The Impact of Hedge Funds on the Volatility of Seasoned Equity Offerings

ROB HULL, SUNGKYU KWAK, AND ROSEMARY WALKER*

ABSTRACT

To what extent can hedge funds influence stock price volatility surrounding the announcements of major corporate events? To answer this question, this paper examines one of the more common major corporate events: seasoned equity offerings (SEOs). We test the impact of hedge fund variables on idiosyncratic and systematic volatility for a variety of short-run and long-run periods around the initial announcement dates for SEOs. We find that stock price volatility decreases when (i) the total assets under management by the hedge fund industry increases, (ii) the number of hedge funds increase, (iii) the size of individual hedge funds decreases, (iv) leverage is more likely to be used by a hedge fund, and (v) an arbitrage strategy (as opposed to an event-driven or equity hedge) strategy is used. We can find no consistent evidence that hedge funds performance during the SEO announcement month influences volatility.

* Rob Hull is the King Endowed Chair of Finance. Sungkyu Kwak and Rosemary Walker are Associate Professors of Economics. Rosemary Walker is corresponding author. All authors are affiliated with Washburn University, Topeka, KS.

HEDGE FUNDS BEGAN IN 1949 WHEN Alfred Winslow Jones (sociologist and financial journalist) formed the first modern hedge fund.[1] Although a few financial gurus (such as Warren Buffett and Barton Biggs) adopted the structure that Jones created, it was only during the 1980s that Jones' ideas gained widespread practice. From the mid-1980s to the end of the 1990s, the sheer number of hedge funds grew over 20% a year. By the turn of the century, assets under management (*AUM*) by hedge funds were around $0.45 trillion.[2] By 2007, according to Hedge Fund Intelligence (HFI), *AUM* was at $2.65 trillion up 27% for the year. However, according to data from Hedge Fund Research (HFR), *AUM* was only at $1.9 trillion at the end of 2007. They add that *AUM* fell to $1.4 trillion by the end of 2008. The financial crisis that began during 2007 caused the value of hedge fund assets to fall due to a combination of trading losses and the withdrawal of assets from funds by investors. Most recently, HFR reports that $9.5 billion in assets were pulled in for the second quarter of 2010 giving $1.65 trillion in *AUM* with the bulk managed by the large hedge fund firms. By the beginning of 2010, the 25 largest hedge funds had $0.52 trillion in *AUM* with around 8,000 active hedge funds that are on track to reach an *AUM* of $2 trillion by the end of 2010.[3]

[1] Jones used a factor-based approach to portfolio construction and bought as many stocks as he sold so that market-wide movements up or down could not influence his investment portfolio. His hedge fund dodged the requirements of the Investment Company Act of 1940 by restricting itself to fewer than 100 investors in a limited partnership. Jones set today's hedge fund fee standard by keeping 20 percent of the profits.

[2] From "The Brave New World" (September 2007), we find that Merrill Lynch Financial Institutions Group and Casey, Quirk & Associates estimated (before the financial crisis) that by 2011 alternative investments like hedge funds will be about 1/6 of the amount of traditional investments. This compares to a fraction of 1/9 in 2006. They also state that hedge funds asset growth has been accompanied by greater hedge fund profits. Since 2000 hedge funds have outperformed either equity or bonds by over two percent per year on average.

[3] It should be noted that hedge fund statistics quoted depend on the sources as we find discrepancies.

The continued growth of hedge funds over time has led to their capacity to influence the investment market. However, the nature and strength of this influence are difficult to discern because hedge fund data is sparse. This sparseness results because, unlike other institutional investors, hedge funds are seldom required by the Securities and Exchange Commission (SEC) to file buy and sell reports. This is because domestic U.S. hedge funds tend to be limited partnerships that escape regulation as decreed by the Investment Company Act of 1940. In addition, offshore hedge funds are non-U.S. corporations that are not subject to SEC regulation.

There are three factors that can cause domestic U.S. hedge funds to file with the SEC. *First*, the hedge fund would have to file if it is considered an insider by the five percent rule. This rule requires a hedge fund to report its buying and selling to the SEC if it has five percent or more ownership in a company.[4] Because of this rule, most hedge funds limit their ownership below five percent. By doing this, they avoid revealing their investment approaches including any wealth enhancing scheme that could conceivably be based on price manipulation. *Second*, as investment advisors, hedge fund managers would have to register with the SEC if their clients withdraw their invested funds within two years. If managers can prevent such withdrawals, the only required SEC report from hedge fund managers would be to disclose the amount of money under management in long positions. *Third*, if the hedge fund has ownership that is greater than $100 million, it is required by the SEC to file Form 13F. This filing is uncommon because most hedge funds maintain assets under management that are less than $100 million.

[4] Five percent ownership requires that a hedge fund files a Scheduled 13D or Schedule 13G. The latter schedule requires less information and less frequent amending and is filed if the hedge fund has acquired its five percent ownership in the ordinary course of business (and without intent to influence the company).

Researchers who examine SEC 13F filings can only draw conclusions that characterize larger institutional investors and thus larger hedge funds.[5] Gompers and Metrick (2001) use data from SEC 13F filings and discover that large institutional investors caused a 4.5 percent increase in the demand for large stocks and a 29.1 percent decrease in the demand for small stocks. This research is revealing and leads one to ask if this impact by large institutional investors might also be found in just the hedge fund industry.

Despite the difficulty of getting data for a diversified body of hedge fund companies, the hedge fund research has been on the rise. Ackermann, McEnally, and Ravenscraft (1999), Fung and Hsieh (2000a), Brunnermeier and Nagel (2004), Agarwal et al. (2009), and Aggarwal and Jorion (2010) are among those who have been active in hedge fund research. These researchers often focus on either (i) the actual performance of hedge funds or (ii) the market and economic impact of hedge funds. The latter is the major focus of the paper as we look at the impact of hedge funds on stock price volatility around the initial announcement dates of seasoned equity offerings (SEOs). Concerning any general impact of hedge funds, any influence is *a priori* disputable because hedge funds (despite their great growth) remain a relatively small fraction of the overall market.[6] This smallness factor brings into question the capacity of hedge funds to influence market and economic events in a consistent and significant fashion. The results of empirical studies on the influence of hedge funds are ambiguous lending some credence to the belief that

[5] Large institutional investors include investment advisers (such as hedge funds), banks, insurance companies, broker-dealers, pension funds, and corporations.

[6] For our period of study, we find different estimates of hedge fund assets in terms of the percentage of all other financial institutions (with estimates ranging from around 2% to 10%). With an average of about 2,500 hedge funds at the time of an SEO announcement for our period of study from 1999−2005, any one hedge fund by itself would have difficulty manipulating stock prices unless there is a relative low volume of trading by other traders.

hedge funds cannot significantly impact events. The ambiguous evidence can be seen earlier on from the study by Fung and Hsieh (2000b) who found uncertain results as to whether hedge fund activity had an impact on major economic events such as the stock market crash of 1987, the Asian Currency Crisis, and the European bond market rally. While hedge funds as a group did not seem to cause the turmoil, Fung and Hsieh argue that hedge funds may have had an impact in the aftermath.

As noted by King and Maier (2009), hedge funds are important price-setters and reportedly dominate trading activity in markets with broader economic importance. For such reasons, a number of researchers argue that hedge fund advisors, like other institutional investors, can impact market and economic events. Gabaix et al. (2006) provide a theoretical model in which trades by institutional investor can generate excess stock market volatility in relatively illiquid markets. King and Maier (2009) contend that the sale of hedge fund assets can indirectly affect market volatility with the capacity to influence volatility especially true when hedge funds have more assets, greater leverage, and larger attrition rates.[7] King and Maier further assert that hedge fund activity can increase systemic (or uninsurable) risk.

Notwithstanding hedge funds capacity to increase volatility, an argument can be made that hedge fund advisors and other institutional investors can reduce market volatility by taking an opposing position on a security relative to other traders (or even taking opposite positions among themselves). Bohl et al. (2009) argues that institutional investors can be characterized as informed

[7] The attrition rate refers to the proportion of hedge funds exiting a data base due to managers not reporting hedge fund data (as opposed to a liquidation rate where a hedge fund exits the data base due to liquidation). For our period of study, we estimate the attrition rate to be around 8% -9% (with the liquidation rate about one-third the attrition rate).

investors who speed up the adjustment of stock prices to new information thereby making the stock market more efficient and less volatile. Their findings suggest that institutional investors can reduce the volatility created by the trading of irrational investors. Of importance, institutional investors (and thus hedge funds) can prevent extreme volatility by trading misvalued securities before the misvaluation gets out of hand.

As market timers, hedge funds can affect price volatility by taking positions in misvalued securities to gain a profit. If they perceive misvaluation will continue such as during a stock market bubble period, then they can ride the bubble based on dominant investor sentiments so as to gain profits while they last. When documenting the role of arbitragers during the technology bubble, Brunnermeier and Nagel (2004) found that hedge funds managers failed as market arbitragers but rode the overpricing to their own advantage. One can speculate that hedge fund managers used an event-driven strategy that increased volatility.

Besides riding periods of bubbles or misvaluations, hedge funds can also act so as to help the misvaluation come to a quick halt. In regards to the potential impact of hedge funds on misvalued seasoned equity offerings (SEOs), hedge funds can time the market to buy shares of SEO firms that are considered undervalued and short shares that are judged to be overvalued. As market timers, hedge funds increase the demand and therefore the price of undervalued stocks while they decrease the demand and thus price of overvalued stocks. By stabilizing demand, they reduce extreme swings in security prices. This should be especially true around SEOs where prices are known to increase dramatically up to the time of the SEO before falling in the post-SEO market.

The more hedge fund firms that use techniques to arbitrage misvalued stocks, the less volatility there should be in individual securities and thus in the market as a whole.

Building on the reduction in volatility notion, this paper hypothesizes that the SEO market becomes less volatile over time as hedge funds proliferate. Since our time period is from 1999 through 2005, this hypothesis would be tested during a time frame when the internet-technology bubble bursts and the equity markets were in disarray with stock prices declining after peaking in 2000. The volatility can be further reduced based on use of leverage or use of a relative value (arbitrage) strategy. In our tests, we also investigate whether hedge funds can induce more volatility through strategies that generate extreme profits. Such profits can be achieved by taking advantage of opportunities through either a hard-to-detect nonconventional strategy or a commonly recognized hedge fund strategy. Two recognized strategies more likely to secure hedge fund profits (and thus greater volatility) around SEOs are event-driven (special situations) and directional (equity hedge) strategies. We also hypothesize that volatility will increase when hedge funds are experiencing higher profits.

We use two measures of stock price volatility to test our research hypotheses on the impact of hedge fund variables on volatility around SEOs. These two measures of volatility are idiosyncratic and systematic. Idiosyncratic volatility focuses on the volatility in the firm-specific component of the excess return, while systematic volatility measures that portion of the volatility that is inherent in the market and outside the firm's control. Independent hedge fund variables tested include assets under management by the hedge fund industry, the number of hedge funds, average and median hedge fund sizes during the month of the SEO announcement (month 0), average hedge return during the month 0, the use of leverage during the month 0, and the use of three hedge fund strategies during month 0. For the latter, the three strategies tested are the proportion of hedge funds using (i) a relative value (or arbitrage) strategy, (ii) an event-driven (or special situations) strategy, and (iii) a directional (or equity hedge) strategy.

To test our research hypotheses, we supplement independent hedge fund variables with thirteen non-hedge fund control variables expected to influence SEO price behavior. These thirteen "non-hedge" independent variables included in our regression model are: the firm's inside ownership proportion at the time of its SEO; the change in the firm's inside ownership proportion caused by its SEO; fraction of SEO's total shares issued that are primary (or new) shares; underpricing as computed by the log of the ratio of the estimated offer price to the offer price; time period of SEO announcement as represented by a dummy variable capturing the internet-technology bubble period; purpose of offering as classified as either expansion versus non-expansion; trading liquidity as captured by the SEO's listing on NASDAQ versus AMEX/NYSE; growth as represented by the relative amount of capital expenditures; the use of debt as captured by the financial leverage ratio; profitability given by the relative amount of operating income before depreciation; financial liquidity as defined by the relative amount of cash and other short-term investments); tangibility signified by the relative amount of tangible assets; and, Tobin's Q ratio.

