms of reducing interest conflicts.

The rest of the paper is organized as follows. In the next section, I develop the main hypotheses to prove the relation between incentive conflicts and mispricing. Section III describes the data sources and measures of main variables. Section IV introduces empirical methodology and reports test results. Section V conducts additional tests

[19] See Aboody and Kaznik (2000), Watts and Zimmerman (1986), Gao and Shrieves (2002), and Bergstresser and Philippon (2006).

utilizing managerial compensation data and provides a more detailed explanation of the relation between agency costs and mispricing. Section VI includes a summary and concluding remarks.

II. Hypotheses Development

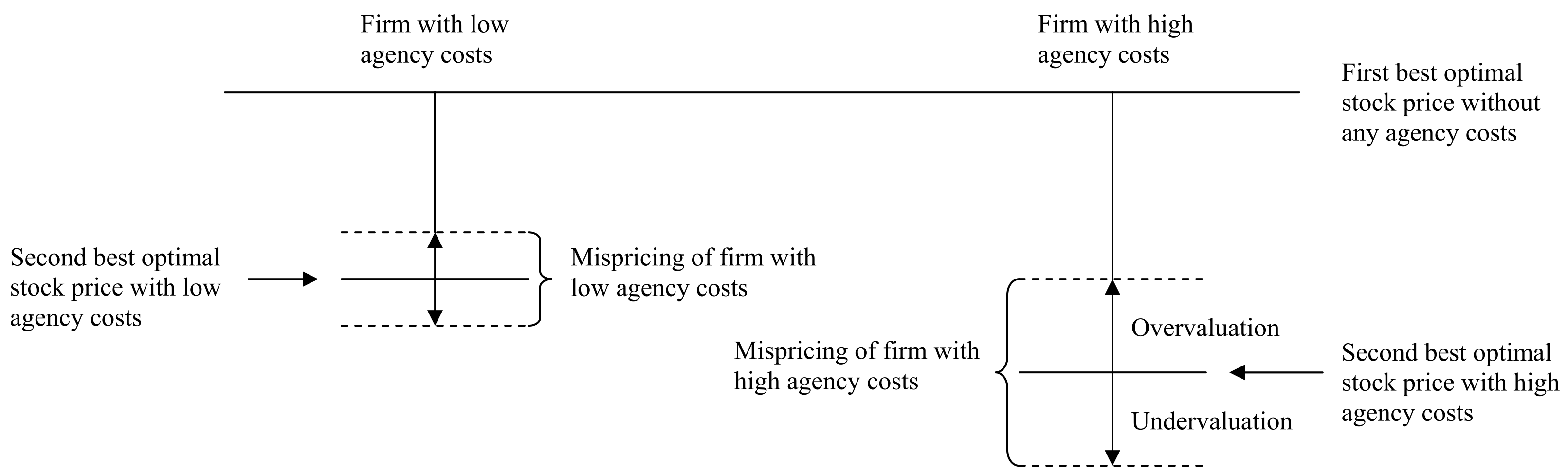
I assume that a sizeable component of stock mispricing is due to the lack of transparency (i.e., opacity) at the corporate level, which stems from two sources. First, outside investors' ambiguity about firms' future cash flows increases when they have limited access to information or when investors' information is of poor quality relative to that of firm insiders. Therefore, the more opaque the information available to investors about a firm's true but unobservable distribution of future cash flows, the greater the degree of deviation of market value from intrinsic value.[20] Second, the lack of transparency can be also caused by the severity of the conflict of interests that may exist between managers and investors. If this is true, the mispriced firms should have greater agency costs than other firms. This relation is graphically depicted in Figure 5

Hypothesis # 1: Firms with high agency costs are more likely to display high levels of equity mispricing.

[20] Since Myers and Majluf (1984) showed that firms subject to higher information asymmetry are more likely to refuse valuable investment opportunities and to suffer from unfavorable misvaluation, many authors have documented the impact of asymmetry information on misevaluation. Nanda and Narayanan (1999) formally develop an information related argument in the context of divestitures through a model of asymmetric information about firm value between the managers and the market. They assume that the market can observe the aggregate cash flows of the firm but not the individual divisional cash flows, which results in misvaluation of the firm's securities. Healey and Palepu (2001) argue that misvaluation arises when there is information asymmetry between managers and investors that is not fully resolved.

Figure 5
Agency Costs, Fundamental Value, and Equity Mispricing

This figure graphically describes the relation between agency costs and equity mispricing.



Agency costs, by definition, are the costs incurred by a firm that are associated with problems such as divergent objectives between management and shareholders and/or information asymmetry where insiders discriminately have access to better/more information than outside shareholders. If mispricing is due to the information asymmetry, equity-based compensation should not be significantly related to the level of mispricing. In contrast, if mispricing is due to the degree of the conflict of interests between managers and shareholders, it should be related to components of managerial incentive compensation.

Hypothesis # 2: The positive impact of agency costs on equity mispricing is mainly attributed to the conflict of interests rather than to information asymmetry.

The finance literature has adopted two different views on the linkage between agency problems and executive compensation. First, many authors[21] regard managerial compensation as a potential agency conflict resolution mechanism. Under this view, corporate boards design compensation packages to provide managers with the correct incentives to maximize shareholder value. Several studies found that firm's stock performance is positively related to the fraction of equity-based compensation suggesting that equity-based compensation resolves agency problems.[22]

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[21] They are Bhagat *et al.* (1985), Jensen and Murphy (1990a and 1990b), DeFusco *et al.* (1990), Mehran (1995), Core and Guay (2001), Datta *et al.* (2001), and Core and Larcker (2002).

[22] For example, Bhagat *et al.* (1985) find that the adoption of employee stock purchase plans result in an increase in shareholder wealth, and that equity-based compensation schemes motivate top managers more than lower-level employees. Jensen and Murphy (1990a and 1990b) suggest that equity-based, rather than cash-based, compensation is more efficient in aligning the interests of managers and shareholders. DeFusco et al. (1990) find that implicit share price variance and stock return variance increase after the firm approves an executive stock option plan. Moreover, their event study analysis results indicate that the announcement of approval of stock option plans leads to an increase in stock price along with a significant negative reaction in the bond market, suggesting that executive stock options may transfer wealth from bondholders to stockholders. Mehran (1995) shows that firm performance is positively related to the

The alternative view of executive compensation found in the literature is that of executive compensation being part of the agency problem itself. Recent corporate scandals involving excessive managerial pay coupled with abysmal performance and wealth expropriation of outside shareholders, such as those at Enron and WorldCom, have cast doubts over prior beliefs about the effectiveness of equity-based compensation. Moreover, researchers suggesting stock-based compensation as an efficient mechanism used to solve agency problems typically treated all stock-based incentives equally and related them to lowered agency costs as well as enhanced firm stock value. The skepticism about the effectiveness of equity-based compensation motivated my decision to analyze equity-based compensation by separately considering its stock options- and restricted stock grants components.

It is intuitively appealing to think that incentive stock options should have a positive impact on firm performance. But options may also impose a penalty on the firm because they tend to make managers more myopic. In particular, because managers' gains from stock option grants are exponentially greater than stock appreciation returns,

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managers' ownership and the amount of shares provided by their compensation packages. He also shows that firms with higher percentage of shares held by outside blockholders use less equity-based compensation. Based on theses findings, he suggests that the monitoring by outside blockholders can be a substitute for incentive equity compensation for executives. Core and Guay (2001) show that firms use options to attract and retain certain types of employees as well as to create incentives to increase firm value. Datta *et al.* (2001) document a positive relation between equity-based compensation received by acquiring managers' equity-based compensation and acquirer firms' stock price response around and following corporate acquisition announcements. They also find that acquiring firms with high equity-based compensation do not show underperformance documented by Loughran and Vijh (1997) and others. Frye (2004) provides evidence that firms with high percentage of equity-based compensation show better performance measured by Tobin's q. Core and Larcker (2002) show that mandatory increases in the level of managerial equity ownership result in improvements in accounting returns and stock returns. Nam *et al.* (2006) examine the effectiveness of equity-based compensation in mitigating the agency costs in single- and multi-segment firms, and find that the effect for multi-segment firms, where agency costs are expected to be higher, is much greater than for single-segment firms.

managers have an incentive to maximize short-term stock price appreciation to increase their options' exercise value. It is conceivable then that an increase in stock value could lead to a substantial enough increase in the value of the stock option grants to provide the managers with an incentive to cash out and leave the company. Such a scenario would be especially true if projects and investments chosen by the managers have a short-term focus at the expense of long-term wealth creation.

The finance and accounting literatures broadly document that executives have the ability to manage the timing of stock option grants and/or the information flow around option grants. [23] In a recently published study Lie (2005) proposes an alternative way in explaining the abnormal return pattern around options grants (i.e., return which is abnormally negative before executive option grants and abnormally positive afterward). Unlike previous studies (e.g., Yermak (1997)) that argue conventional grant timing, Lie (2005) argues that, to enrich their senior executives, firms may simply *backdate* the stock option grant date to a time period where the market price was particularly low.[24, 25]

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[23] Yermack (1997) investigates corporate managers' influence over the terms of their own compensation by analyzing the timing of CEO stock option awards. He finds that CEO option awards are followed by significantly positive abnormal returns. Aboody and Kasznik (2000) suggest that CEOs make opportunistic voluntary disclosure decisions to maximize their stock option compensation. Chauvin and Shenoy (2001) show that stock price significantly decreases in the 10 days prior to stock option grants. Carpenter and Remmers (2001) find that abnormal stock returns after exercises by top managers at small firms are significantly negative. Huddart and Lang (2003) examine the stock option exercise decisions of over 50,000 employees at seven corporations and present evidence that stock exercise is high before the stock price decreases and low before stock price increases. They suggest that the timing when both senior and junior employees exercise their stock options can be used to predict future stock returns.