We find support for our research hypotheses in that price volatility around SEOs is significantly reduced when the assets under management of all hedge funds and the sheer number of hedge funds are greater. Volatility is also decreased when (i) leverage and an arbitrage strategy are more likely to be used by the hedge fund, (ii) the average or median hedge fund size during month 0 is smaller, and (iii) an event-driven or equity hedge strategy is less likely to be used. We could find no consistent evidence that hedge fund returns during month 0 affect volatility. In general, both volatility measures tend to give (i) the same coefficient sign for any variable tested and (ii) the same results for both short-run and long-run tests. Results for total volatility are not reported because they are virtually identical to those for the idiosyncratic tests.[8] These near identical results, along with the weaker coefficients for the systematic tests, indicate that idiosyncratic volatility drives the total volatility that occurs around SEOs.

The remainder of the paper is organized as follows. *Section one* presents our regression model and our two hypotheses (*H–1* and *H–2*). *Section two* describes the data and reports the descriptive statistics. *Section three* presents the empirical results. *Section four* offers conclusions.

I. Hypotheses and Regression Model

A. Hypotheses

Hedge funds are designed to earn positive returns through a variety of trading strategies. A general classification might include the following strategies: global macro, relative value (arbitrage), directional (equity hedge), event-driven (special situations), and miscellaneous. Hedge fund strategies strive to reduce risk, preserve capital, and deliver positive returns under all market conditions. In regards to SEOs, hedge funds can apply strategies to take advantage of (i) the

[8] Total volatility is the standard deviation of the daily excess stock returns ($r_{i,\tau}$) for stock i for day τ and consists of both idiosyncratic and systematic risk. When computing total volatility, $r_{i,\tau}$ is the logarithm of one plus the excess return for day τ for stock *i* during period *t*. Using logarithmic returns lessen the mechanical effect from skewness when positive returns are extremely large.

long-run price increases that exist prior to SEOs and short-run price increases that occur immediately after the SEO announcement, and (ii) short-run price decreases that occur immediately before SEO announcements and long-run price decreases that take place after SEOs are completed.[9] Strategies applied by institutional investors can be based on either price manipulation (trading in the opposite direction of their private information) or informed trading (trading in the same direction of their information). Below we discuss these two types of trading.

In regards to price manipulation, Brunnermeier (2005) discusses how a trader can exploit information received before it is revealed to the public. As applied to a significant corporate announcement (such as an SEO announcement), Brunnermeier would suggest that a trader could not only exploit the news when first received, but could also exploit it again after it is revealed to the public. This is because the trader knows the extent to which the information has been reflected in the pre-announcement price. Given their information, the trader expects the price to overshoot and intends to partially reverse any trade made. Brunnermeier asserts that while information leakage makes the price process more informative in the short-run, it reduces its informativeness in the long-run.

To illustrate a manipulative trading strategy around an SEO, we can refer to the study by Henry and Koski (2009) who examine the relation between returns and short sales for a trading period that begins before the initial SEO announcement (day 0). If larger SEO underpricing is

[9] Beginning on August 25, 1988, the SEC adopted Rule 10b-21 that imposed restraints to the covering of short sales using shares purchase on the SEO offer date. For example, if the registration date was April 15 and the offer date May 15, Rule 10b-21 prevents traders from covering short positions (during the period from April 15 to May 15) with the new shares purchased on May 15 at the offer price. In April 1997, the SEC adopted Rule 105 of Regulation M as a replacement for Rule 10b-21. This rule change significantly relaxed the restrictions on short selling around SEOs.

known in advance by traders, then this knowledge will make a short selling strategy prior to an SEO more profitable.[10] Henry and Koski discover that higher levels of pre-issue short selling before day 0 are significantly related to larger SEO price discounts or underpricing. They also document that pre-issue short selling is associated with a post-issue price recovery, which would be expected given the temporary price impact of manipulative trading. They argue that manipulative trading occurs around SEOs.

In contrast to Henry and Koski's finding, Chemmanur et al. (2009) examines trading around SEOs and find that institutional investors trade in the same direction of their private information (informed trading) and not in the opposite direction of their information (manipulative trading). They also discover that investment institutions are able to identify and obtain more allocations in SEOs with better long-run stock returns. In particular, these institutions outperform a naive buy-and-hold trading strategy in the long-run post-SEO price aftermarket. Additionally, greater pre-offer institutional net buying and larger institutional SEO allocations are associated with a smaller SEO discount.

Can anything positive result from the profit-taking when hedge funds buy and sell large quantities of shares around SEOs? Yes, even if hedge funds are concerned with strategies geared totally towards profit taking, these very strategies can result in lower volatility. Consider the following trading strategy. In purchasing shares of underpriced SEOs (say sometime before or on

[10] Because short sellers are borrowing shares from their broker, they must be able to acquire the shares when prices have bottomed where the bottom is greater when there is greater underpricing. For our sample, the average closing price falls –4.9% from day –6 to day 0. Even if a firm had to wait to until day +1, the fall would still be –4.2%. Thus a short-selling strategy can be profitable even without extending the trading period to past the offer date as does Henry and Koski (2009). The model by Gerard and Nanda (1993) predicts that knowledgeable traders may attempt to influence offering prices by selling shares prior to an SEO and profit subsequently from lower prices in the offering.

the day that offer price is set on day 0, a hedge fund's buying behavior can increase demand and prevent a further price decline. The hedge fund can turn around and sell these same shares during the post-issue recovery at a price above what they purchase their shares.[11] This further selling prevents any additional rise in stock price, thus once again reducing volatility. Long-run strategies by hedge funds can also be used to decrease volatility given the well-document price run-ups that precede SEOs and price declines that follow SEOs.

The extra buying and selling of SEO shares by hedge fund managers leads to our first research hypothesis (*H–1*):

> *H–1: A greater amount of assets under management by the hedge fund industry (or any hedge fund characteristic correlated with this amount such as a greater number of hedge funds or smaller individual hedge fund asset size) will cause less volatility in SEO stock prices for periods surrounding SEOs. The volatility can be further diminished when the hedge fund uses leverage and a relative value (arbitrage) strategy.*

The first part of *H–1* argues that the reduction in stock price volatility takes place as the overall industry size and the number of hedge funds both increase because such an increase leads to greater clout as taking opposite positions in trades. How might this work? The desire by hedge funds for profit-taking for misvalued or inefficiently priced shares can (i) increase the demand for the SEOs when the price is low, thus causing the price to increase, and (ii) increase the supply for the SEOs when the price is high, thus causing the price to fall. The end process of this profit-taking

[11] For our sample, an investor could make 2.5%, on average, from buying all SEOs in our sample at the closing pricing on day 0 and selling two days later. If investors had information on which shares would be heavily underpriced then much larger returns could be made for longer holding periods that includes days immediately before and after the initial announcement day (e.g., immediately before and after day 0).

is that prices become less volatile. The first part of *H–1* also argues that due to the nature of the hedge fund industry (where there is a limit on the size of hedge funds where most hedge funds do not survive the medium size stage but only a few can successfully become large and dominate), we expect a negative correlation between total assets under management by the hedge fund industry and the asset size for an individual hedge fund. Successful hedge managers would be reaching $100 million assets under management quicker and thus would be exiting their prior work places to often start new hedge funds, which would (on average) be smaller in size for upcoming years compared to the hedge fund that they left. Thus, we would expect volatility to decrease as individual hedge fund size decreases due to the fact there is a negative correlation over time between the individual size of a hedge fund and the size of the overall industry.

The second part of *H–1* maintains that certain strategies can also reduce volatility. *First*, greater reduction can be achieved when a hedge fund uses greater leverage. Greater leverage works like the increase in the hedge fund industry size because greater leverage magnifies the size of the assets under management by the hedge fund industry. Consequently, volatility is reduced when the proportion of hedge funds using leverage increases. *Second*, an arbitrage strategy reduces volatility because it entails that traders take opposite positions thus lessening the probability of wide swings in prices. Consequently, volatility is reduced when the proportion of hedge funds increase their use of an arbitrage strategy.

While the reduction in market volatility can be a by-product of hedge fund characteristics and strategies, it is also possible for hedge fund characteristics to increase volatility. Lakonishok et al. (1992) look at large institutional investors (primarily pension funds) and find some evidence for increased volatility by these investors for smaller stocks. In regards to their insufficient evidence for increased volatility for large stock, they suggest their finding can be explained in terms of the elasticity of demand for stocks. To the extent that the demand curve is not perfectly elastic, Chan and Lakonishok (1995) suggest that aggregate trading by hedge funds in the same direction will tend to increase volatility. Noting that stock return volatility rises after stock prices fall, Duffee (1995) finds that this positive relation is strongest for both small firms and firms with little financial leverage.

Additionally, it is possible that the zeal for financial gain can cause an increase in volatility. This should be especially true when hedge funds find exorbitant profit opportunities and actually succeed in making handsome profits through recognized strategies such as an event-driven (special situations) or an directional (equity hedge) strategies, either of which could involve price manipulation. Thus, hedge funds will vigorously pursue the purchase of SEOs with the greatest undervaluation and the short sell of those with the greatest overvaluation. This means that greatest price volatility in the SEO markets will be caused by the greatest profit taking and by strategies specifically geared towards equity offerings. This leads to our second research hypothesis:

H–2: *Strategies linked to SEOs, such as event-driven (special situations) and directional (equity hedge) strategies, will cause greater volatility in SEO stock prices for periods surrounding SEOs. The volatility can be further enhanced if greater hedge fund returns lead to more volatility in SEO stock prices.*

The first part of *H–2* suggests that strategies specially related to taking profit around SEOs will increase volatility. The last part of *H–2* advocates that greater success at profit-taking by hedge funds can be viewed as further enhancing volatility. However, if we find a negative relation between hedge fund performance and volatility then we have some evidence that hedge funds reduce volatility even when successfully pursuing their own profit-taking strategies.

While the above hypotheses will be tested for both measures of volatility (idiosyncratic and systematic), it remains to be seen if homogeneity in signs will be found for both measures for all time periods. We expect idiosyncratic volatility to be the dominant measure because the firm-specific component of stock price variability is what is likely being manipulated and/or hedged in the SEO market.

B. The Model

In testing our hypotheses, we will use regression analysis to explain the volatility in the stock prices surrounding SEOs. The general regression model we will use is:

$$VOL = \beta_0 + \beta_i HFV + \beta_j NFV + \varepsilon \tag{1}$$

where

VOL = *Daily Excess Stock Return Volatility* (Section II.B will provide details on the two volatility measures used in tests and how they are computed. For regression tests, the logs are used.)

HFV = *Hedge Fund Variables* (The nine hedge fund variables are described below.)

NFV = *Non-Hedge Fund Variables* (The thirteen hedge fund variables are described below.)

The nine hedge fund variables (*HFVs*) tested using equation (1) are:

AUM = *Hedge Fund Assets under Management* during month 0.
NHF = *Number of Hedge Funds* during month 0.
AHS = *Average Hedge Fund Size* during month 0.
MHS = *Median Hedge Fund Size* during month 0.
PLV = *Proportion of Hedge Funds Using Leverage* during month 0.
PED = *Proportion of Hedge Funds with an Event-Driven (Special Situations) Strategy* during month 0.
PRV = *Proportion of Hedge Funds with a Relative Value (Arbitrage) Strategy* during month 0.
PEH = *Proportion of Hedge Funds with a Directional (Equity Hedge) Strategy* during month 0.
AHR = *Average Equal-Weighted Hedge Fund Return* during month 0.

While all of the above variables are tested, we will only focus on four of these variables (*AUM*, *PED*, *PEH*, and *AHR*) for reporting purposes due to collinearity problems.