[24] Heron and Lie (2007) look at a 2002 change in regulatory law that requires companies to report option grants within 48 hours. They document that the return pattern (i.e., returns which are abnormally negative before executive option grants and abnormally positive afterward) weakens after the SEC requirement. They find that when companies reported options the same day they were granted, there was no pattern of share prices quickly rising. But the pattern continued when companies delayed reporting option grants. These findings support the Lie's backdating theory.

[25] The theory has been also supported by the recent anecdotal evidence from the SEC's investigation of many cases (e.g., Mercury Interactive). *"SEC investigators previously had posited that companies were*

Another negative aspect of option grants is that options appear to lead executives to take risks that might not be in the best interest of shareholders. This can occur because stock option grants offer substantial upside potential, but impose little downside risk on managers (see Sanders (2001)). They serve as motivational "carrots" but lack the complementary disciplinary "stick." Thus, executives may view the potential option payouts as a form of compensation lottery.[26] Watts and Zimmerman (1986) argue that managers of firms with earnings based compensation incentives maximized their awards by choosing income increasing accounting methodologies.[27]

Based on the above evidence I expect that options grants effectively make CEOs more myopic. In other words, as the proportion of options in a CEO's compensation package increases, so does the incentive to make short-term wealth maximization decisions that might not be in the best interest of long-term stakeholders.

Restricted stock grants endow managers with a number of shares of firm's equity, but also restrict managers from reselling or transferring shares and contain provisions that invalidate the award if managers quit or are fired before the restricted period. While options have been shown to induce managerial myopia, restricted stock grants have been shown to reduce managerial myopia.[28] Another important difference between restricted

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timing grants to benefit from positive corporate news that would drive up stock prices, such as strong earnings. But increasingly they are focusing on backdating" (11/11/2005, Wall Street Journal).

[26] Warren Buffett shares this opinion as he conceded that "we don't give options because it would be a lottery ticket".

[27] Gao and Shrieves (2002) find that option grants and exercisable in-the-money options are positively correlated with earnings management intensity. Bergstresser and Philippon (2006) provide evidence that during years of high discretionary accruals CEOs exercise unusually large numbers of options and sell large quantities of shares.

[28] For example, Narayanan (1996) theoretically investigated the relationship between two types of compensation, cash and non-cash, and the manager's decision horizon. He did not investigate the effect of options as a form of non-cash compensation but rather focused on restricted stock grants. He found that all-

stock and options is that restricted stock grants have more of a linear payoff relative to stock option grants.[29] It is also reasonable to argue that restricted stock grants provide less incentive for earnings management because the reversion of earnings management accruals will likely manifest before managers can realize large personal gains (see Gao and Shrieves (2002)). Therefore, it is expected that restricted stock grants are effective in resolving agency problems and thereby improving firm performance.

Because, as discussed above, options have been shown to induce managerial myopia, while restricted stock grants have been shown to induce managers to become less myopic, I focus on the two incentive compensation plans separately. On one hand, mispricing can be reduced when incentive conflicts are resolved by a compensation package, which contains a high proportion of restricted stocks. On the other hand, mispricing can be exaggerated when firms provide CEOs with compensation packages which have many stock options.

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cash contracts induce managers to underinvest in the long term while restricted stock grants induce managers to overinvest in the long term. He concluded that a combination of both cash and restricted stock produces efficient investment. Kole (1997) finds that stock options and restricted stocks are common in R&D intensive industries, but the difference in corporate use of restricted stocks between high- and low-R&D intensive industries is economically and statistically more significant than the difference of corporate use of stock options. However, Ryan and Wiggins (2002) report that R&D investment is positively related to stock options but negatively related to restricted stocks. This finding is, they interpret, because the linear payoff of restricted stock encourages managers to avoid risky investment and the nonlinear payoff of options motivates risk-taking behavior.

[29] Bryan, Hwang and Lilien (2000), and Ryan and Wiggins (2002) contend that restricted stock grants, due to their linear payoffs, are relatively inefficient in inducing risk-averse CEOs to accept risky, value-increasing investment projects. On the other hand, it is plausible that the linear payoff of restricted stock grants does not adversely affect CEO decisions because it precludes the potential of earning a windfall in the short-term and discourages CEOs from making decisions that could be harmful to stakeholders' long-term interests.

Hypothesis # 3a: All other things equal, equity mispricing caused by agency conflicts between managers and outside investors should be mitigated by the use of restricted stock grants in CEO compensation packages.

Hypothesis # 3b: All other things equal, equity mispricing caused by agency conflicts between managers and outside investors should be exaggerated by the use of stock option grants in CEO compensation packages.

III. Data and Measures

I extract return data from the Center for Research in Securities Prices (*CRSP*) where NYSE, AMEX, and Nasdaq stocks are listed. The initial sample includes all firms in CRSP from 1985 to 2004, omitting financial (SIC 6000-6999) and utility (SIC 4900-4999) firms. Accounting and financial data are drawn from *COMPUSTAT*. Firms with market value of equity less than $20 million are excluded in order to avoid cases of firms with distorted valuation multiples in the mispricing measures. I collect CEO compensation data from the sample of firms in Standard and Poor's (S&P) *ExecuComp* database. The S&P's *ExecuComp* database covers the period from year 1992 to 2003, and includes executive compensation data for firms in the S&P 1500 index, which comprises the S&P 500, the S&P 400 mid cap, and the S&P 600 small cap indices. *ExecuComp* also contains information on firms that are not currently in the S&P500, the S&P400, and the S&P 600 indices, but were previously included in one of the aforementioned indices. According to *ExecuComp*, CEOs' total compensation is comprised of seven items: 1) salary, 2) bonus, 3) stock options granted, 4) restricted stock grants, 5) long-term incentive plan, 6) other annual compensation, and 7) all other compensation. Details of all compensation variables are provided in Table 10 and summary statistics are documented in Table 11.

The final sample includes 38,781 firm-year observations with 6,446 firms during the sample period. For the tests that utilize CEO compensation data the sample is reduced to 8.657 firm-year observations.

A. Measures of Equity Mispricing

Firm mispricing is measured as the deviation of a firm's equity value from its intrinsic or fundamental value. I develop six alternative mispricing measures. The first four measures employ alternative techniques in estimating intrinsic value benchmarks, the fifth measure is based on a standard asset pricing model, and the last one is an index that combines all measures. The mispricing measures are as follows.

1) $|EXVRI_{i,t}|$, the absolute value of the natural logarithm of the ratio between the stock price and its intrinsic value from Ohlson's (1995) residual income value approach. *EXVI* is computed at the end of June of each year.

$$EXVRI_{i,t} = \ln\left[\frac{PRICE_{i,t}}{I(V)_{i,t}}\right], \tag{1}$$

where $PRICE_{i,t}$ is the stock price at the end of June of each year from CRSP, and $I(V)_{i,t}$ is intrinsic value using the residual income model (Ohlson (1995)) and median values of analysts' forecasts issued in June, as in Frankel and Lee (1998). There is strong empirical evidence in support of the residual income valuation, V/P, as an indicator of mispricing.[30]

2) $|EXVBO_{i,t}|$, the absolute value of excess value computed at the end of June of each year as the natural logarithm of the ratio between a firm's capital and its imputed value, based on Berger and Ofek (1995) approach.

$$EXVBO_{i,t} = \ln\left[\frac{CPTL_{i,t}}{I(CPTL)_{i,t}}\right], \tag{2}$$

where $CPTL_{i,t}$ is total capital, which is market value of equity plus book value of debt, $I(CPTL_{i,t})$ is the imputed value derived as the product of firm sales and the median capital to sales ratio in the firm's industry. The industry classification here is based on the Fama-French 48 sectors. This measure of mispricing is constructed in a similar fashion as the first one ($EXVRI_{i,t}$), but uses firm's total capital instead of price and computes imputed value based on Fama-French 48 industry classification.

3) $|EXVRK_{i,t}|$, the absolute value of the firm-specific component of the difference between market value and fundamental value, based on Model III of Rhodes-Kropf *et al.* (2005). This procedure differs from the residual income valuation approach in the sense that it does not rely on analysts' earnings forecasts. According to Rhodes-Kropf *et al*. (2005), fundamental value, *V* is estimated by decomposing the market-to-book into two components: a measure of price to fundamentals (ln(M/V)), and a measure of

[30] Lee, Myers and Swaminathan (1999) report that V/P predicts one-month-ahead returns on the Dow 30 stocks better than aggregate book-to-market. Frankel and Lee (1998) also show that the residual income value is a better predictor than book value of the cross-section of contemporaneous stock prices, and that V/P is a predictor of the one-year-ahead cross-section of returns. In addition, Ali *et al.* (2003) show that after controlling for several possible risk factors, V/P continues to significantly predict future returns. D'Mello and Shroff (2000) apply V/P to measure mispricing of equity repurchases, and Dong *et al.* (2006) to takeovers.

fundamentals to book value (ln(V/B)). The first component captures the part of book-to-market associated with mispricing. In extreme cases where markets perfectly anticipate, this component would be equal to zero, otherwise positive (over-valuation) or negative (under-valuation). This component is further decomposed into firm-specific and industry-specific misprising. In my tests, I use the firm-specific mispricing component based on Model III of Rhodes-Kropf *et al*. (2005) that also accounts for net income and leverage effects.

$$\ln(M_{i,t}) = \alpha_{0j,t} + \alpha_{1j,t} \ln(B_{i,t}) + \alpha_{2j,t} \ln(NI)^{+}_{i,t} + \alpha_{3j,t} I_{(<0)}\ln(NI)^{+}_{i,t} + \alpha_{4j,t} \ln(LEV_{i,t}) + \zeta_{i,t} \tag{3}$$

where M is firm value, B is book value, NI^{+} is absolute value of net income, $I_{(<0)}\ln(NI)^{+}$ is an indicator function for negative net income observations, and LEV is the leverage ratio.