The thirteen non-hedge fund variables (*NFVs*) tested using equation (1) are:

ILA = *Inside Ownership Proportion after SEO*: (Insider Shares after SEO) / (Shares Outstanding after SEO).
CIL = *Change in Inside Ownership Proportion*: *ILA* – *ILB* where *ILB* is *Inside Ownership Proportion before SEO* defined as: *ILB* = (Insider Shares before SEO) / (Shares Outstanding before SEO).
PRI = *Primary Shares as a Proportion of Total Shares Offered*
UND = *Underpricing*: log of (Estimated Price) / (Offer Price) where Estimated Price is given by the *Investment Dealer's Digest*.
ITB = *Internet-Technology Bubble* dummy variable equals 1 if SEO before 1/1/2002; else *ITB* = 0.
POP = *Purpose of Proceeds* dummy variable equals 1 if major purpose is expansionary; else *POP* = 0
TLQ = *Trading Liquidity* dummy variable equals 1 if NYSE/AMEX; else *TLQ* = 0.
FLQ = *Financial Liquidity Ratio*: (Cash and Other Short-Term Investments) / (Book Value of Equity)
GRO = *Growth Ratio*: Capital Expenditures / Total Assets
LEV = *Leverage Ratio*: Total Liabilities / (Market Value of Common Stock + Total Liabilities).
PFT = *Profitability Ratio*: Operating Income before Depreciation / Total Assets.
TAN = *Tangible Assets Ratio*: Net Plant and Equipment / Total Assets
TBQ = *Tobin's Q Ratio*: (Common Value + Total Asset – Book Value Equity) / Total Assets

While other variables are tested, only results for the above non-hedge variables are reported. The other variables tested (such as a size variable, relative size variable, flotation cost, and variations of the above variables) did not add to our regression findings. While a size variable is documented in the literature as influencing volatility the inclusion of a great number of other variables better captures a "size effect", which is really an effect covering a variety of firm-specific aspects (such as *ILA*, *CIL*, *TLQ*, *GRO*, and so forth).

As seen above, thirteen additional non-hedge fund control variables have been added to the regression model. Three of these are dummy variables that we now describe in more detail. *First*, a dummy variable (*ITB*) represents the occurrence of an SEO during a time period that will best capture any effects from the internet-technology bubble. For this variable, *ITB* = 1 if the SEO occurs from 1999–2001. Given our analysis of price volatility for a four-year period around SEOs, these three years are judged to be the best for creating the time period variable *ITB*. *Second*, a dummy variable (*POP*) will attempt to capture any influence related purpose of the proceeds through a simple classification of either expansionary or non-expansionary. We set *POP* = 1 if that major purpose of the proceeds is related to expansion in some form such as merger or increase in capital expenditures where the latter can also include proceeds spent on aspects accompanying the expansion such as sales and marketing or research and development. Third, a dummy variable represents trading liquidity variable (*TLQ*) through a simple listing classification. For this variable, *TLQ* = 1 if the SEO firm is traded on NASDAQ and not AMEX/NYSE.

We now discuss the predicted signs of all independent variables when regressed against our two volatility measures (*VOL*). *First*, we look at our nine hedge fund variables. As discussed earlier, *H–1* predicts that coefficients for the total amount of assets under management by the hedge fund industry (*AUM*), the number of hedge funds (*NHF*), the use of leverage (*PLV*) and a relative value (arbitrage) strategy *PRV* should all be negatively related to the volatility in daily stock returns (*VOL*), while the average hedge fund size (*AHS*) and the median hedge fund size (*MHS*) should be positively related to *VOL*. *H–2* suggests that the coefficient for an event-driven (or special situations) strategy (*PED*), a directional (or equity hedge) strategy (*PEH*), and the average equal-weighted hedge fund return (*AHR*) should be positively related to *VOL*. The prediction for *AHR* is based on the expectation that greater profits during the month of the SEO for hedge funds indicate successful trading activities that would increase volatility. However, to the extent this profit is related to mispriced securities, the profit-taking by hedge funds may actually reduce volatility and thus generate a negative coefficient for *AHR*.

Second, we now discuss expectations for the signs of the thirteen non-hedge fund variables when regressed against volatility measures (*VOL*). Signaling theory premised in Myers and Majluf (1984) argues that greater inside ownership proportions (or levels) cause a more negative market response to an SEO announcement. We suspect that this negativity will be accompanied by greater volatility, not only at the time of the SEO announcement, but also during the well-documented (i) pre-SEO price run-up period and (ii) post-SEO price decline period. Thus, we predict a positive coefficient for *ILA* as greater positive values for inside ownership proportions will be associated with greater price volatility.

Leland and Pyle (1977) predict that investors will react negatively to a fall in inside ownership. Thus, SEOs with greater decreases in inside ownership proportions should evoke more volatility. Consistent with these predictions about inside ownership being influential, Du and Wei (2004) find that countries with more prevalent insider activity have more volatile stock markets. Our variable *CIL* will test for the impact of changes in inside ownership. Since values for *CIL* are negative (because inside ownership proportions are decreased for virtually all SEOs in our sample), we predict a negative coefficient for *CIL* in regression tests.

We predict a negative relation between the proportion of primary or new shares to total shares offer (*PRI*) and volatility as greater values for *PRI* indicate less secondary selling and thus less negative information and less uncertainty about dovetailing prices. However, it is possible a positive coefficient can result to the extent that the market perceives (i) more primary shares as indicating more negative news about overvaluation and (ii) secondary selling (in whatever proportion) as the result of exercising expiring options or diversification needs. As will be seen in Table I, greater underpricing is computed as a greater positive number. Thus, we expect a positive relationship between underpricing variable (*UND*) and stock price volatility as greater underpricing should be associated with more volatility resulting from more negative information about overvaluation. Corwin (2003) finds greater price volatility when there is greater SEO underpricing.[12]

We expect greater volatility when SEOs occur during the internet-bubble period (*ITB* = 1), expansion-related purpose of proceeds (*POP* = 1), and when there is less trading liquidity (*TLQ* = 1). The prediction of positive coefficients for these three dummy variables is now described. *First*, our variable *ITB* is designed to capture any impact for volatility that might be more affected by the internet-technology bubble. Of importance, the earlier years of our study capture the internet-technology bubble period and so we need to be aware of the potential for these years to have greater volatility. In particular, SEOs that occur during year 2000 when stock prices peaked (e.g., when *ITB* = 1) are best positioned to capture both the greater volatility of the pre-SEO price run-ups and the greater volatility of the post-SEO drop off in prices. *Second*, in regards to *POP*, we expect that firms undergoing expansion should be seen as taking on more risk and uncertainty by expanding their assets. Thus, we expect more volatility when *POP* = 1. *Third*, as regards *TLQ*, Xu and Malkiel (2003) and Brown and Kapadia (2007) are among those who acknowledge greater volatility in stock prices for smaller sized firms (like NASDAQ listed firms) that have less liquidity

[12] Greater volatility in general may just imply greater risk and so these stocks would tend to be overvalued and thus require greater underpricing. These stocks would experience more volatility for all periods surrounding an SEO.

and greater growth opportunities. Thus, we anticipate a positive coefficient when *TLQ* = 1 because there should greater price volatility for a NASDAQ listing.[13]

Firms with greater financial liquidity (*FLQ*) may have to keep higher balances of cash and short-term assets on hand due to greater volatility in stock prices. Thus, we expect a positive coefficient for *FLQ*. Cao et al. (2008), Xu and Malkiel (2003) and Brown and Kapadia (2007) are among those who suggest that volatility is positively related to earnings growth. Thus, we predict a positive coefficient for *GRO* is regression tests. Black (1976) and Christie (1982) offer evidence that highly leveraged firms have higher volatility indicating a positive coefficient for *LEV*. However, agency theory based in Jensen and Meckling (1976) predicts a negative coefficient for *LEV* because more debt creates covenants that can prevent managers from undertaking riskier (more volatile) projects. Furthermore, Duffee (1995) suggests a negative coefficient for *LEV* for our sample as he finds that firms with less leverage and smaller sizes will experience greater volatility for periods where its stock price decreases.[14]

Campbell et al. (2001) hypothesize (and also find) that deteriorating earnings quality is associated with higher volatility. Thus, greater profitability should decrease volatility and so we

---

[13] The listing can also represent a size effect, which may explain why adding a size variable to our tests add little. Size variables can also proxy for access to external markets where such access can influence both idiosyncratic and systematic volatility. However, the research has had conflicting results in regards to the homogeneity in these two volatility measure. For example, Comin and Philippon (2006) find that increased access to external financing increased idiosyncratic volatility but decreased market volatility.

[14] In regards to less leverage, this characterizes our sample because SEOs experience stock price run-ups prior to the SEO announcement. Thus, an increase in stock prices increases volatility while lowering leverage (when computed as total debt to total firm value). In regards to smaller size, our sample is also composed of SEOs where the prospectus reports inside ownership data. Smaller firms tend to have inside ownership that is greater than five percent and so are more likely (compared to larger firms) to report this information. Finally, for SEO firms, there are short-run stock price decreases prior to the SEO announcement and long-run post-SEO decreases. In conclusion, our sample satisfies Duffee's criteria that predict greater volatility, thus predicting a negative coefficient for *LEV*.

predict a negative coefficient for *PFT*. As noted by Korteweg and Pohlsen (2009), greater amounts of tangible assets should reduce uncertainty in cash flows and so we predict a negative coefficient for *TAN*. Greater values for Tobin's Q ratio indicate higher market values for securities compared to book values. This indicates greater increases in market values associated with greater volatility in prices. Thus, we predict a positive coefficient for *TBQ*.

II. Sample, Methodology, and Descriptive Statistics

A. Sample and Data

Our initial sample of 2,371 SEOs was identified from the *Investment Dealer's Digest* for the period from January 1999 to December 2005. From this sample, we found 2,305 SEOs that had trading data recorded by the Center for Research in Security Prices (CRSP). Of these SEOs, we were able to locate 1,571 with registration prospectuses filed with the SEC. The lack of a prospectus indicates an offering is likely a private placement since these offerings do not have to be filed with the SEC. Prospectuses serve to identify the registration date, which is used as day 0 where day 0 is defined as the day that the new offering is initially announced to the public. However, we suspect that days –2 or –1 can on occasion be the actual day that the announcement is first revealed to the market. Besides the registration date, prospectuses also report other information such as shares outstanding at the time of the announcement, the offer price, issuance expenses, number of primary and secondary shares being issued, and purpose of offering.

We found that 706 of the 1,571 prospectuses also provided insider data. This data enabled us to compute the proportion of shares owned by insiders at the time of registration (but before the actual offering) compared to the shares outstanding at that time. It also allowed us to calculate the proportion of insider ownership of shares after the actual offering is carried out. From the proportion before and after, we compute the change in inside ownership proportion through a simple subtraction process that reveals in virtually every computation the decrease that occurs. We define insiders as (i) the directors and officers as a group, and (ii) all five percent owners of outstanding common stock. While some studies use ten percent, prospectuses state that five percent is the magic number that indicates a privileged behavior can affect the firm. While these 706 firms all had *Compustat* data, this data was not always complete for all *Compustat* variables used in our empirical tests. This caused a loss of 55 observations when conducting regression tests leaving a working sample of 651 SEOs.

We used hedge fund data from Hedge Fund Research (HFR), which is one of the three commercial databases that have more than ten years of data collecting experience.[15] Of importance for our tests, the HFR database contained monthly data for all active hedge funds from which we can gather monthly values for the nine hedge fund variables: hedge fund assets under management by the industry; the number of hedge funds; the average (or mean) hedge fund size; the median hedge fund size; the proportion of hedge funds using leverage; the proportion of hedge funds using three hedge fund strategies (event-driven, relative value, and directional); and, average hedge fund return (net of fees). These nine variables were described in detail earlier when presenting our regression model and are also described in the Appendix.

[15] Fung and Hsieh (2006) describe the potential biases in the three commercial data sets: TASS, HFR, and CISDM.

To get the proper data from HFR, we had to match the announcement date (or day 0) for each SEO with the month of the hedge fund data.[16] Doing this enabled us to merge the HFR data with our 651 SEOs based on the month of the SEO. Below we illustrate our merging procedure by describing how we get a monthly average hedge fund return for the variable "*Average Hedge Fund Return*" ("*AHR*").

Consider an SEO with a registration date of June 15, 2003 (with the 15th being the date of registration or "day 0") with June being "month 0". The monthly June return for each active hedge fund in the data base would be computed from its ending price of Friday, May 30, 2003 to its ending price on Monday, June 30, 2003. We used all of these returns to compute an average equal-weighted monthly return for June 2003.[17] While we used the 15th day of June in this illustration, any SEO with a registration date during June would have June as its month 0. If June is month 0, then May would be "month –1" while July would be "month +1" and so forth for the year of 2003. In brief, aggregating HFR data by month enables us to calculate (for any given month) desired values for all nine hedge fund variables.

B. Methodology

For each of the 651 SEOs, we used CRSP data to compute volatility in excess daily returns is

$$ER_{i,\tau} = r_{i,\tau} - r^{e}_{i,\tau} \tag{2}$$

[16] Since we are using up to a twenty-day window both before and after the offering for our short-run tests, we are on average matching the SEO window with the hedge fund month for these tests.
[17] As will be seen in Table III, the average number of hedge funds during 2003 is 3,215. This average includes the month of June as well as the other eleven months. For June, the number of hedge funds is about 2,800. Thus, the average return would be based on this number of active hedge funds.

where $ER_{i,\tau}$ is the SEO's daily excess return for stock i for day τ; $r_{i,\tau}$ is the SEO's daily raw return for stock i for day τ; and $r^{e}_{i,\tau}$ is the daily expected return for stock i for day τ. The expected return is given by its exchange-based, value-weighted index where "exchange-based" indicates the exchange on which the stock is traded: NYSE, AMEX or NASDAQ. Volatility in excess returns was computed for various short-run and long-run t periods (i) before day 0 (and including day 0), (ii) after day 0, and (ii) surrounding day 0 (and including day 0). These two measures are:

(1) idiosyncratic volatility (firm-specific component of total volatility); and,
(2) systematic volatility (market or nondiversified component of total volatility).

The roots of our computation procedure can be gleaned from prior research (Duffee, 1995; Grullon et al. (2008); Ang et al., 2006, 2009). Following Grullon et al. (2008), we compute our two volatility measures as described below.

First, we compute the firm-specific component of total volatility.[18] This component is called the idiosyncratic volatility ($IVOL_{i,t}$) for stock i for period t and is calculated as

$$IVOL_{i,t} = \sqrt{\frac{\sum_{\tau \in t} \varepsilon^{2}_{i,\tau}}{n_t - 1}} \tag{3}$$

where n_t is the number of non-missing returns during period t and $\varepsilon_{i,\tau}$ is the Fama and French (2009) residual for day τ. $\varepsilon_{i,\tau}$ is calculated from the following regression:

$$r_{i,\tau} - r^{f}_{\tau} = \alpha + \beta 1_{i,t}(MKT_{\tau} - r^{f}_{\tau}) + \beta 2_{i,t}(HML_{\tau}) + \beta 3_{i,t}(SMB_{\tau}) + \varepsilon_{i,\tau} \tag{4}$$

[18] As noted previously, total volatility is the standard deviation of the daily excess stock returns and consists of both idiosyncratic and systematic risk. As also noted previously, we tested total volatility but found that its results were identical to idiosyncratic risk. Thus, for brevity and to avoid redundancy, we do not report results for total volatility.

where $r_{i,\tau}$ is the raw return on stock i for day τ; MKT_τ is the return on the value-weighted CRSP index for day τ; r_τ^f is the risk-free return for day τ given by the one-month T-bill; HML_τ is the average return for day τ for the two value portfolios minus the average return for day τ for the two growth portfolios; and, SMB_τ is the average return for day τ for the three small portfolios minus the average return for day τ for the three big portfolios.[19]

Second, we compute the market (or nondiversified) component of total volatility. This component is called the systematic volatility ($SVOL_{i,t}$) for stock i for period t and is computed as

$$SVOL_{i,t} = \sqrt{\frac{\sum_{\tau \in t} (ER_{i,\tau} - \varepsilon_{i,\tau} - \overline{ER_{i,t}})^2}{n_t - 1}}\ . \tag{5}$$

where $ER_{i,\tau}$ is the excess return for day τ for stock i during period t given in equation (2); $\varepsilon_{i,\tau}$ is the Fama and French (2009) residual for day τ calculated from (4); $\overline{ER_{i,t}}$ is the mean of all $ER_{i,\tau}$ values; and, n_t is the number of non-missing returns during period t.

We also will test differences in volatility between pre-SEO and post-SEO periods. These changes in idiosyncratic and systematic volatility between periods, $\Delta VOL_{i,\Delta t}$, are computed as:

$$\Delta IVOL_{i,\Delta t} = IVOL_{i,t} - IVOL_{i,t-1}, \text{ and} \tag{6}$$

$$\Delta SVOL_{i,\Delta t} = SVOL_{i,t} - SVOL_{i,t-1}. \tag{7}$$

[19] The left-hand side of equation (4) estimates the stock's risk-free adjusted raw return (e.g., a return that captures all risk premiums), while the right-hand side equation (4) estimates factors that systematically influence the stock's risk-free adjusted raw return. These factors are the market risk premium, the size premium earned by small firms, and the value premium earned by firms with high book to market ratios. The residual is the portion of the risk-free adjusted raw return that cannot be explained by the market premium, the size premium, or the value premium. The volatility of this unexplained risk-free adjusted raw return is the idiosyncratic risk.

C. Descriptive Statistics

Descriptive statistics (means, medians, and standard deviations) are given in the first three tables. Table I reports descriptive statistics for independent variables tested in regression analysis, while Table II gives statistics for three dependent variables used in regression tests. These three variables are the two volatility measures just described in the previous section. Statistics for these volatility variables are reported for seven short-run and six long-run periods. Table III provides means by year for hedge fund variables and the two volatility measures. This table enables us to understand how these variables can change over time.

Panel A of Table I reports that hedge fund assets under management for all active funds averages $763 billion, while the number of active hedge funds averages 2,551. The average hedge fund size has a mean of $366 million, but the median hedge fund size has a mean of only $79 million. The latter two statistics indicate there are a relatively small number of extremely large hedge fund firms that create an overall high average asset size even though most hedge fund firms are much smaller and below $100 million. This suggests that it would be rare for a hedge fund in our sample to be required by the SEC to file Form 13F according to the $100 million criterion. On average, the proportion of hedge funds using leverage is 0.595. This proportion is much greater that the proportions for the three hedge fund strategies as the means for these strategies are 0.084 for event-driven (special situations) strategy, 0.104 for a relative value (arbitrage) strategy, and 0.131 for a directional (equity hedge) strategy. All active hedge funds earn a mean monthly return (net of fees) of 1.22%. Compounding monthly, we get a mean APY of 15.66% (about 16% annualized), which is a healthy rate of return given our sample takes place during a period of overall poor market performance as major indices fell and hedge funds charge exorbitant fees of about 21% (management fees about 2% and incentive fees about 20%).[20] Thus, the mean APY before fees would be very high (about 16% + 21% = 37%). Because the market was overall stagnant from 1999–2005, the mean APY of 37% would also be a performance-adjusted APY.

Panel B of Table I reports that the mean market value of outstanding common stock is $1.86 billion, while the median is only $0.66 billion. Insiders held, on average, 0.492 of the outstanding shares before the SEOs and 0.386 after the SEOs. This fall from before to after the SEOs renders a mean change in inside ownership proportion of –0.106. Thus, while there is a large sell-off of shares by insiders (over one share sold per five shares owned), insiders typically maintain slightly over one-third ownership of shares as judged by the median value of 0.350 for the inside ownership proportion after an SEO. On average, 0.604 of the total shares offered are primary shares. Thus, nearly 40% of the total shares being offered are being sold by current owners (with about half of these current shares being sold by insiders).

Insert Table I (about here)

The mean underpricing of 0.042 indicates that the average offering price is set over 4% below its estimated price where the estimated price is given by *Investment Dealer's Digest*. The estimated price is assumed to be based on the market price prior to the announcement of the offer price. The amount of cash and other short-term assets relative to total assets averages 0.271. Growth, as measured by capital expenditures to total assets, averages 0.061. SEO firms have a

[20] A 2007 report by the Institute for Policy Studies and United for a Fair Economy found that the top 20 private-equity and hedge fund managers made more in 10 minutes than average-paid U.S. workers earned in a year. Top executives at hedge funds averaged $12.6 million a week, or $210,700 an hour based on a 60-hour week, compared with the $29,500 the average worker made in 2006.

mean leverage ratio of 0.228 and a mean profit ratio of 0.031. However, the median is 0.103 indicating that the typical SEO firm is (from a book standpoint) experiencing double-digits profits. Finally, the means for the tangibility ratio (net plant and equipment to total assets) and the Tobin's Q ratio are 0.232 and 6.998, respectively. Thus, the average market value of assets is nearly seven times greater than the book value of assets. However, this high number is explained by outliers as the median is less than three times greater. While the Tobin's Q ratio peaked near 1.8 during the height of the internet-technology bubble, the median of 3 indicates that our SEO sample is abnormally high in terms of its market to book values.

While not given in Table I, we can point out three other important characteristics of our sample. *First*, 352 firms (54% of the total sample of SEOs) are found for the first three years of our study (1999–2001) and this is the period that best captures the volatility associated with the internet bubble period given that we will look at volatility for up to two years before SEO announcements. *Second*, 140 firms (21.5% of our sample) indicate that expansion is the major purpose for the proceeds being raised. However, only 446 firms were issuing over one-third of their total shares as primary shares. Thus, for those 446 SEO firms with a significant amount of proceeds to use, nearly 31.4% of these firms earmark funds for expansion-related purposes. *Third*, 448 firms (about 69% of our sample) are listed on NASDAQ with the remaining 203 listed on NYSE/AMEX.

Panel A of Table II reports volatility results for seven short-run periods used in regression tests. This panel reveals that the mean daily idiosyncratic volatility in stock price (*IVOL*) was greater for short-run periods before (and including) day 0 compared to the short-run period after day 0. For example, the ten days before plus the announcement day (days –10 to 0) had a mean of 0.0432 and the ten days after (days +1 to +10) had a mean of 0.0377. For the twenty days before plus the announcement day (days –20 to 0) had a mean of 0.0429 and the twenty days after (days +1 to +20) had a mean of 0.0391. Systematic volatility (*SVOL*) results before versus after (for either a ten-day period or a twenty-day period) are virtually indistinguishable. Of importance, the means for *SVOL* are diminutive compared to those for *IVOL*. The panel also reveals that medians are always smaller than means indicating large outliers are driving the larger mean volatility statistics.

Most event studies of SEOs focus on the announcement impact that occurs immediately before and on the announcement day. For our sample, the mean negative excess returns for days –2 to 0 are –2.60% (which is typically of the announcement day impact for prior studies). Panel A reveals that the mean *IVOL* of 0.0415 for these three days is similar to the mean volatility of 0.0419 for either the 21 days around SEOs (days –10 to +10) or for the mean volatility of 0.0418 for the 41 days around SEOs (days –20 to +20). However, the standard deviation for the three-day *IVOL* of 0.0319 is 32.5% greater for the 21-day mean *IVOL* of 0.0241 and 39% greater than the 41-day mean *IVOL* of 0.0230.

Insert Table II (about here)

Panel B of Table II reports volatility results for six long-run periods used in regression tests. Consistent with stock price run-ups that are known to occur for periods prior to SEOs, we generally find greater pre-SEO volatility compared to post-SEO. However, the differences in volatility measures for pre-SEO versus post-SEO long-run comparisons are small relative to the pre-SEO versus post-SEO short-run comparisons.[21] For example, the mean *IVOL* of 0.0453 for days –260 to 0 compares favorably to that of 0.0432 for days +1 to +260. This long-run difference of 0.0021 is small compared to the difference of 0.0055 between days –10 to 0 versus days 1 to +10. On a percentage basis, the difference would be even more pronounced given that short-run means are smaller. As was true for the short-run results, medians for volatility measures are smaller than means.

Panel B reports that the *SVOL* results are similar except for the mean comparison between days –260 to 0 and days 0 to +260 (or one year before to one year after). While both of these *SVOL* means are relatively small, the mean *SVOL* of 0.0057 for days –260 to 0 is 84% greater than the mean *SVOL* of 0.0031 for days 0 to +260. The fall from 0.0057 to 0.0031 for the one-year before and one-year after SEOs cannot be found for the two-year before and two-year after mean *SVOL*. Instead of a fall, we see a slight increase from 0.0035 to 0.0038.