4) $|MBIA_{i,t}|$, the absolute value of the industry-adjusted market-to-book ratio.

$$MBIA_{i,t} = \ln\left[\frac{MB_{i,t}}{Med(MB)_{j,t}}\right], \tag{4}$$

where, $MB_{i,t}$ is the market to book ratio for firm i at time t, and $Med(MB_{j,t})$ is the j^{th} industry median of MB_t. Several empirical studies have utilized MB as a mispricing measure (see, among others, Walkling and Edmister (1985), Rau and Vermaelen (1998) and Ikenberry, Lakonishok and Vermaelen (1995)).

5) $|ARET|$, the absolute value of a firm's average monthly abnormal return for each year. The expected return of month t is computed using the factor coefficients obtained from the Fama/French three-factor model estimated over the five-year period

immediately preceding month t. For example, the 60-month period from January 1987 to December 1991 is used to estimate the parameters used to compute the expected return for January 1992. The estimation of the parameters is based on the following model:

$$E(R_{i,t}) - R_{f,t} = \beta_0 + \beta_M (R_{m,t} - R_{f,t}) + \beta_{SMB}\, SMB_t + \beta_{HML}\, HML_t + \psi_{it} \qquad (5)$$

where $E(R_{it})$ is the rate of return on the ith company's common stock in month t, $R_{f,t}$ is risk-free rate, $R_{m,t}$ is the value-weighted market portfolio return, and SMB_t and HML_t are the size and book-to-market factors as in Fama and French (1993, 1996). Abnormal returns, $ARET_{i,t}$, are computed as differences of actual returns, $R_{i,t}$, from the expected returns derived from the parameters of model (5). The mispricing from standard asset pricing model is:

$$|ARET_{i,t}| = |R_{i,t} - E(R_{i,t})| \qquad (6)$$

6) $MI_{i,t}$, a mispricing index that combines all five mispricing measures described above.[31] The mispricing index is constructed each year for each observation $i = 1,\ldots,N$ as:

$$MI_i = \frac{1}{N}\frac{1}{K}\sum_{k}^{K} RANK_k(|\,EXV_{i,k}\,|)\,, \qquad (7)$$

where $Rank_k(|EXV_{i,k}|)$ is the rank function which assigns a rank for each observation from least misvalued (rank of one) to most misvalued (rank of N). $|EXV_{i,k}|$ is the k^{th} measure of mispricing for firm i in the sample, and K represents the dimensions of mispricing measures. The denominator, K, averages the ranks by the number of

[31] In constructing MI, I employ the methodology outlined in Butler, Grullon, and Weston (2005). In their paper, they create a liquidity index that comprises the effects of ranking on 6 different liquidity measures.

mispricing values available for each firm in the sample in a particular year. For example, the sum of the $Rank_k(|EXV_{i,k}|)$ values of a firm that has only 3 mispricing measures is divided by K=3. Finally, dividing by N, I scale the *MI* from 0 (least mispriced) to 1 (most mispriced). By computing average of all ranks from five different mispricing measures, *MI* has the advantage that it balances out the effects and shortcomings of all other mispricing measures while aggregating their informativeness, and thereby provides a more complete picture of mispricing.

Detailed descriptions for all variables used to construct *MI* and their summary statistics can be found in Tables 10 and 11, respectively. Panel A of Table 12 shows the coefficients of correlations between the different mispricing measures. As expected, all mispricing measures are significantly positively correlated at the one percent level, or better, even though these valuation measures are based on widely different theoretical concepts and their measurements rely on a variety of accounting and/or financial variables. All individual mispricing measures are more significantly and positively correlated with the mispricing index (*MI*) than with the other individual measures, suggesting that *MI* is an appropriate aggregate measure of mispricing for use in the tests.

Table 10
Variable Definitions

Variables	Descriptions
Mispricing measures	
$\lvert EXVRI\rvert$	Absolute value of excess value based on Ohlson's (1995) residual income value approach. $EXVRI_{it} = \ln\left[PRICE_{it}/I(V)_{it}\right]$,where $PRICE_{it}$ is the stock price at the end of June of each year from CRSP, and $I(V)_{it}$ is intrinsic value using the residual income model (Ohlson (1995)) and median values of analysts' forecasts issued in June, as in Frankel and Lee (1998).
$\lvert EXVBO\rvert$	Absolute value of excess value based on Berger and Ofek (1995) approach. $EXVBO_{i,t} = [CPTL_{i,t} / I(CPTL)_{i,t}]$, where $CPTL_{i,t}$ is total capital, which is market value of equity plus book value of debt, $I(CPTL_{i,t})$ is the imputed value derived as the product of firm sales and the median capital to size ratio in the firm's industry. The industry classification here is based on the Fama-French 48 sectors. This measure of mispricing is constructed in a similar fashion as the first one ($EXVRI_{i,t}$), but uses firm's total capital instead of price and computes imputed value based on Fama-French 48 industry classification. Thus the intrinsic value here is a size and industry benchmark.
$\lvert EXVRK\rvert$	Absolute value of the excess value based on Rhodes-Kropf *et al.* (2005). Fundamental value, V is estimated by decomposing the market-to-book into two components: a measure of price to fundamentals (ln(M/V)), and a measure of fundamentals to book value (ln(V/B)). The first component captures the part of book-to-market associated with mispricing. This component is further decomposed into firm-specific and industry-specific misprising. I use the firm-specific mispricing component based on Model III of Rhodes-Kropf *et al*. (2005) that also accounts for net income and leverage effects. $\ln(M_{i,t}) = \alpha_{0j,t} + \alpha_{1j,t}\ln(B_{i,t}) + \alpha_{2j,t}\ln(NI)^{+}_{i,t} + \alpha_{3j,t} I_{(<0)}\ln(NI)^{+}_{i,t} + \alpha_{4j,t}\ln(LEV_{i,t}) + \zeta_{i,t}$, where M is firm value, B is book value, NI^{+} is absolute value of net income, $I_{(<0)}\ln(NI)^{+}$ is an indicator function for negative net income observations, and LEV is the leverage ratio.
$\lvert EXVMB\rvert$	Absolute value of the industry-adjusted market-to-book ratio. $MBIA_{i,t} = \ln[MB_{i,t} / Med(MB)_{j,t}]$, where, $MB_{i,t}$ is the market to book ratio for firm i at time t, and $Med(MB_{j,t})$ is the j^{th} industry median of MB_t.
$\lvert ARET\rvert$	Absolute value of a firm's average monthly abnormal return for each year. The expected return of month t is computed using benchmarks from the Fama/French three-factor model estimated over the five-year period immediately preceding month t. The estimation of the parameters is based on the model, $E(R_{i,t}) - R_{f,t} = \beta_0 + \beta_M (R_{m,t} - R_{f,t}) + \beta_{SMB}\, SMB_t + \beta_{HML}\, HML_t + \psi_{it}$, where $E(R_{it})$ is the rate of return on the ith company's common stock in month t, $R_{f,t}$ is risk-free rate, $R_{m,t}$ is the value-weighted market portfolio return, and SMB_t and HML_t are the size and book-to-market factors as in Fama and French (1993, 1996). Abnormal returns, $ARET_{i,t}$, are computed as differences of actual returns, $R_{i,t}$, from the expected returns derived from the parameters of model, and $\lvert ARET_{i,t}\rvert = \lvert R_{i,t} - E(R_{i,t})\rvert$
MI	Mispricing index. $MI_i = (1/N)(1/K)\sum_k^K RANK_k(\lvert EXV_{i,k}\rvert)$, where $Rank_k(\lvert EXV_{i,k}\rvert)$ is the rank function which assigns a rank for each observation from least misvalued (rank of one) to most misvalued (rank of N). $\lvert EXV_{i,k}\rvert$ is the k^{th} measure of mispricing for firm i in my sample, and K represents the dimensions of mispricing measures. The denominator, K, averages the ranks by the number of mispricing values available for each firm in the sample in a particular year. N is number of observations. MI is scaled from 0 (least mispriced) to 1 (most mispriced).

Table 10 (Continued)

Variables	Descriptions
Agency cost measures	
FCF	Free cash flows computed as the interaction of the growth with free cash flows. $FCF_{i,t} = \left(Free\ cash\ flows_{i,t} / Total\ assets_{i,t}\right) \times Gowth\ dummy_{i,t}$, where *Free cash flow* = operating income before depreciation – (taxes + interest expense + dividends paid). *Growth dummy* = 1 if the firm's Tobin's q is less than 1 and 0 otherwise. Tobin's q = [market value of common equity + preferred stock liquidating value + long-term debt – (short-term assets – short-term liabilities)] / (total assets).
EXPR	Expense ratio which measures the inefficiency in the management control of operating costs. $EXPR_{i,t} = Operating\ expense_{i,t} / Sales_{i,t}$.
AUR	Asset utilization ratio which measures the effectiveness of firm's management in deploying assets. $AUR_{i,t} = Sales_{i,t} / Total\ assets_{i,t}$
INDB	Proportion of independent directors on corporate board.
IO	Institutional ownership which is the percentage of shares that are owned by institutional investors.
GI	Corporate governance index constructed by Gompers et al. (2003) to proxy for the level of shareholder rights. The Governance Index is constructed by counting 28 provisions listed in 5 categories: *Delay*, *Protection*, *Voting*, *Other*, and *State*. Among 28 provisions, 24 are unique and equally weight in index. A firm with high governance index (i.e., many anti-takeover provisions) is expected to have high level of agency problem.
CMPT	Product market competition which is computed as the inverse value of Herfindahl concentration index. $CMPT_i =$ $= 1 - \left[\sum_j \left(Sales_j\right)^2 \Big/ \left(\sum_j Sales_j\right)^2 \right]$, where $Sales_j$ is the annual sales of j^{th} firm belonging to the industry in which firm i is included. A higher *CMPT* (i.e., lower Herfindahl index) thus indicates that a product market is more competitive.
ACOV	Analyst coverage is computed as residual from the regression of analyst coverage on firm size. Forecast variable is extracted from security analyst' one fiscal year-ahead forecasts collected every June from *I/B/E/S* Detail History Database.
AFE	Analyst earnings forecast error. $AFE_{i,t} = \left[\lvert Med(AF)_{i,t} - EPS_{i,t+1} \rvert / \lvert Med(AF)_{i,t} \rvert \right]$, where $Med(AF)_{i,t}$ is the median forecast and the actual earnings per share $EPS_{i,t+1}$ is the actual earnings per share. Variables are extracted from security analyst' one fiscal year-ahead forecasts collected every June from *I/B/E/S* Detail History Database.
AFD	Analyst earnings forecast dispersion. $AFD_{i,t} = Std.Dev.(AF)_{i,t} / \lvert Med(AF)_{i,t} \rvert$, where $Std.Dev.(AF)_{i,t}$ is standard deviation of one year ahead forecasts. Variables are extracted from security analyst' one fiscal year-ahead forecasts collected every June from *I/B/E/S* Detail History Database.
ACI	Agency cost index. *ACI* is constructed by using the same methodology for mispricing index (*MI*) and by combining all ranks of five variables (*FCF*, *EXPR*, *GI*, *AFE*, and *AFD*) and inverse ranks of five variables (*AUR*, *INDB*, *IO*, *CMPT*, and *ACOV*). *ACI* is scaled from 0 (least agency costs) to 1 (greatest agency costs).

Table 10 (Continued)

Variables	Descriptions
Compensation variables	
TCOMP	Total compensation (in thousand $) which comprises 7 items: 1) salary, 2) bonus, 3) exercised options, 4) restricted stock grant, 5) long-term incentive plan, 6) other annual compensation, and 7) all other compensation.
SALARY	Salary which is the dollar value (in thousand $) of the base salary (cash and non-cash).
BONUS	Bonus which is the dollar value (in thousand $) of a bonus (cash and non-cash).
RSTOCK	Restricted stock grant which is the value (in thousand $) of restricted stock granted which is determined as of the date of the grant.
OPTION	Stock option grant is the aggregated dollar value (in thousand $) of stock options granted to the CEO during the year as valued using S&P's Black-Scholes methodology.
LTIP	Long-term incentive plan is the dollar value (in thousand $) paid out to the CEO under the company's long-term incentive plan. forgiveness, 3) imputed Interest, 4) payouts for cancellation of stock options, 5) payment for unused vacation, 6) tax reimbursements, 7) signing bonuses, 8) 401K contributions, and 9) life insurance premiums.
OTHERC	Other annual compensation which is the dollar value (in thousand $) of other annual compensation not properly categorized as salary or bonus. This includes items such as: 1) perquisites and other personal benefits, 2) above market earnings on restricted stock, options/SARs or deferred compensation paid during the year but deferred by the officer, 3) earnings on long-term incentive plan compensation paid during the year but deferred at the election of the officer, 4) tax reimbursements, and 5) the dollar value of difference between the price paid by the officer for company stock and the actual market price of the stock under a stock purchase plan that is not generally available to shareholders or employees of the company (Note: This does not include value realized from exercising stock options).
ALLOC	All other compensation which is the dollar value (in thousand $) listed under "All Other Compensation" in the Summary Compensation Table. This is compensation that does not belong to other categories, which includes items such as: 1) severance payments, 2) debt forgiveness, 3) imputed Interest, 4) payouts for cancellation of stock options, 5) payment for unused vacation, 6) tax reimbursements, 7) signing bonuses, 8) 401K contributions, and 9) life insurance premiums.
%RSTOCK	Restricted stock grant / total compensation.
%OPTION	Stock option grant / total compensation.
Firm characteristic	
SIZE	Log of total assets.
LEV	Leverage. The ratio of long-term debt to total assets.
ROA	Return on assets. The ratio of net income to total assets.
AGE	Firm age. *AGE* = ln(1+ *age*), where age is the number of years since the stock inclusion in the *CRSP* database.
DIVER	Diversification dummy that equals one if a firm operates in multi-segments and zero otherwise.
DD	Dividend-payer dummy that equals one if a firm pays dividends and zero otherwise.

Table 11
Descriptive Statistics

Reported are descriptive statistics for my sample firms. The sample contains 38,781 firm-year observations (6,446 firms) over the period 1985 – 2004. All variables are as defined in Table 10.

Variables	N	Mean	Std.Dev.	5%	Median	95%
Mispricing measures						
Ohlson (1995) approach (|*EXVRI*|)	36,115	0.794	0.841	0.077	0.677	1.889
Berger and Ofek (1995) approach (|*EXVBO*|)	38,582	0.641	0.608	0.036	0.489	1.739
Rhodes-Kropf *et al.* (2005) approach (|*EXVRK*|)	38,779	0.385	0.355	0.025	0.288	1.081
Market-to-book ratio approach (|*EXVMB*|)	38,781	0.404	0.379	0.018	0.302	1.155
Abnormal return approach (|*ARET*|)	38,775	0.102	0.056	0.039	0.089	0.207
Mispricing index (*MI*)	38,781	0.502	0.172	0.240	0.489	0.805
Agency cost measures						
Free cash flow (*FCF*)	27,129	0.013	0.035	0	0	0.084
Expense ratio (*EXPR*)	27,815	0.375	4.196	0.047	0.228	0.692
Asset utilization ratio (*AUR*)	38,781	1.208	0.807	0.243	1.071	2.648
Independent board of directors (*INDB*)	9,373	0.626	0.193	0.273	0.667	0.889
Institutional ownership (*IO*)	30,483	0.503	0.243	0.093	0.513	0.892
Governance index (*GI*)	15,613	9.073	2.748	5	9	14
Product market competition (*CMPT*)	38,781	0.876	0.105	0.669	0.914	0.971
Analyst coverage (*ACOV*)	36,827	-2×10^{-9}	5.517	-7.623	-0.574	10.39
Analyst earnings forecast error (*AFE*)	34,022	0.823	6.306	0.005	0.130	2.587
Analyst earnings forecast dispersion (*AFD*)	33,097	0.220	1.272	0.009	0.048	0.706
Agency cost index (*ACI*)	38,781	0.505	0.130	0.295	0.503	0.724
Compensation variables						
Total compensation (*TCOMP*)	10,812	3,768	13,820	322.9	1,366	12,919
Salary (*SALARY*)	10,812	592.0	338.7	206.1	530.0	1102
Bonus (*BONUS*)	10,812	580.5	1061	0	311.8	2000
Restricted stock grant (*RSTOCK*)	10,812	425.0	9053	0	0	1307
Stock options (*OPTION*)	10,812	1851	9684	0	0	8460
Long-term incentive plan (*LTIP*)	10,812	139.4	793.4	0	0	714.0
Other annual compensation (*OTHERC*)	10,812	43.20	225.9	0	0	182.1
All other compensation (*ALLOC*)	10,812	136.8	794.4	0	16.64	400.3
% of restricted stock grant (*%RSTOCK*)	10,812	0.052	0.142	0	0	0.393
% of stock options (*%OPTION*)	10,812	0.182	0.296	0	0	0.858
Firm characteristics						
Firm size (*SIZE*)	38,781	19.76	1.677	17.36	19.56	22.86
Leverage (*LEV*)	38,647	0.163	0.179	0	0.103	0.536
Return on assets (*ROA*)	38,781	0.031	0.121	-0.182	0.049	0.161
Firm age (*AGE*)	38,781	2.334	0.843	1.099	2.398	3.555
Diversification dummy (*DIVER*)	31,798	0.328	0.469	0	0	1
Dividend-payer dummy (*DD*)	37,350	0.381	0.486	0	0	1

Table 12
Correlations Coefficients between Index and Individual Measures

This table shows the correlations coefficients between index and individual measures and corresponding p-values in brackets. All variables are as defined in Table 10. *, **, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Panel A: Correlations between mispricing index (*MI*) and individual measures

	Constructed sign of correlation with *MI*	*MI*	|*EXVRI*|	|*EXVBO*|	|*EXVRK*|	|*EXVMB*|
Ohlson (1995) approach (|*EXVRI*|)	+	0.323*** [0.000]				
Berger and Ofek (1995) approach (|*EXVBO*|)	+	0.514*** [0.000]	0.084*** [0.000]			
Rhodes-Kropf *et al.* (2005) approach (|*EXVRK*|)	+	0.688*** [0.000]	0.175*** [0.000]	0.252*** [0.000]		
Market-to-book ratio approach (|*EXVMB*|)	+	0.705*** [0.000]	0.142*** [0.000]	0.300*** [0.000]	0.749*** [0.000]	
Abnormal return approach (|*ARET*|)	+	0.435*** [0.000]	0.117*** [0.000]	0.206*** [0.000]	0.200*** [0.000]	0.191*** [0.000]