Panel C in Table II offers comparison tests for the volatility measure for the four pre-SEO periods versus the four corresponding post-SEO periods. For the two short-run and the two long-run tests for *IVOL*, we find negative mean differences and negative parametric *t* and nonparametric (Wilcoxon signed rank) *z* statistics that are significant beyond the 1% level. These negative results indicate that the idiosyncratic (firm-specific) volatility is dramatically falling around SEOs. However, the statistics for the *SVOL* tests switch signs for three tests. For example, if we focus on the short-run tests, we get insignificant negative *t* and *z* statistics for "+1 to +10

[21] Technically, pre-SEO periods should not include day 0 (the day of the SEO announcement) but, for simplicity purposes, we refer to these periods as pre-SEO periods.

minus –10 to 0" comparison test, but positive *t* and *z* statistics for the "+1 to +20 minus –20 to 0" comparison tests that are significant beyond the 1% and 5% levels, respectively. This indicates a significant increase in systematic (market) risk around SEOs only for the longer short-run period of 41 days around SEOs. For the long-run tests, we get negative *t* and *z* statistics for "+1 to +260 minus –260 to 0" comparison test that are significant beyond the 1%. However, for the "+1 to +520 minus –520 to 0" comparison tests, we only get a negative statistic for nonparametric test with a *z* statistic that is significant beyond the 1% level. However, the parametric test is not only positive but its *t* statistic is also significant beyond the 1% level. This perplexing difference in signs (that are both significant) for systematic volatility for the four years around SEOs is explainable in terms of a greater number of SEOs with higher positive increases in volatilities. In conclusion, we only state that there is a fall in systematic risk around SEOs for the two-year period surrounding SEOs.

Table III shows means by year for key variables used in empirical tests. Panel A reports means for the nine hedge variables and Panel B and Panel C give means for the two volatility measures for selected time periods surrounding SEOs. Panel A illustrates the growth in the hedge fund industry taking place for our sample's seven-year period from 1999─2005. For example, the total assets under management controlled by the hedge funds grew from $448 billion in 1999 to $1.311 trillion in 2005, which is a 193% increase for these seven years. Furthermore, while there were only 1,306 hedge funds in 1999, this number grew to 5,045 by 2005, which is a 286% increase for these seven years. While the hedge fund industry was nearly doubling, hedge fund firms were downsizing between 1999─2005. This is seen by the variables representing the average and median hedge fund sizes, which are falling by –16% and –34%, respectively, for these years. The fall is consistent each year and insures that more and more hedge funds will be under the $100 million and thus avoid filing Form 13F. The use of leverage is gradually increasing (albeit inconsistently) over time achieving a 9% increase from 1999–2005. Other than the event-driven (special situations) strategy that is constantly decreasing over our time period (falling –25% for our seven year period), the proportion of hedge funds using a relative value (arbitrage) strategy and directional (equity hedge) strategy are gradually increasing by 19% and 5%, respectively, from 1999–2005.

Insert Table III (about here)

Panel B of Table III shows, in contrast to the remarkable increase in the number of funds and the asset size of these funds found in Panel A, that the average daily idiosyncratic volatility (*IVOL*) for "days –20 to 0" and "days +1 to +20" fell dramatically and in a very similar manner. For "days –20 to 0," *IVOL* fell from a high of 0.0683 in 2000 to a low of 0.0258 in 2005, which is a drop of –62%. For "days +1 to +20," *IVOL* fell from a high of 0.0665 in 2000 to a low of 0.0223 in 2005, which is a drop of –67%. The year of 2000 is not only the year that the internet-technology bubble peaked but also the year the bubble began bursting. Thus, it is not surprising that this year represents the most volatile period for the periods immediately surrounding SEOs. The daily systematic volatility, *SVOL*, also decreases in a similar fashion but its magnitude for each year is minuscule compared to daily idiosyncratic volatility. The long-run results for "days –520 to 0" and "days +1 to +520" for *IVOL* mirror the short-run results as it falls in a similar manner from 2000–2005 (albeit the fall is less than that for "days –20 to 0" and "days +1 to +20"). However, the long-run results for *SVOL* differ from the short-run as there is no consistent pattern as systematic volatility goes up and then goes down over time.

While not reported in Table III due to brevity concerns, it can be pointed out that the volatility results for periods of "days –20 to 0," "days +1 to +20," "days –520 to 0," and "days +1 to +520" correspond with the respective shorter periods of "days –10 to 0," "days +1 to +10," "days –260 to 0," and "days +1 to +260." The lone exception is the systematic volatilities when comparing "days –260 to 0" and "days –520 to 0" where the volatilities for "days –260 to 0" are less. However, they are less only in a percentage sense given the relative smallness of all systematic volatilities.[22]

The volatility results in Panel C of Table III look at periods surrounding SEOs and are very similar to those just described in Panel B in that volatility measures are falling. For example, for the short-run results, the average daily idiosyncratic volatility (*IVOL*) for "days –10 to +10" and "days –20 to +20" both drop considerably over time and in a very similar manner. To illustrate, consider "days –10 to 10" where *IVOL* fell from a high of 0.0680 in 2000 to a low of 0.0254 in 2005, which is a fall of –63%. The fall for "days –20 to +20" is –64% for the same period. The daily systematic volatility, *SVOL*, also decreases in a similar fashion but its magnitude is once again small in scale relative to daily idiosyncratic volatility. The long-run results in Panel C for "days –260 to +260" and "days –520 to +520" for *IVOL* mirrors the short-run results in Panel C as it falls in a similar manner from 2000–2005 (albeit the fall is slightly less than that for "days –10 to +10" and "days –20 to +20"). However, the long-run results for *SVOL* differ from the short-run as there is no consistent pattern as systematic volatility goes up and then down over time. Although

[22] Although also not reported in table format, we also tested the total daily volatility and it mirrored the daily idiosyncratic volatility as it decreased in an almost identical fashion from 2000–2005.

not reported in Table III, the volatility results for the days of –2 to 0 are similar to the other short-run results in Panel C in that both volatility measures show the same general downward trend for our period of study.

The general decline in idiosyncratic volatility that we document agrees with the study by Comin and Philippon (2006). They discover that volatility falls for a period of 2001–2003, which is within our study's period of 1999–2005. However, most studies (e.g., Campbell et al., 2001; Cao et al., 2008) find that idiosyncratic risk has been increasing over time when lengthier periods are examined. However, these studies can agree with our findings by showing the existence of periods of reduced idiosyncratic volatility.

III. Empirical Results

A. Correlation Results

Table IV reports Pearson and Spearman correlations between independent variables to be used in regression tests. Pairs of variables are marked with bold print if they have correlation coefficients greater than 0.3. These coefficients are considered as having potential for collinearity problems. Furthermore, a high degree of correlation among a group of variables indicates potential multicollinearity problem when conducting regression analysis. Thus, one should pay particular attention to their variance inflation factors (*VIFs*) to help determine multicollinearity problems. Although not marked with asterisks, those variables in Table IV with correlation coefficients over 0.08 are significant at the 5% level and beyond, while those with correlation coefficients over 0.10 are significant at the 1% level and beyond.

When conducting regression tests, our rule of thumb will be to not use independent variables together if their correlation coefficients are 0.8 or greater unless we form residuals from these variables that overcome the collinearity problems that would otherwise exist. Due to the number of hedge variables that have correlation coefficients greater than 0.8, we are limited in how many we can use at one time. In essence, many of these hedge variables are nearly perfect substitutes for one another.

Insert Table IV (about here)

We now describe those variables that exhibit the most potential for collinearity problems. *First*, Table IV reveals that seven hedge fund variables (which are the first seven variables in the table) have correlation correlations among themselves that are all greater than 0.68 and some are nearly perfectly correlated. While we will test all of these seven variables, we will focus on *AUM* and *PED* when reporting our regression results in table format. We choose *AUM* because it captures the total increase in assets under management over time and this is considered more representative of the hedge fund industry size compared to other hedge fund variables such as the number of hedge funds (*NHF*). We selected the "event-driven" variable (*PED*) because our study is an event study and *PED* also performs as well or better when explaining our volatility measures (*VOL*). Since *PED* and *AUM* have correlation coefficients that average –0.975, we use the residuals for *PED* that are uncorrelated with *AUM* to resolve the collinearity concern between these variables. The highly negative correlation of –0.90 and over between *PED* and *PLV* and between *PED* and *PRV* indicate that hedge firms that use an event-driven strategy are much less likely to simultaneously use either leverage or a relative value (arbitrage) strategy. However, because our data is only as accurate as our HFR source (and those hedge funds reporting to HFR), one does not know for sure if such mutually exclusively behavior actually occurs with such a high degree of negative correlation in the real world.

Second, Table IV also indicates that using *ITB* with any of the first seven hedge fund variables can create problems unless corrected for collinearity by using uncorrelated residuals. Using the residuals for *ITB* that are uncorrelated with *AUM* serves to resolve this collinearity concern for *ITB* while also eliminating collinearity problems with *PED*'s residual (the *VIF* for all three variables are no higher than a miniscule 1.4). While it is possible that the correlation between hedge fund variables and a time period variable makes it hard to capture a time period effect, there is evidence that it does not. For example, despite the full bursting of this bubble by 2001, all hedge variables (except *PEH*) have consistent percentage changes from year to year and not just during the bubble period or post-bubble period. As can be seen by looking at Table III, this is particularly true if one looks at the four variables that capture a size effect associated with hedge funds (*AUM*, *NHF*, *AHS*, and *MHS*). Like *AHS* and *MHS*, four other hedge fund variables (*PLV*, *PED*, *PRV*, and *PEH*) do not have large percentage changes from year to year. In conclusion, we have no real reason to think that any impact on volatility from hedge fund variables can be explained by a time period variable.

Third, due to the potential for collinearity given the number of correlation coefficients that are greater than (or even near) 0.3, all regression results should be checked. Besides the hedge fund variables just described, the Spearman (more so than the Pearson) tests indicate potential collinearity problems between two sets of variables: *LEV* with *TBQ* and *GRO* with *TAN*. Thus, these variables should be particularly checked for collinearity. Since the Spearman correlation coefficient between *LEV* and *TBQ* is greater than 0.8, we apply our rule of thumb and use a residual for *TBQ* that is uncorrelated with *LEV*.

Fourth, regression tests should be checked for *VIFs*. However, because we avoid using highly correlated variable or use uncorrelated residuals for variables with correlation coefficients greater than 0.8, all of our reported regression results are well below generally accepted cutoffs ranging from 4.0 to 10.0 for *VIFs*. Thus, we do not formally report *VIFs* in table format. Of interest, our largest *VIF* is only 2.6. While also not reported, we verified our results by conducting tests using uncorrelated residuals and for which the largest *VIF* was only 1.4. These tests serve to tell us which variables have significance levels that are potentially influenced by multicollinearity. Thus, we are able to report on which variables may have results influenced by multicollinearity. *Fifth*, all of our reported regression results have been checked for heteroskedasticity, autocorrelation, and non-normality with nothing found.

Insert Table V (about here)

Table V summarizes the predicted signs for the coefficients discussed in Section I.B when our regression model was presented. The independent variables are given in the first column and their predicted sign in the second column. The predicted sign holds for both the idiosyncratic volatility test (*IVOL*) and the systematic volatility (*SVOL*) test. The signs that we actually get in Table VI and Table VII are reported in the last column of Table V. The actual sign entered in the last column for any variable almost always occurs for each test. However, if more than one sign occurs for all tests, then we enter the sign that occurs most frequently.

After all the regression results are presented in Table VI and Table VII, then Table VIII will summarize the significant signs found for all regression tests. These results in Table VIII will not be as uniform as suggested by the last two columns in Table V where the last column only gives the most common occurring sign. As seen in Table V, the only variables that do not live up to its predicted sign is the monthly average hedge fund return (*AHR*) and even here tests can differ depending on the volatility measure and time period tested.