Table 12 (Continued)

	Constructed sign of correlation with *ACI*	*ACI*	*FCF*	*EXPR*	*AUR*	*INDB*	*IO*	*GI*	*CMPT*	*ACOV*	*AFE*
Free cash flow (*FCF*)	+	0.160*** [0.000]									
Expense ratio (*EXPR*)	+	0.049*** [0.000]	-0.012* [0.051]								
Asset utilization ratio (*AUR*)	-	-0.438*** [0.000]	0.139*** [0.000]	-0.044*** [0.000]							
Independent board of directors (*INDB*)	-	-0.163*** [0.000]	0.008 [0.453]	-0.026** [0.020]	-0.017 [0.109]						
Institutional ownership (*IO*)	-	-0.415*** [0.000]	-0.027*** [0.000]	-0.013* [0.041]	-0.038*** [0.000]	0.244*** [0.000]					
Governance index (*GI*)	+	0.074*** [0.000]	0.024*** [0.007]	-0.027*** [0.002]	0.034*** [0.000]	0.263*** [0.000]	0.103*** [0.000]				
Product market competition (*CMPT*)	-	-0.346*** [0.000]	-0.003 [0.659]	-0.006 [0.328]	0.115*** [0.000]	-0.037*** [0.000]	0.057*** [0.000]	-0.032*** [0.000]			
Analyst coverage (*ACOV*)	-	-0.364*** [0.000]	-0.147*** [0.000]	0.001 [0.923]	-0.017*** [0.001]	-0.012 [0.253]	0.043*** [0.000]	-0.018** [0.023]	0.015*** [0.005]		
Analyst earnings forecast error (*AFE*)	+	0.150*** [0.000]	0.002 [0.817]	0.001 [0.831]	-0.026*** [0.000]	-0.019* [0.090]	-0.044*** [0.000]	-0.005 [0.570]	-0.008 [0.165]	-0.031*** [0.000]	
Analyst earnings forecast dispersion (*AFD*)	+	0.184*** [0.000]	-0.005 [0.460]	0.011 [0.103]	-0.050*** [0.000]	-0.013 [0.210]	-0.040*** [0.000]	-0.001 [0.862]	-0.015*** [0.006]	-0.020*** [0.000]	0.684*** [0.000]

B. Measures of Agency Costs

Financial economists have attempted to measure firms' propensity for agency conflicts by using measures of internal and external agency problem resolution mechanisms. Agrawal and Knoeber (1996) address the empirical implications of the interdependence among such mechanisms. They examine seven mechanisms that potentially can control agency problems and present evidence of interdependence, suggesting that results obtained from cross-sectional OLS regressions of firm performance on several single mechanisms may be misleading. Therefore, to avoid this problem, I utilize ten measures used in past studies, and combine them into an agency costs index for each firm. These measures are described below.

1) *FCF*, free cash flow. Agency conflicts involving free cash flows are likely to be prevalent in low growth firms because they generally have substantial free cash flow, which managers could decide to overinvest. In contrast, high growth firms are not as likely to suffer from the free cash flow problem because they are usually short of cash after using internal funds for funding new projects and often need to rely on external financing to cover their financing needs. Therefore, following Doukas, Kim, and Pantzalis (2000) I proxy agency costs of free cash flow using the interaction of a poor growth opportunities indicator with free cash flows standardized by total assets.

$$FCF_{i,t} = \left(\frac{Free\ cash\ flows_{i,t}}{Total\ assets_{i,t}} \right) \times Gowth\ dummy_{i,t}, \tag{8}$$

where *Free cash flow* is measured as operating income before depreciation minus the sum of taxes, interest expense, and dividends paid (see Lehn and Poulsen (1989)).

Growth dummy takes the value of 1 if the firm's Tobin's q is less than 1 (indicating a poorly managed firm) and the value of 0 otherwise, where Tobin's q is computed as [market value of common equity + preferred stock liquidating value + long-term debt – (short-term assets – short-term liabilities)] / (total assets), as in Chung and Pruitt (1994).

2) *EXPR*, the expense ratio which measures managers' inefficiency in terms of controlling operating costs. High *EXPR* represents high agency costs.

$$EXPR_{i,t} = \left(\frac{Operating\ expense_{i,t}}{Sales_{i,t}} \right). \tag{9}$$

3) *AUR*, the asset utilization ratio which measures the effectiveness of firm's management in deploying assets. The idea behind the asset utilization ratio as a measure of agency costs is that when a firm has low sales-to-asset ratio, it is likely that managers act inefficient ways by making poor investment decisions, consuming executive perquisites, etc. Therefore, *AUR* should be inversely related to agency costs.

$$AUR_{i,t} = \left(\frac{Sales_{i,t}}{Total\ assets_{i,t}} \right). \tag{10}$$

Both *EXPR* and *AUR* have been used in Ang, Cole, and Lin (2000).

4) *INDB*, the proportion of independent directors on corporate board. A smaller *INDB* is an indicator of higher potential for agency conflicts. Cotter, Shivdasani, and Zenner (1997) show that target shareholder gains from tender offers are higher when the target's board is more independent, suggesting that independent directors are more

likely to use resistance strategies to enhance shareholder wealth. This notion is also supported by the findings of Uzun, Szewczyk, and Varma (2004). They show that the likelihood of corporate fraud declines as the fraction of independent directors increases.

5) *IO*, the institutional ownership which is the percentage of shares that are owned by institutional investors. Given institutional investors' monitoring role, *IO* should be inversely related to agency costs. Brickley, Lease, and Smith (1988) show that institutional investors and other blockholders vote more actively on anti-takeover amendments than non-blockholders, and that institutional opposition is greater when the proposal seems to harm stockholders. McConnell and Servaes (1990) find a significant and positive relation between Tobin's q and the fraction of shares owned by institutional investors. Jiambalvo, Rajgopal, and Venkatachalam (2002) find that the extent to which stock prices lead earnings is positively associated with the level of institutional ownership. Hartzell and Starks (2003) find that institutional ownership concentration is positively related to the pay-for-performance sensitivity of managerial compensation and negatively related to the level of compensation. They suggest that the institutional investors serve a monitoring role in mitigating the agency problems between shareholders and managers. Therefore, the higher the percentage ownership by institutions, the lower should be the agency costs.

6) *GI*, the corporate governance index constructed by Gompers, Ishii, and Metrick (2003) to proxy for the level of shareholder rights. The Governance Index is constructed by counting 28 provisions related to shareholder protection and listed in 5

categories: *Delay*, *Protection*, *Voting*, *Other*, and *State*. Among the 28 provisions, 24 are unique and enter the index with equal weight. Gompers *et al.* (2003) construct the governance index without requiring any judgment about the efficacy or wealth effects of any of these provisions but consider their impact on the balance of power between managers and outside shareholders. Based on Jensen's (1986) argument that threat of takeover is a strong form of managerial discipline, a firm with high governance index (i.e., many anti-takeover provisions) is expected to have high level of agency problem.

7) *CMPT*, product market competition. The competition in the product markets drives prices towards minimum average cost in an activity, thereby motivating managers to increase firm efficiency. Hart (1983), in a theoretical model shows that the competition in the product market reduces the amount of managerial slack. Some studies have empirically tested the relation between product market competition and corporate agency costs. For example, Jagannathan and Srinivasan (1999) show that competition in the product market reduces agency costs. My proxy for the competition in the product market is computed as the inverse value of Herfindahl concentration index.

$CMPT_i$ = 1 – Herfindahl concentration index

$$= 1 - \left[\sum_j \left(Sales_j \right)^2 \Big/ \left(\sum_j Sales_j \right)^2 \right], \tag{11}$$

where $Sales_j$ is the annual sales of j^{th} firm belonging to the industry in which firm i is included. If the total amount of sales in the industry is dominated by few firms, then the Herfindahl index will show a high value near one. Higher values of *CMPT* (i.e., lower Herfindahl index) thus indicate that the product market is more competitive, and therefore *CMPT* should be negatively related to agency costs.

8) *ACOV*, analyst coverage. Security analysis can act as a monitoring mechanism in reducing agency costs (Doukas *et al.* (2000)), and therefore *ACOV* is expected to be negatively related to agency costs. Hong, Lim, and Stein (2000) point out that there is a strong firm-size effect on analyst coverage. Therefore, the analyst coverage measure is based on the residuals from the regression of analyst coverage on firm size.

9) *AFE*, analyst earnings forecast error. The forecast error captures forecasting ability of security analysts covering the firm. The absolute forecast error has been also used by several studies as a proxy of information asymmetry (e.g., see Atiase and Bamber (1994), and Christie (1987)). If a firm is transparent, the considerable amount of information about future earnings is available to market participants, and so analysts make accurate earnings forecasts. Therefore, *AFE* should be positively related to agency costs.

$$AFE_{i,t} = \frac{|\,Med(AF)_{i,t} - EPS_{i,t+1}\,|}{|\,Med(AF)_{i,t}\,|}, \tag{12}$$

where $Med(AF)_{i,t}$ is the median forecast and the actual earnings per share $EPS_{i,t+1}$ is the actual earnings per share.

10) *AFD*, analyst earnings forecast dispersion. Barron, Kim, Lim and Stevens (1998) show that analyst forecast dispersion reflects both diversity of analyst beliefs and the lack of precision in analyst forecasts. Prior studies have also used the dispersion of analyst forecasts as an information asymmetry proxy (e.g., see Krisnhnaswami and

Subramaniam (1999)). *AFD* is therefore supposed to be positively related to agency costs.

$$AFD_{i,t} = \frac{Std.Dev.(AF)_{i,t}}{|\,Med(AF)_{i,t}\,|}, \tag{13}$$

where $Std.Dev.(AF)_{i,t}$ is standard deviation of one year ahead forecasts. Analyst coverage, *ACOV*, and the two analyst forecast-based variables (*AFE* and *AFD*) are constructed from security analysts' one fiscal year-ahead forecasts collected every June from the *I/B/E/S* Detail History Database.