B. Short-Run Regression Results

Table VI reports our short-run regression results with idiosyncratic volatility (*IVOL*) and systematic volatility (*SVOL*) as our two dependent variables. Short-run tests include the following: days –20 to 0 (in Panel A), days –10 to 0 (in Panel B), days +1 to +10 (in Panel C), days +1 to +20 (in Panel D), days –2 to 0 (in Panel E), days –10 to +10 (in Panel F), and days –20 to +20 (in Panel G).[23] As seen in these panels, R^2 values range from 0.19 to 0.65 with F values all significant beyond the 1% level (with values ranging from 11.6 to 67.8). Of importance, the period consisting of days –20 to +20 (in Panel G) has the highest R^2 and F values. Thus, for a 41-day trading period surrounding SEOs, our regression model explains almost 2/3 of the idiosyncratic volatility and close to 2/5 of the systematic volatility. The 2/3 also holds if we test total volatility, which as noted previously gives virtually the same results as idiosyncratic volatility (and so is not reported in table format).

[23] Besides the need to capture short-run trading strategies around SEOs, another reason for looking at longer short-run periods is that some offerings can have prior public announcements indicating the offering is being planned and so the registration day may not always be day 0. Even without these prior announcements, there can be leakage such as might occur when information is given to hedge fund managers (or any investors or institutions). This information can include these two details: (i) date of public announcement through a registration statement, and (ii) the extent of the underpricing. Together these two details reveal strategies that hedge funds might use for profitable trading strategies.

For the twenty-one day period consisting of days –20 to 0, Panel A reports a positive coefficient for assets under hedge fund management by the hedge fund industry (*AUM*) that is statistically significant beyond the 1% level for both the idiosyncratic (*IVOL*) and systematic (*SVOL*) tests. This is consistent with our first hypothesis, *H–1*. Since logs are used for the dependent and independent variables, this panel reveals that a 10% increase in assets under hedge fund management by the hedge fund industry will cause a 6.14% reduction in idiosyncratic volatility (*IVOL*) and a 2.59% reduction in systematic volatility (*SVOL*) for days –20 to 0.

Insert Table VI (about here)

Except for the prediction concerning average hedge fund returns for month 0 (*AHR*), the results in Panel A offer support for our second hypothesis, *H–2*. This support takes two forms. *First*, the proportion of hedge funds with an event-driven strategy (*PED*) has a positive coefficient that is significant beyond the 1% level for the *IVOL* and *SVOL* tests for days –20 to 0. It appears that hedge funds using event-driven strategies around an SEO event might be actively manipulating stock prices in a fashion that increases volatility. Of interest, hedge funds using an event-driven strategy rarely use leverage or an arbitrage strategy and (as described below) these two hedge fund variables are associated with volatility reduction. Thus, hedge fund firms busy increasing volatility for days –20 to 0 shy away from use of leverage and arbitrage. *Second*, as predicted by *H–2*, the variable for the proportion of hedge funds that use an equity hedge strategy (*PEH*) has a significant positive coefficient for the *IVOL* test and thus has a significant effect on increasing idiosyncratic (firm specific) volatility. However, we do not find evidence that *PEH* affects systematic volatility as predicted by *H–2*.

For the fourth and last independent hedge fund variable, average hedge return (*AHR*), we do not find evidence that greater hedge returns during month 0 are associated with greater idiosyncratic volatility for days –20 to 0. On the contrary, we get a negative coefficient that is almost significant at the 5% level indicating that *AHR* reduces idiosyncratic volatility.[24] For the *SVOL* test, we find some evidence that *AHR* increases systematic volatility as its *t* statistic is 1.51 (which would be significant at the 7% level for a two-sided test).

While not reported in Table VI, we tested other hedge fund variables (first defined in Panel A of Table I and also reported in Table IV) that are nearly perfectly correlated with *AUM* and *PED*. All of these results were consistent with the expectations found in *H–1*. We now describe these tests for days –20 to 0 (where the results also generally hold for all other short-run periods tested in the other panels of Table VI).

First, we substituted the number of hedge funds variable (*NHF*) and got the same results given in Panel A of Table VI. This also holds for other panels in Table VI. The similar result is expected since *AUM* and *NHF* are almost perfect substitutes for one another as shown in Table IV by their correlation coefficients, both of which are 0.99. *Second*, we also tested hedge fund size variables (*AHS* and *MHS*) separately and they performed the same as *AUM* and *NHF* except with an opposite coefficient signs indicating that the downsizing of the individual hedge fund size reduces volatility in stock prices for days –20 to 0. *Third*, we found that results for *PLV* and *PRV* yielded virtually the same regression results (albeit opposite coefficient signs) if either of these two variables replaced *PED* when used with *AUM* (or *NHF* or *AHS* or *MHS*). Thus, an increase by

[24] The *t* statistic for *AHR* increases to 2.12 if we correct for collinearity by running the residuals that are uncorrelated with either *AUM* or *PED*. This offers more evidence that superior hedge fund performance reduces volatility.

hedge fund firms in their use of leverage and use of a relative value (arbitrage) strategy reduces volatility. Because *AUM*, *NHF*, *AHS*, *MHS*, *PED*, *PLV*, and *PRV* are all highly correlated, it is difficult to discern which of these hedge fund characteristics might be more dominant in determining volatility in SEO stock prices for days –20 to 0 (or any period tested). Indeed, it appears impossible to fully separate the influence of all of these variables (e.g., *PED* is rarely used with *PLV* and *PRV* while *PLV* and *PRV* tend to always be used together). Finally, when we tried to add a hedge fund variable to those four hedge funds variables given in our regression model, the R^2 values typically increased by no more than 0.002 per variable added (which is a trivial amount given our high R^2 values). Furthermore, unless corrected by using uncorrelated residuals, the addition of hedge fund variables beyond those four reported caused *VIFs* to go past conventional cut-off levels (thus indicating multicollinearity problems).

Of the non-hedge fund control variables used in our test for days –20 to 0, a reduction in idiosyncratic volatility (*IVOL*) is significantly associated with smaller decreases in insider ownership levels (*CIL*), lower proportions of primary shares (*PRI*), less underpricing (*UND*), a non-expansion purpose (*POP* = 0), more trading liquidity (*TLQ* = 0), lower growth ratios (*GRO*), greater leverage (*LEV*), greater tangible assets ratio (*TAN*), and lower Tobin's Q (*TBQ*). All of these results are significant at the 5% level or better. However, one of these non-hedge fund variables (*PRI*) had the opposite sign of that predicted earlier in the paper in Section II.B. Thus, greater proportions of primary shares do not reduce volatility but, on the contrary, greater secondary selling significantly reduces volatility. This runs completely counter to the notion that secondary selling can signal negative news that might be associated with greater volatility. As noted earlier when discussing the predicted coefficient sign for *PRI*, this means that a higher proportion of primary shares indicate (i) more negative news about overvaluation, and (ii) greater secondary selling signifies that current sellers are not signaling negative news. The latter suggests that the market knows that greater secondary selling results simply from exercising options (that are expiring) and from diversification needs of current sellers.

Of the non-hedge fund control variables used in our regression model for days –20 to 0, a reduction in systematic volatility (*SVOL*) is significantly associated with lower inside ownership proportions (*ILA*), less underpricing (*UND*), time period outside the internet-technology bubble period (*ITB* = 0), more trading liquidity (*TLQ* = 0), lower growth ratios (*GRO*), and lower Tobin's Q (*TBQ*). All of these variables for the *SVOL* test had their predicted coefficient signs and were significant at the 5% level or better. Thus, *CIL*, *PRI*, *POP*, and *LEV* (which were significant for the *IVOL* test for days –20 to 0) are now insignificant, while *ILA* and *ITB* (which were insignificant for the *IVOL* test) are now significant for the *SVOL* test.

It should be pointed out that multicollinearity appears to prevent two variables from being significant for both the *IVOL* and *SVOL* tests. These two variables are the financial liquidity variable (*FLQ*), and the profitability ratio (*PFT*). Performing tests that correct for collinearity, these two variables were significant at the 5% level or better with their predicted signs. Thus, reduced volatility is associated with SEO firms that (i) can safely maintain lower cash and other short-term assets and (ii) can attain greater operating income before depreciation. However, the impact of *FLQ* and *PFT* together on R^2 values are negligible (less than 0.01) indicating their presence in our regression model is redundant and their impact may be better captured by other variables. Finally, for the *SVOL* test, *LEV* is significant with its predicted negative coefficient. Thus, greater leverage is associated with reduced systematic volatility.

Panel B of Table VI reports the results for days –10 to 0. The results in this panel are like those in Panel A for days –20 to 0 with the following exceptions. *First*, *PEH*, *GRO*, and *LEV* are no longer significant for the *IVOL* test. *Second*, *ITB* is no longer significant for the *SVOL* test. *Third*, *FLQ* is now significant for the *SVOL* test. Fourth, the R^2 value for the *IVOL* test falls from 0.56 to 0.47, while the R^2 value for the *SVOL* test only falls from 0.30 to 0.29. Thus, for a short-run period prior to SEOs, our regression model performs better if we go back to day –20 instead of day –10. Besides the similarities just mentioned between Panels A and B, all other results mentioned previously for days –20 to 0 are also similar for days –10 to 0. In particular, the results mentioned previously for the five other hedge fund variables (*NHF*, *AHS*, *MHS*, *PLV*, and *PRV*) also hold when we test days –10 to 0. In conclusion, Panel B offers the same support for *H–1* and *H–2* found in Panel A.

Panels C and D in Table VI provide results for the tests estimating post-SEO short-run volatility.[25] The results in Panels C and D, like those in Panels A and B, indicate (i) the same high level of support for *H–1* and *H–2* and (ii) many of the same factors impact both pre-SEO short-run and post-SEO volatility. Hedge fund factors for post-SEO short-run tests performed like those for pre-SEO tests. For example, *IVOL* and *SVOL* fall as *AUM* increases and *PED* decreases, while only *IVOL* decreases as *PEH* decreases. *AHR* also remains an insignificant factor for post-SEO short-run tests with one exception: it now has a significant negative coefficient for the *SVOL* test

[25] To distinguish between Table VI results in Panels A and B from those in Panels C and D, we refer to the results in Panels A and B as pre-SEO short-run results and those in Panels C and D as post-SEO short-run results.

for days +1 to +10 indicating that greater performance by hedge funds are associated with lower systematic volatility. In terms of the other five hedge fund factors not found in table format (*NHF*, *AHS*, *MHS*, *PLV*, and *PRV*), once again each has its predicted sign.

In terms of control independent variables, we find similarities between the post-SEO short-run results in Panels C and D and the pre-SEO short-run results in Panels A and B. In general, pre-SEO and post-SEO short-run *IVOL* and *SVOL* are both reduced when *UND*, *TLQ*, *GRO*, and *TBQ* are all lower, while only *IVOL* is reduced when *TAN* and *LEV* increase and only *SVOL* is reduced when *ILA* decreases. Unlike pre-SEO short-run *IVOL* results, *CIL*, *PRI*, and *POP* no longer influence *IVOL*, while *FLQ* now tends to have its predicted positive coefficients for post-SEO volatility tests even without correcting for collinearity (Recall that *FLQ* has significant positive coefficient for pre-SEO volatility if we corrected for collinearity.) If we correct for collinearity for *PFT*, then the post-SEO short-run results are both significant with greater profitability reducing volatility. This result is like the pre-SEO result when corrected for collinearity.

The last three panels in Table VI look at results for three periods: Panel E for days –2 to 0; Panel F for days –10 to +10, and, Panel G for days –20 to +20. Because of the symmetry in the way independent variables affect volatility both for pre-SEO and post-SEO short-run period, it is not surprising that these three panels report results like those in the first four panels. In terms of the hedge fund variables, there are only two minor differences and they are (i) *PED* is now not quite significant for the *IVOL* test in Panel E for days –2 to 0, and (ii) *AHR* now has a significant negative coefficient for the *IVOL* test in Panel F for days –10 to +10. The latter indicates some significant support for a reduction in idiosyncratic volatility when hedge funds perform better. In terms of the non-hedge fund control variables, we find greater agreement of results with one noticeable exception. The results for *CIL*, *PRI*, *ITB*, and *POP* in the last three panels show more agreement for the pre-SEO short-run results in Panels A and B.