11) *ACI*, an agency cost index that combines all ten agency cost measures described above. Five variables (*FCF*, *EXPR*, *GI*, *AFE*, and *AFD*) are positively related to agency costs, while the other five variables (*AUR*, *INDB*, *IO*, *CMPT*, and *ACOV*) are inversely related. Thus, I construct an index (*ACI*) for firm's agency costs by combining ranks of former five measures and inverse ranks of later five variables. The methodology used in the construction of *ACI* is the same as the one used for the mispricing index (*MI*).

Table 10 provides detailed descriptions of all variables used to construct *ACI* and Table 11 documents descriptive statistics. Correlation coefficients are reported in Panel B of Table 12. By construction, free cash flows, expense ratio, governance index, forecast error, and forecast dispersion are positively associated with the agency cost index. In contrast, asset utilization ratio, proportion of independent directors, institutional ownership, product market competitiveness, and analyst coverage are negatively related to agency cost index.

IV. Agency Costs and Equity Mispricing

In this section, I present analysis based on univariate tests, the design of my multivariate tests' empirical methodology, and regression evidence on the relation between agency costs and equity mispricing.

A. Univariate Analyses

Table 13 illustrates how high agency cost firms differ from low agency cost firms in terms of firm characteristics. It reports mean values of all variables used in the study for the quintile groups classified based on the level of the agency cost index (*ACI*). Also reported are the mean differences across the two extreme groups (highest versus lowest *ACI* quintiles) and the corresponding t-statistics for the mean difference tests. In line with hypothesis #1, the mispricing index (*MI*) shows a positive relation with the level of agency costs. The mean difference of *MI* between the highest and lowest *ACI* quintile groups is 0.038 with t-statistic of 13.92. The dollar amount of the different CEO compensation components, in most cases, is on average lower for firms in the highest *ACI* quintile compared to firms in the lowest *ACI* quintile. The evidence from the remaining firm-specific variables is consistent with prior studies examining the relationship of agency costs and firm characteristics. Firms with high levels of agency costs are generally younger, smaller, more levered and less profitable than firms with low levels of agency costs. They are also more likely to be diversified across many industries, and less likely to pay dividends.

Table 13
Univariate Tests

Reported are mean values of variables for the quartile subsamples sorted on agency cost index (*ACI*). Also reported are the differences in mean values between high- and low-*ACI* firms and the corresponding t-statistics. All variables are as defined in Table 10. * and *** indicate significance at the 10%- and 1%-levels, respectively.

	Sorted on agency cost index (*ACI*)						
	Low Q1	Q2	Q3	Q4	High Q5	Mean diff.: High - Low	t-stat: Diff.=0
Mispricing measure							
Mispricing index (*MI*)	0.504	0.479	0.482	0.502	0.541	0.038***	13.92
Compensation variables							
Total compensation (*TCOMP*)	4899	3926	3202	3388	2367	-2531***	-4.30
Salary (*SALARY*)	613.4	611.9	577.3	573.8	553.1	-60.34***	-5.28
Bonus (*BONUS*)	660.9	651.8	534.2	526.2	403.5	-257.4***	-7.97
Restricted stock grant (*RSTOCK*)	829.5	266.8	327.3	255.5	244.0	-585.4	-1.18
Stock options (*OPTION*)	2518	2061	1393	1712	874.1	-1644***	-5.78
Long-term incentive plan (*LTIP*)	109.7	190.8	152.3	121.9	101.8	-7.949	-0.32
Other annual compensation (*OTHERC*)	45.19	40.88	40.57	43.25	48.27	3.079	0.38
All other compensation (*ALLOC*)	122.3	102.7	177.3	155.0	142.4	20.12	0.93
% of restricted stock grant (*%RSTOCK*)	0.054	0.047	0.057	0.048	0.055	0.001	0.28
% of stock options (*%OPTION*)	0.238	0.203	0.162	0.146	0.094	-0.144***	-14.08
Firm characteristics							
Firm size (*SIZE*)	20.04	19.98	19.78	19.58	19.42	-0.614***	-23.57
Leverage (*LEV*)	0.104	0.139	0.165	0.188	0.217	0.114***	38.96
Return on assets (*ROA*)	0.084	0.059	0.037	0.006	-0.031	-0.114***	-61.95
Firm age (*AGE*)	2.399	2.440	2.383	2.301	2.150	-0.250***	-18.96
Diversification dummy (*DIVER*)	0.299	0.339	0.346	0.340	0.314	0.015*	1.80
Dividend-payer dummy (*DD*)	0.471	0.472	0.418	0.332	0.202	-0.269***	-36.15

B. Multivariate Analyses

Univariate tests can only provide limited insight into whether the positive impact of agency costs on equity mispricing is driven by other firm variables. This potential limit of univariate testing can be overcome in a multivariate test setting. I perform the multivariate analysis of the relation between agency costs and mispricing by using time-series average of cross-sectional regressions (as in Fama and MacBeth (1973)).[32] I estimate the following regression equation:

$$MI_{i,t} = \beta_0 + \beta_1\, ACI_{i,t} + \beta_2\, SIZE_{i,t} + \beta_3\, LEV_{i,t} + \beta_4\, ROA_{i,t} + \beta_5\, AGE_{i,t} + \beta_6\, DIVER_{i,t} + \beta_7\, DD_{i,t} + \mu_{i,t}, \tag{14}$$

where i indexes firms, t is a yearly time index, and *ACI* is the agency cost index. Based on the literature on equity mispricing, I use a number of different control variables. They are market capitalization (*SIZE*), leverage (*LEV*), profitability (*ROA*), firm age (*AGE*), a diversification dummy (*DIVER*), and a dividend-payer dummy (*DD*). Descriptions of all variables are in Table 10 with descriptive statistics provided in Table 11.

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[32] Following Fama and MacBeth (1973), I estimate separate annual regressions and calculate t-statistics as follows. $t(\overline{\hat{\beta}_j}) = \dfrac{\overline{\hat{\beta}_j}}{s(\hat{\beta}_j)/\sqrt{n-1}}$, where $\overline{\hat{\beta}_j}$ is the mean coefficient over the sample years, $s(\hat{\beta}_j)$ is the standard deviation of the yearly estimates, and n is the number of years.

Table 14
Agency Cost and Equity Mispricing

This table shows time-series average of cross-sectional regressions of mispricing on idiosyncratic volatility and other firm characteristics. All variables are as defined in Table 10. ** and *** indicate significance at the 5%- and 1%-levels, respectively.

	Dep. var. = *MI*		Dep. var. = Log of *MI*	
	[1]	[2]	[3]	[4]
Intercept	0.448***	0.771***	0.360***	0.584***
	(70.37)	(24.94)	(72.46)	(27.35)
Agency cost index (*ACI*)	0.106***	0.031***		
	(8.39)	(2.87)		
Log of *ACI*			0.100***	0.024**
			(8.04)	(2.25)
Log of total assets (*SIZE*)		-0.008***		-0.005***
		(-4.48)		(-4.62)
Leverage (*LEV*)		-0.198***		-0.126***
		(-10.81)		(-10.18)
Return on assets (*ROA*)		-0.069**		-0.047**
		(-2.47)		(-2.61)
Log of firm age (*AGE*)		-0.029***		-0.019***
		(-21.04)		(-20.00)
Diversification dummy (*DIVER*)		-0.030***		-0.020***
		(-10.06)		(-9.64)
Dividend-payer dummy (*DD*)		-0.065***		-0.044***
		(-16.59)		(16.40)
N	38,781	30,716	38,781	30,176
Average R^2	0.91%	21.61%	0.83%	21.57%

The regression results appear in Table 14.[33] Columns [1] and [2] display the models where the mispricing index (*MI*) is the dependent variable, while columns [3] and [4] show results for models where the log-transformed mispricing index is used as dependent variable.[34] The results show a significant positive relation between agency costs and mispricing, suggesting that higher agency costs are strongly associated with higher levels of equity mispricing. In regressions [1] and [2], the estimated coefficient of

[33] It should be noted that the results I obtained using the individual mispricing measures compiled in *MI* are qualitatively similar to the ones reported here. They are left out of the paper for the sake of brevity, but are available upon request.
[34] This transformation is to guard against a possibility that mispricing index (*MI*) which takes value from 0 to 1 can lead to erroneous interpretation of results. I find that the results are, as shown, very similar to ones obtained from the original regressions.

the agency cost index is 0.106 with a t-statistic of 8.39 and 0.100 with a t-statistic of 8.04, respectively. Controlling for other firm characteristics does not qualitatively change the result, even though the coefficients of the agency cost variable and the corresponding t-statistics are reduced. The coefficients of the control variables suggest that equity mispricing is especially high for firms that are small, less leveraged, less profitable, young, and less likely to pay dividends. Contrary to previous studies, e.g. Berger and Ofek (1995), industrial diversification is found to be negatively related to equity mispricing. Overall, the results from Table 14 indicate that the level of agency costs is a strong determinant of equity mispricing in support of hypothesis #1.