When looking at all seven panels, we see that Panel E for days –2 to 0 tends to manifest a few more differences when compared to the other six panels in Table VI. *First*, coefficients for independent variables in Panel E manifest some sharp differences relative to the other six panels. For example, the coefficient for *AUM* for days –2 to 0 is only –0.224 for the *SVOL* test. The next smallest coefficient for *AUM* for the *SVOL* test was –0.347 found in Panel F, which is a 35.4% percent reduction. There is also a large reduction of 34.9% in the coefficients for *PED* for the *IVOL* test. *Second*, coefficients for *POP*, *FLQ*, *GRO*, *LEV*, *TAN*, and *TBQ* in Panel F for the *IVOL* test are no longer significant compared to most other panels, while *PFT* is now significant. In brief, many non-hedge fund variables affect volatility differently for days –2 to 0.

We now attempt to offer an overall summary of the volatility findings suggested by our short-run regression tests in Table VI. *First*, a 10% increase in the hedge fund assets under management will cause short-run idiosyncratic volatility to have an average fall of –6.01% for all short-run tests and systematic volatility to have an average fall of –3.19%. Thus, we have support for *H–1* as greater hedge funds under management for the total industry reduces both idiosyncratic (firm-specific) volatility and systematic (market) volatility. *H–1* is also supported when we look at other hedge fund characteristics discussed in connection with this hypothesis. Namely, we find a reduction in idiosyncratic and systematic volatilities when there are increases in (i) the number of hedge funds, (ii) the use of leverage, and (iii) use of an arbitrage strategy. Finally, there is also a decrease in volatilities when individual hedge fund sizes are smaller.

Second, consistent with *H–2*, hedge funds with greater proportions of event-driven strategy increase both idiosyncratic and systematic volatilities. Additionally, higher proportions of hedge funds that follow equity hedge strategies can increase idiosyncratic volatility but this evidence is only solidly established when we look at lengthier short-run time periods extending to –20 and +20. *Third*, while greater average monthly hedge fund returns tend to reduce both idiosyncratic and systematic volatilities (most coefficients for *AHR* are negative), the relation is not statistically significant. In this regards, we cannot support *H–2*. Thus, we conclude that a better performance by hedge funds during event month 0 tends to reduce both idiosyncratic and systematic volatilities.

Fourth, the short-run regression results show that all forms of volatility are significantly reduced by lower underpricing, greater trading liquidity (e.g., listing on NYSE/AMEX), lower growth ratios, greater tangibility in assets, and lower Tobin's Q ratios. All of these results are as predicted. Fifth, there are other non-hedge fund variables that can have an impact on volatility but their impact depends on the period covered and the type of volatility examined. In brief, lower proportions of inside ownership are associated with less systematic volatility, while smaller changes in inside ownership proportions can significantly reduce idiosyncratic volatility. These results offer some evidence for signaling theories based in Myers and Majluf (1984) and Leland and Pyle (1977) in that less negative news (linked to lower insider proportions and lower decreases in these proportions) cause lower volatility.

C. Long-Run Regression Results

Table VII reports our long-run regression results. Long-run tests include the following: days –520 to 0 (in Panel A), days –260 to 0 (in Panel B), days +1 to +260 (in Panel C), days +1 to +520 (in Panel D), days –260 to +260 (in Panel E), and days –520 to +520 (in Panel F). As described below, these results mirror our short-term results in that our regression model does a good job of explaining volatility, coefficient signs for hedge variables (except *AHR*) are generally as predicted and significant, and non-hedge variables perform similarly in terms of the sign of their coefficients and significant levels.

As seen in six panels of Table VII, R^2 values range from 0.45 to 0.72 with F values all significant beyond the 1% level (with values ranging from 30.4 to 92.1). The period consisting of days –260 to +260 (in Panel E) explains almost 3/4 of the idiosyncratic volatility and close to 3/5 of the systematic volatility.

For the two-year pre-SEO period consisting of days –520 to 0, Panel A reports a positive coefficient for *AUM* that is statistically significant beyond the 1% level for both the idiosyncratic (*IVOL*) and systematic (*SVOL*) tests. This is consistent with our first hypothesis, *H–1*. This panel reveals that a 10% increase in assets under hedge fund management by the hedge fund industry will cause a 3.69% reduction in idiosyncratic volatility (*IVOL*) and a 5.78% reduction in systematic volatility (*SVOL*) for days –520 to 0.

The predictions of *H–2* for the proportion of hedge funds with an event-driven strategy *PED* and the hedge fund returns for month 0 (*AHR*) do not fully hold in Panel A. However, support for *H–2* by these two variables can be found in the other panels. Thus, we can conclude that Table VII offers overall support for *H–2*. Let us explain. *First*, in contrast to the significant negative coefficient for the *SVOL* test for *PED* in Panel A, we find that *PED* has a highly significant positive statistic for almost all other *SVOL* tests. *Second*, in regards to the *IVOL* test using *PED*, the coefficient for *PED* is of its predicted sign in Panel A as given by *H–2*. Furthermore, significant support for *H–2* can be found for most of the other long-run post-SEO tests in Table VII when *PED* is used. As discussed previously, hedge funds using an event-driven strategy rarely use leverage (*PLV*) or an arbitrage strategy (*PRV*). When we substitute either *PLV* or *PRV* for *PED* in our *IVOL* test for days –520 to 0, these two hedge fund variables are significantly associated with idiosyncratic volatility reduction at the 5% level.[26] Thus, consistent with *H–1*, hedge fund firms using leverage and an arbitrage strategy are associated with a decrease in idiosyncratic volatility for days –520 to 0.

Although the *PED* may not support *H–2* (albeit only for Panel A), the variable for the proportion of hedge funds that use an equity hedge strategy (*PEH*) does support *H–2*. For example, *PEH* has a significant positive coefficient for both the *IVOL* and *SVOL* tests and thus has a significant effect on increasing idiosyncratic and systematic volatilities. As can be seen in the other panels in Table VII, *PEH* is significant beyond the 1% for all but one test. This consistent support for *H–2* by *PEH* for long-run tests differs from short-run tests where *PEH* is never significant for the *SVOL* test.

For the fourth and last independent hedge fund variable, average hedge return (*AHR*), we do not find evidence that greater hedge returns during month 0 are associated with greater

[26] Normally, if *PED* is significant, then *PLV* and *PRV* would be significant since *PED* is highly negatively correlated with either *PLV* or *PRV* (as shown in Table IV, *rho* values average about –0.94).

idiosyncratic or systematic volatilities for days –520 to 0. This is true for all long-run tests. Thus, unlike the short-run tests where there was some evidence that *AHR* was associated with reduced idiosyncratic volatility, we cannot find any such consistent association for long-run tests. This is true even if we correct for collinearity by running the residuals that are uncorrelated with either *AUM* or *PED*.

Insert Table VII (about here)

While not reported in Table VII, we tested other hedge fund variables that are nearly perfectly correlated with *AUM* and *PED*. All of these results were consistent with the expectations found in *H–1*. We now discuss the results of these tests for days –520 to 0 (where the results also generally hold for all other long-run periods tested in the panels of Table VII).

First, we substituted the number of hedge funds variable (*NHF*) and got the same results given in Panel A of Table VII. This is expected because (as shown in Table IV) their correlation coefficients are both 0.99. *Second*, we also tested hedge fund size variables (*AHS* and *MHS*) separately and they performed the same as *AUM* and *NHF* except with an opposite coefficient signs indicating that the downsizing of the individual hedge fund size reduces volatility in stock prices for days –520 to 0. *Third*, we found that tests for *PLV* and *PRV* yielded similar regression results (albeit opposite coefficient signs) if either replaced *PED* when used with *AUM* (or *NHF* or *AHS* or *MHS*). Thus, an increase by hedge fund firms in their use of leverage and use of a relative value (arbitrage) strategy reduces volatility. As noted previously when discussing short-run regression findings, because *AUM*, *NHF*, *AHS*, *MHS*, *PED*, *PLV*, and *PRV* are all highly correlated, it is difficult to discern which of these hedge fund characteristics might be more dominant in determining volatility in SEO stock prices for days –520 to 0 (or any period tested).

Of the non-hedge fund control variables used in our test for days –520 to 0, a reduction in idiosyncratic volatility (*IVOL*) is significantly associated with smaller decreases in insider ownership levels (*CIL*), lower proportions of primary shares (*PRI*), less underpricing (*UND*), occurrence during the internet-bubble period (*ITB* = 1), more trading liquidity (*TLQ* = 0), less financial liquidity (*FLQ*), greater profitability (*PFT*), greater leverage (*LEV*), greater tangible assets ratio (*TAN*), and lower Tobin's Q (*TBQ*). All of these results are significant at the 5% level or better and tend to hold for all panels in Table VII and just not Panel A. However, two non-hedge variables do not have their predicted sign. *First*, as was true for short-run results, *PRI* had the opposite sign of that predicted in Section II.B. As mentioned earlier when discussing the short-run results in Section III.B, the market seems to behave as if a greater proportion of primary shares indicates more negative news about overvaluation, while the greater secondary selling is seen simply as current sellers exercising options and diversifying their investment portfolios. *Second*, *ITB* has its opposite predicted coefficient indicating that occurrence during the internet bubble does not increase volatility. However, all other panels in Table VII have positive coefficients that are often statistically significant.

Of the non-hedge fund control variables used in our regression model for days –520 to 0, a reduction in systematic volatility (*SVOL*) tends to be significantly associated with lower inside ownership proportions (*ILA*), less underpricing (*UND*), time period outside the internet-technology bubble period (*ITB* = 0), more trading liquidity (*TLQ* = 0), lower growth ratios

(*GRO*), and greater tangible assets ratio (*TAN*). All of these variables for the *SVOL* test had their predicted coefficient signs and were significant at the 5% level or better. Thus, *CIL*, *PRI*, *FLQ*, *PFT*, *LEV*, and *TBQ* (which were significant for the *IVOL* test for days –520 to 0) are now insignificant, while *ILA* and *GRO* (which were insignificant for the *IVOL* test) are now significant for the *SVOL* test. While there are exceptions, the above non-hedge results generally hold for all long-run tests and also agree with the short-run results (especially when we correct for potential multicollinearity problems that inflate the standard deviations used in computing *t* statistics).

The remaining panels of Table VII are similar to Panel A. Thus, to avoid redundancy (in repeating the results just described for days –520 to 0), we will focus primarily on the dissimilarities between the other five panels with Panel A.[27] *First*, as noted above, the variable capturing the proportion of hedge funds using an event strategy (*PED*) is often significant in the other panels of Table VII for the *IVOL* and *SVOL* tests, especially for post-SEO long-run tests. Thus, in support of *H–2*, the use of an event strategy does significantly increase volatility. *Second*, the results for the proportion of hedge funds using an equity hedge strategy (*PEH*) is generally consistent in their support for *H–2* as there is only one *IVOL* test and two *SVOL* tests where *PEH* is not statistically significant. *Third*, while not found in Table VII, an increase in the proportion of hedge funds using leverage (*PLV*) reduced systematic volatility for days –520 to 0; however, this is not true for all other long-run tests. In fact, the use of leverage was associated with a significant increase in systematic volatility for all other long-run periods tested. This supports *H–1*. *Fourth*, as discussed above, the coefficient for *ITB* changes for the other five panels and thus is consistent

[27] The similarities and dissimilarities between Tables VI and VII will be summarized in Table VIII.

with greater stock price volatility during the internet-technology bubble period. *Fifth*, *POP* was not significant in Panel A, but has a significant positive coefficient for most other tests found in the other five panels. Thus, as predicted, an expansion purpose of proceeds tends to be associated with greater volatility. *Sixth*, while the *IVOL* test using *GRO* is not significant in Panel A, it is significant for all other tests. Thus, as predicted, growth firms are associated with greater volatility.