C. Robustness Tests

In this sub-section I present several robustness checks aimed at ensuring that the findings in Table V are not due to the particular estimation methodology used. First, since my study relies on cross-sectional/time-series data, I use a fixed-effects model which regards differences between firms as parametric shifts of the regression function and controls for possible differences across firms. Second, I compute difference-in-differences estimates by including year fixed-effects as well as firm fixed-effects. Third, I compute statistical significances using White's (1980) standard errors which are robust to heteroskedasticity. Finally, I estimate a model using only the first-year observation of each firm. This robustness check with the first-year data allows me to assess whether or not previous results are driven by the existence of multiple observations on the same firms. The results of these robustness checks are reported in Table 15. To save space,

Table 15 only reports the results of regression models that include all firm-specific control variables. I find that all regressions show a consistent pattern of coefficients on the agency costs index (*ACI*). They all remain positive and statistically significant. Therefore, the previous results shown in Table 14 are confirmed by these alternative regression models.

V. Interpretation of the Positive Relation between Agency Costs and Equity Mispricing

So far, I have found that the level of agency costs is significantly and positively related with equity mispricing. As discussed earlier, agency theory defines agency costs as the costs incurred by an organization that are associated with problems such as interest conflicts between management and shareholders and/or information asymmetry where managers discriminately have better and/or more information than shareholders. In my previous results, I cannot convey whether mispricing is caused by informational asymmetry or incentive conflicts. To directly test this, I control for equity-based compensation which can potentially resolve agency problems, but not necessarily reduce information asymmetry.

Table 15
Robustness Checks of Regression of Equity Mispricing on Agency Cost

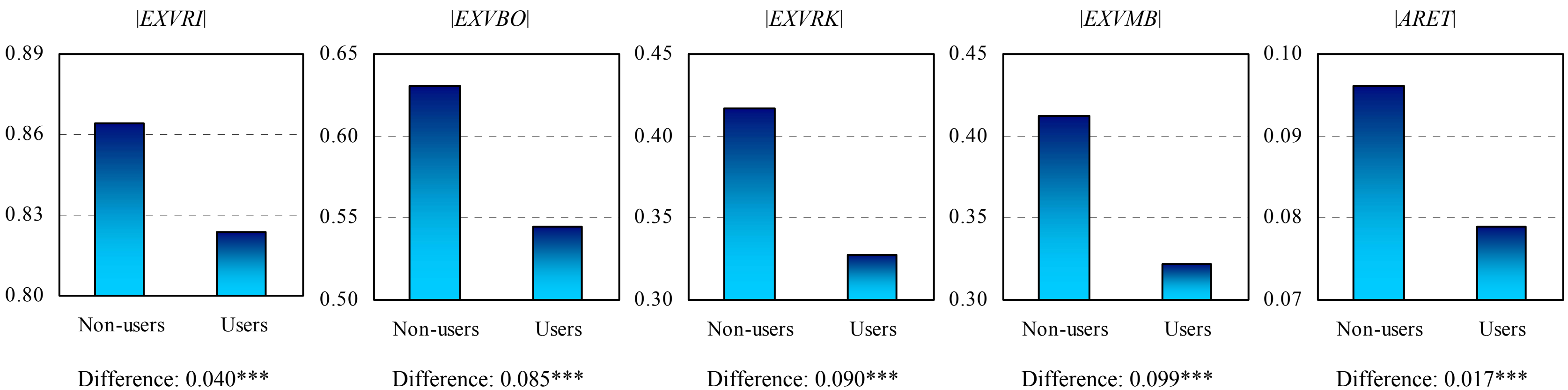
This table reports robustness checks of regressions of mispricing on agency cost and other firm characteristics. Reported are the coefficients and t-statistics of regression models [2] and [4] in Table V. Columns [1] and [2] report results using panel regressions. Columns [3] and [4] report results of regressions computing difference-in-difference estimates (i.e., including firm fixed-effects and year fixed-effects). Columns [5] and [6] report results using White's (1980) heteroskedasticity correction model. Columns [7] and [8] report results only using the first-year data of each firm. All variables are as defined in Table 10. *, **, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	Panel regression model		Difference-in-differences		White's (1980) heteroskedasticity correction model		First-year regression	
	[1] Dep. var = *MI*	[2] Dep. var = Log of *MI*	[3] Dep. var = *MI*	[4] Dep. var = Log of *MI*	[5] Dep. var = *MI*	[6] Dep. var = Log of *MI*	[7] Dep. var = *MI*	[8] Dep. var = Log of *MI*
Intercept	0.961***	0.700***	0.957***	0.694***	0.789***	0.596***	0.749***	0.567***
	(54.42)	(59.44)	(50.17)	(54.70)	(31.44)	(34.72)	(20.77)	(24.15)
Agency cost index (*ACI*)	0.035***		0.035***		0.031**		0.051***	
	(4.19)		(4.17)		(2.52)		(2.95)	
Log of *ACI*		0.030***		0.031***		0.024*		0.043**
		(3.65)		(3.71)		(1.94)		(2.55)
Log of total assets (*SIZE*)	-0.018***	-0.012***	-0.017***	-0.011***	-0.008***	-0.006***	-0.007***	-0.005***
	(-19.01)	(-18.90)	(-16.86)	(-16.43)	(-6.23)	(-6.50)	(-3.60)	(-3.98)
Leverage (*LEV*)	-0.139***	-0.090***	-0.145***	-0.094***	-0.227***	-0.146***	-0.270***	-0.169***
	(-21.79)	(-21.28)	(-22.12)	(-21.75)	(-25.54)	(-24.42)	(-19.47)	(-18.98)
Return on assets (*ROA*)	-0.104***	-0.070***	-0.108***	-0.072***	-0.140***	-0.091***	-0.153***	-0.097***
	(-13.29)	(-13.36)	(-13.44)	(-13.58)	(-11.72)	(-12.03)	(-9.25)	(-9.14)
Log of firm age (*AGE*)	-0.033***	-0.022***	-0.033***	-0.021***	-0.029***	-0.019***	-0.017***	-0.011***
	(-20.21)	(-19.96)	(-18.97)	(-18.63)	(-13.58)	(-13.20)	(-5.50)	(-5.42)
Diversification dummy (*DIVER*)	-0.010***	-0.007***	-0.014***	-0.010***	-0.026***	-0.018***	-0.035***	-0.023***
	(-4.40)	(-4.72)	(-5.89)	(-6.01)	(-7.46)	(-7.46)	(-6.11)	(-6.23)
Dividend-payer dummy (*DD*)	-0.041***	-0.029***	-0.042***	-0.030***	-0.061***	-0.042***	-0.063***	-0.042***
	(-14.29)	(-15.05)	(-13.97)	(-15.01)	(-14.73)	(-14.90)	(-10.05)	(-10.37)
No. of observations	30,716	30,716	30,716	30,716	30,716	30,716	4,883	4,883
Average R^2	19.56%	19.57%	20.05%	20.10%	20.86%	20.74%	19.39%	19.37%

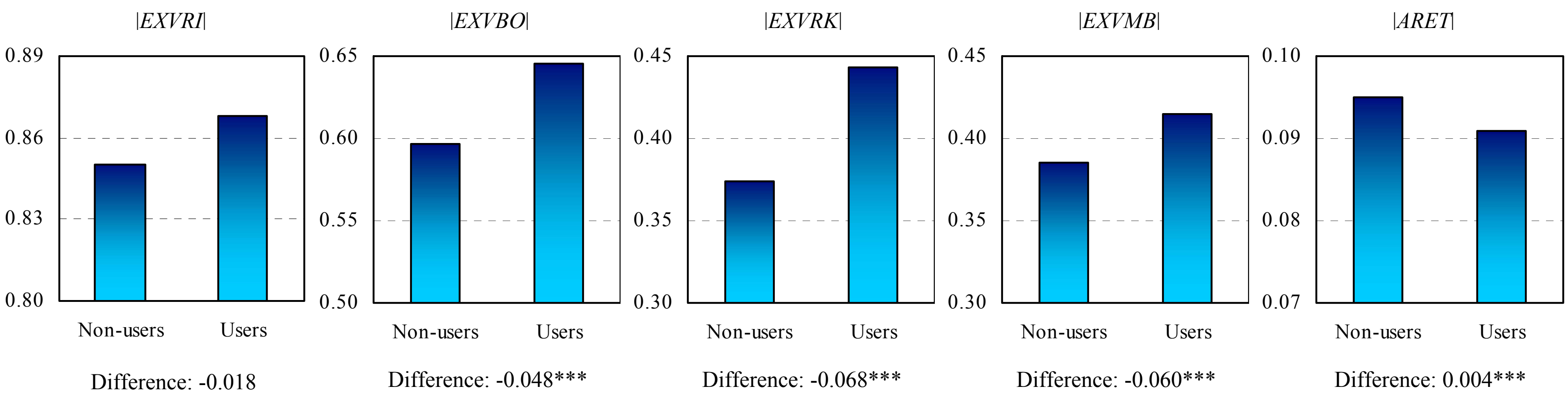
Figure 6
Comparisons of Equity Mispricing Levels

This figure presents averages of mispricing measures for users and non-users of restricted stock grant (in Panel A) or stock options (in Panel B). *** indicates significance at the 1%-level.

Panel A: Comparisons of mispricing levels between users and non-users of restricted stock grants.



Panel B: Comparisons of mispricing levels between users and non-users of stock options.



My tests focus on equity-based compensation, i.e., restricted stock and stock option grants. I create two dummy variables which take the value of one if a firm uses restricted stock grant (alternatively, stock options) for CEO compensation, and take the value of zero otherwise. The relationship between equity based compensation components and the different mispricing measures is graphically reported in Figure 6. Panel A shows how the five individual mispricing measures differ for firms that use versus firms that do not use restricted stock grants, while Panel B shows the corresponding comparison between firms that use versus firms that do not use stock options. Figure 6 clearly shows that firms providing restricted stock grants to their CEOs are substantially less mispriced than firms which do not. All differences are economically and statistically significant. As shown in Panel B, however, the use of stock option grants for CEOs is positively associated with mispricing. This evidence provides support for the notion that CEOs may want to induce stock mispricing when their compensation relies heavily on stock options.

The univariate tests results that correspond to Figure 6 are in line with the second hypothesis, which suggests that the impact of agency costs on mispricing gets stronger (weaker) when the proportion of the CEO's compensation that comes from options (restricted stocks) increase. This implies that the coefficient of the agency cost index (*ACI*), β_1 in equation (14), can be expressed as:

$$\beta_1 = \delta_0 + \delta_1 (\%RSTOCK_{i,t}) + \delta_2 (\%OPTION_{i,t}) \tag{15}$$

δ_1 and δ_2 capture the effect of restricted stock grants $(\%RSTOCK_{i,t})$ and option grants $(\%OPTION_{i,t})$ as percentages of total compensation respectively, on agency costs. These two coefficients represent the effect on mispricing from the firm's choice of equity-based compensation, which determine the degree of interest conflicts in an agency problem. Here δ_0 represents the leftover effect of agency costs (i.e., that related to information asymmetry) on mispricing. Subsequently, I plug equation (15) into the expression of equation (14) and re-write the model as:

$$MI_{i,t} = \beta_0 + \beta_1\, ACI_{i,t} + \beta_2\, (ACI_{i,t} * \%RSTOCK_{i,t}) + \beta_3\, (ACI_{i,t} * \%OPTION_{i,t}) + \beta_4\, SIZE_{i,t} + \beta_5\, LEV_{i,t} + \beta_6\, ROA_{i,t} + \beta_7\, AGE_{i,t} + \beta_8\, DIVER_{i,t} + \beta_9\, \mathrm{DD}_{i,t} + \mu_{i,t}. \tag{16}$$

If my tests provide support for the second hypothesis, the first coefficient (β_1, capturing the effect of information asymmetry on mispricing) should no longer be significant. If the third hypothesis is supported, the coefficient of the interaction term between agency cost and restricted stock grant (β_2) will be negative and the coefficient of the interaction term between agency cost and stock options (β_3) will be positive.

Table 16 documents the coefficients of the above regression model. I estimate the time-series average of cross-sectional regressions, as in Table 14 and the three other robustness regressions as in Table 15. My results show that, in contrast to the findings of studies claiming that information asymmetry is a key determinant in equity mispricing, the leftover agency cost (i.e., information asymmetry) is not a powerful explanatory variable in most cases after controlling for the interaction terms of *ACI* with compensation variables that are directly related to the degree of the conflict of interests between CEO and owners. As predicted in hypothesis #3, the interaction between restricted stock grants and agency costs generally shows a negative impact on mispricing.

However, this effect is not statistically significant. Moreover, I find that the coefficient of the interaction term between option grants and agency costs is significant and positive in all models. This result is consistent with the notion that mispricing increases as the use of stock options exaggerates the agency problem between managers and shareholders.

In sum, my findings provide two important insights. First, in addition to the level of information asymmetry, the conflict of interests between management and investors is an important explanatory variable of equity mispricing. Second, the use of stock options does not resolve the interest conflicts, but it exaggerates the problem. The findings suggest that the use of restricted stock grants, which are less likely related to managerial myopia, is a better choice to reduce interest conflicts in that it does not exacerbate mispricing.

Table 16
Different Effects of Agency Cost on Equity Mispricing

Reported are the coefficients and corresponding t-statistics of regression models which control interacted terms of equity compensation variables. Columns [1] and [2] report results using time-series average of cross-sectional regressions. Columns [3] and [4] report results using panel regressions. Columns [5] and [6] report results of regressions computing difference-in-difference estimates (i.e., including firm fixed-effects and year fixed-effects). Columns [7] and [8] report results using White's (1980) heteroskedasticity correction model. Columns [9] and [10] report results only using the first-year data of each firm. All variables are as defined in Table 10. *, **, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Table 16 (Continued)

	Time-series average of cross-sectional regression		Panel regression model		Difference-in-differences		White's (1980) heteroskedasticity correction model		First-year regression	
	[1] Dep. var = *MI*	[2] Dep. var = Log of *MI*	[3] Dep. var = *MI*	[4] Dep. var = Log of *MI*	[5] Dep. var = *MI*	[6] Dep. var = Log of *MI*	[7] Dep. var = *MI*	[8] Dep. var = Log of *MI*	[9] Dep. var = *MI*	[10] Dep. var = Log of *MI*
Intercept	0.824*** (12.37)	0.613*** (13.48)	1.058*** (26.34)	0.752*** (28.01)	1.040*** (24.25)	0.738*** (25.80)	0.758*** (14.04)	0.566*** (15.67)	0.982*** (13.07)	0.708*** (14.57)
Agency cost index (*ACI*)	0.005 (0.30)		0.011 (0.65)		0.012 (0.67)		0.031 (1.20)		0.064* (1.76)	
ACI * (*%RSTOCK*)	0.032 (1.05)		-0.003 (-0.14)		-0.002 (-0.07)		0.001 (0.03)		-0.008 (-0.12)	
ACI * (*%OPTION*)	0.112*** (5.89)		0.067*** (6.55)		0.069*** (6.63)		0.128*** (8.09)		0.156*** (5.63)	
Log of *ACI*		0.002 (0.11)		0.012 (0.70)		0.013 (0.74)		0.029 (1.12)		0.044* (1.90)
Log of *ACI* * (*%RSTOCK*)		0.027 (1.04)		-0.005 (-0.28)		-0.04 (-0.21)		0.0005 (0.02)		-0.008 (-0.14)
Log of *ACI* * (*%OPTION*)		0.089*** (5.85)		0.054*** (6.30)		0.055*** (6.41)		0.101*** (7.99)		0.121*** (5.40)
Log of total assets (*SIZE*)	-0.008** (-2.50)	-0.005** (-2.47)	-0.020*** (-9.53)	-0.012*** (-9.06)	-0.019*** (-8.71)	-0.012*** (-8.18)	-0.005* (-1.83)	-0.003** (-1.83)	-0.017*** (-4.56)	-0.011*** (-4.55)
Leverage (*LEV*)	-0.252*** (-9.75)	-0.160*** (-9.39)	-0.137*** (-9.66)	-0.090*** (-9.50)	-0.139*** (-9.74)	-0.091*** (-9.58)	-0.273*** (-14.29)	-0.177*** (-13.81)	-0.252*** (-8.04)	-0.159*** (-7.85)
Return on assets (*ROA*)	-0.058* (-1.85)	-0.042* (-2.11)	-0.112*** (-6.54)	-0.078*** (-6.79)	-0.113*** (-6.44)	-0.078*** (-6.65)	-0.106*** (-4.14)	-0.074*** (-4.58)	-0.070 (-1.46)	-0.046 (-1.49)
Log of firm age (*AGE*)	-0.029*** (-9.22)	-0.018*** (-9.34)	-0.039*** (-10.54)	-0.025*** (-10.26)	-0.038*** (-9.99)	-0.024*** (-9.69)	-0.031*** (-6.89)	-0.020*** (-6.67)	-0.031*** (-6.14)	-0.020*** (-5.99)
Diversification dummy (*DIVER*)	-0.029*** (-5.86)	-0.020*** (-6.18)	-0.012*** (-3.12)	-0.009*** (-3.50)	-0.012*** (-2.73)	-0.008*** (-2.94)	-0.035*** (-5.79)	-0.024*** (-5.87)	-0.018* (-1.95)	-0.013** (-2.13)
Dividend-payer dummy (*DD*)	-0.078*** (-17.38)	-0.052*** (-18.59)	-0.054*** (-9.85)	-0.036*** (-10.11)	-0.056*** (-9.80)	-0.038*** (-10.15)	-0.075*** (-10.29)	-0.050*** (-10.37)	-0.082*** (-8.44)	-0.054*** (-8.57)
No. of observations	8,657	8,657	8,657	8,657	8,657	8,657	8,657	8,657	1,481	1,481
R^2	24.68%	24.22%	21.21%	21.01%	21.41%	21.22%	24.14%	23.68%	27.22%	26.91%

VI. Summary and Conclusions

Recently, the finance literature has emphasized the importance of equity mispricing. The contribution of this paper is that it reconciles different views of mispricing and its causes, and specifically develops evidence on a link between agency theory and stock mispricing. Finance theory defines agency costs of equity as the organizational costs associated with problems arising from conflicts of interest between managements and shareholders in the presence of information asymmetry, i.e. in cases where managers discriminately have better and/or more information than shareholders. Previous studies have found that there is a strong positive relation between information asymmetry and equity mispricing, but have generally neglected the effect of conflicts of interest on mispricing.

In this paper, I utilize ten agency costs proxies and provide evidence that the level of agency costs is significantly and positively related with equity mispricing. Unlike the existing literature, I find that the conflict of interests is a more important variable than information asymmetry in explaining the equity mispricing. Previous studies suggesting that stock-based compensation is an efficient mechanism for resolving agency problems typically treat all stock-based incentives equally and relate them to both lowered agency costs and enhanced firm stock value. Given both academic evidence and the recent skepticism about the effectiveness of equity-based compensation fueled from financial scandals (i.e., Enron and WorldCom), I separately analyze two different components of equity-based compensation, i.e., stock options and restricted stock grants. I find that the use of stock options, originally intended to resolve interest conflicts, actually exaggerates the problem and results in more stock mispricing. The evidence suggests that the use of restricted stock grants which are not related to managerial myopia is a better choice to reduce interest conflicts.

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