We now attempt to offer an overall summary of the volatility findings suggested by our long-run regression tests in Table VII. In the process, we compare the long-run findings with the short-run findings. To aid this comparison process, we use Table VIII. This table shows in summary form whether an independent variable is significant at the 5% level or better for all short-run and long-run volatility tests. If the coefficient signs agree for both the idiosyncratic volatility (*IVOL*) and systematic volatility (*SVOL*) tests, then only that sign is placed in the cell that corresponds with a variable on its volatility test for that period. For example, in the first cell both the IVOL and SVOL tests for AUM render significant negative coefficients so a "–" appears in this cell. If only one of two volatility tests (e.g., if either the *IVOL* test or the *SVOL* test) alone is significant, then the sign for *IVOL* is identified with an "i" while the sign for *SVOL* is accompanied with an "s." For example, in the *PLV* row, the first column has "–i". This indicates a significant negative coefficient for PLV for the *IVOL* test (the SVOL test is not significant). If both volatility tests are significant but with opposite signs (which rarely occurs), then an "i" for the *IVOL* test and an "s" for the *SVOL* test are both displayed with their corresponding signs. For example, consider the *PLV* row again. If we move to the "–260 to 0" column, we find "–i,+s" that indicates the IVOL test is significantly negative but the systematic test is significantly positive. We now summarize the long-run findings while comparing them with the short-run findings.

Insert Table VIII (about here)

First, an increase in the hedge fund assets under management will cause short-run idiosyncratic volatility to have an average fall of –5.39% for all long-run tests and systematic volatility to have an average fall of –3.64%. These long-run average percentages are a bit larger than the short-run average percentages reported earlier, which were –6.01% and –3.19%, respectively. In conclusion, we have strong support for *H–1* as greater hedge funds under management for the total industry reduces both idiosyncratic (firm-specific) volatility and systematic (market) volatility. Like short-run tests, *H–1* is also supported for long-run tests when we look at other hedge fund characteristics discussed in connection with this hypothesis. Namely, we find a reduction in idiosyncratic and systematic volatilities when there are increases in (i) the number of hedge funds, (ii) the use of leverage, and (iii) use of an arbitrage strategy. Finally, there is also a decrease in volatilities when individual hedge fund sizes are smaller.

Second, we find long-run support for *H–2* that is similar to that found for short-run tests. For example, consistent with *H–2*, hedge funds with greater proportions of event-driven strategy generally increase both idiosyncratic and systematic volatilities (with the support a bit stronger for short-run tests). Additionally, higher proportions of hedge funds that follow equity hedge strategies can increase volatility. However, this long-run support is more consistent and stronger than short-run support and also covers both volatility measures (short-run support was only for *IVOL* tests that covered lengthier short-run periods).

Third, like short-run tests, long-run tests generated insignificant coefficients for the average monthly hedge fund returns variable. The only difference is that short-run tests tended to offer more negative coefficients, which are consistent with greater monthly hedge fund returns reducing volatility. Overall, we cannot offer evidence to support *H–2* that predicts greater volatility when hedge funds perform better during event month 0. Thus, we conclude that hedge fund performance has no noticeable impact on idiosyncratic and systematic volatilities regardless of the period examined.

Fourth, the long-run regression results show that all forms of volatility are significantly reduced by a number of hedge fund variables. There are more non-hedge variables influencing long-run returns than short-run returns. Common non-hedge fund variables influencing lower volatility for both long-run and short-run tests are: lower inside ownership proportions (*SVOL* tests only); less decreases in inside ownership proportions (*IVOL* tests only); less primary selling (*IVOL* tests only); lower underpricing; greater trading liquidity (e.g., listing on NYSE/AMEX); less financial liquidity (*IVOL* tests only); lower growth ratios; greater leverage (*IVOL* tests only); greater tangibility in assets (*IVOL* tests only); and lower Tobin's Q ratios (mainly the *IVOL* tests). All of these results are as predicted except for the primary selling proportion where less primary proportions (or greater secondary proportions) reduce idiosyncratic volatility.

IV. Conclusions

With the common belief that hedge funds are playing havoc with the markets, we sought to empirically examine the impact of hedge funds on stock price volatility. In particular, we wanted to answer this question: "*To what extent can hedge funds influence stock price volatility* *surrounding the announcements of major corporate events?*" To answer this question, we examine one of the more common major corporate events: seasoned equity offerings (SEOs). In our examination, we tested the impact of hedge fund variables on idiosyncratic and systematic volatility for a variety of short-run and long-run periods around the initial announcement dates for SEOs. We found that stock price volatility decreased when (i) the total assets under management by the hedge fund industry increased, (ii) the number of hedge funds increased, (iii) the size of individual hedge funds decreased, (iv) leverage was more likely to be used by a hedge fund, and (v) an arbitrage strategy (as opposed to an event-driven or equity hedge) strategy was used. We could find no consistent evidence that hedge funds performance during the SEO announcement month influences volatility. Furthermore, our regression model (composed of hedge fund variables and control variables) explained up to 71% of the variability of our idiosyncratic measure and up to 57% of our systematic volatility measure.

For all short-run and long-run tests, we found that a 10% increase in the assets under management by the hedge fund industry caused an average reduction of –5.70% in idiosyncratic (firm-specific) volatility and an average reduction of –3.41% in systematic (market) volatility. These results along with the impact of other hedge fund characteristics demonstrate that hedge funds can be a major player in influencing volatility around a major corporate event.

REFERENCES

Ackermann, Carl, Richard McEnally, and David Ravenscraft, (1999), The performance of hedge funds: Risk, return, and incentives, *Journal of Finance*, 54, 833–874.

Agarwal, Vikas, Naveen D. Navee, and Narayan Y. Naik, (2009), Role of managerial incentives and discretion in hedge fund performance, *Journal of Finance*, 64(5), 2221–2256.

Aggarwal, Rajesh K., and Phillipe Jorion, (2010), The performance of emerging hedge funds and managers. *Journal of Financial Economics*, 96(2), 238–256.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, (2009), High idiosyncratic volatility and low returns: International and further U.S. evidence, *Journal of Financial Economics*, 91(1), 1–23.

Ang, Andrew, Robert Hodrick, Yuhang Xing and Xiaoyan Zhang, (2006), The cross-section of volatility and expected returns, *Journal of Finance* 61(1), 259–299.

Bohl, Martin T., Janusz Brzeszczyński, and Bernd Wilfling, (2009), Institutional investors and stock returns volatility: Empirical evidence from a natural experiment, *Journal of Financial Stability*, 5(2), 170–182.

Black, Fischer, (1976), Studies in stock price volatility changes, *Proceedings of the 1976 Business Meeting of the Business and Economics Statistics Section, American Statistical Association*, 177–181.

Brown, Gregory and Nishad Kapadia, (2007), Firm-specific risk and equity market development, *Journal of Empirical Finance*, 84(2), 358–388.

Brunnermeier, Markus K., and Stephan Nagel, (2004), Hedge funds and the technology bubble. *Journal of Finance*, 59(5), 2013–2040.

Brunnermeier, Markus K., (2005), Information leakage and market efficiency, *The Review of Financial Studies*, 18(2), 417–457.

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, (2001), Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *The Journal of Finance*, 54(1), 1–43.

Cao, Charles, Timothy Simin, and Jing Zhao, (2008), Can growth options explain the trend in idiosyncratic risk? *Review of Financial Studies*, 21(6), 2599–2633.

Chan, Louis K. C., and Josef Lakonishok, (1995), The behavior of stock prices around instiututional trading. *Journal of Finance*, 50(4), 1147–1174.

Chemmanur, Thomas J., He Shan, and Gang Hu Babson, (2009), The role of institutional investors in seasoned equity offerings, *Journal of Financial Economics*, 94(3), 384–411.

Christie, Andrew A., (1982), The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics*, 10(4), 407–432.

Comin, Diego, and Philippon, Thomas, (2006), The rise in firm-level volatility: Causes and consequences. *NBER Macroeconomics Annual*, 20, 1–43.

Corwin, Shane A., (2003), The determinants of underpricing for seasoned equity offers. *Journal of Finance*, 58(5), 2249–2279.

Du, Julan, and Shang-Jin Wei, (2004), Does insider trading raise market volatility? *The Economic Journal*, 114(October), 916–942.

Duffee, Gregory R., (1995), Stock return and volatility. A firm-level analysis. *Journal of Financial Economics*, 37(3), 399–420.

Fama, Eugene F., and Kenneth R. French, (2009), *Fama/French – Data Library*. Retrieved June 15, 2009, from Fama/French: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Fung, William, and David A. Hsieh, (2000a), Performance characteristics of hedge funds and commodity funds: Natural vs. spurious biases. *Journal of Financial and Quantitative Analysis*, 35(3), 291–307.

Fung, William, and David A. Hsieh, (2000b), Measuring the market impact of hedge funds. *Journal of Empirical Finance*, 7(1), 1–36.

Fung, William, and David A. Hsieh, (2006), Hedge funds: An industry in its adolescence, *Economic Review*, 91(4), 1–34.

Gabaix, Xavier, Parameswaran Gopikrishnan, Vasiliki Plerou, and H. Eugene Stanley, (2006), Institutional investors and stock market volatility, *Quarterly Journal of Economics*, 461–504.

Garbaravicius, Tomas, and Frank Dierick, (2005), Hedge funds and their implications for financial stability, *European Central Bank's Occasional Paper Series*, 34, 1–73.

Gerard, Bruno, and Vikram Nanda, (1993), Trading and manipulation around seasoned equity offerings. *Journal of Finance*, 48(1), 213–245.

Gompers, Paul A., and Andrew Metrick, (2001), Institutional investors and equity prices, *The Quarterly Journal of Economics*, 116(1), 229–259.

Grullon, Gustavo, Evgeny Lyandres, and Alexei Zhdanov, (2008), Real options, volatility, and stock returns. *UBC Winter Finance Conference 2008 Paper, EFA 2008 Athens Meetings Paper*.

Henry, Tyler R., and Jennifer L. Koski, (2009), Short selling around seasoned equity offerings. *AFA 2009 San Francisco Meetings Paper*.

Jensen, Michael C., and William H. Meckling, (1976), Theory of the firm: Managerial behavior, agency costs and ownership structure, *Journal of Financial Economics*, 3(4), 305–360.

King, Michael R., and Philipp Maier, (2009), Hedge funds and financial stability: Regulating prime brokers will mitigate systemic risks. *Journal of Financial Stability*, 5(3), 283–297.

Korteweg, Arthur, and Nick Pohlsen, (2009), Corporate Credit Spreads under Parameter Uncertainty. *AFA 2009 San Francisco Meetings Paper*.

Lakonishok, Josef, Andrei Schleifer, and Robert Vishny, (1992), The impact of institutional trading on stock prices. *Journal of Financial Economics*, 32(1), 23–43.

Leland, Hayne E., and David H. Pyle, (1977), Information asymmetries, financial structure, and financial intermediation. *Journal of Finance*, 32(2), 371–387.

Myers, Stewart C., and Nicholas S. Majluf, (1984), Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13(2), 187–221.

Xu, Yexiao, and Burton G. Malkiel, (2003), Investigating the behavior of idiosyncratic volatility. *Journal of Business*, 76(4), 613–644.

APPENDIX

(*This appendix provides the definitions of the variables used throughout this paper*.)

VOL* = *Daily Excess Stock Return Volatility (See Section II.B for details on the two volatility measures used in tests and how they are computed.) For regression tests, the logs are used.

IVOL = Idiosyncratic volatility in the excess returns as given by equation (3).

SVOL = Systematic volatility in the excess returns as given by equation (5).

***HFV* = *Hedge Fund Variables* (the nine hedge fund variables are all computed during event month)**

AUM = *Hedge Fund Assets Under Management*. For regression tests, the log is used.

NHF = *Number of Hedge Funds*. As seen in Table IV, *NHF* is almost perfectly correlated with *AUM* and so is not used in regression tests as it would cause collinearity problems.

AHS = *Average Hedge Fund Size*. As seen in Table IV, *AHS* is very highly (negatively) correlated with *AUM* and so is not used in regression tests as it would cause collinearity problems.

MHS = *Median Hedge Fund Size*. As seen in Table IV, *MHS* is almost perfectly (negatively) correlated with *AUM* and so is not used in regression tests as it would cause collinearity problems.

PLV = *Proportion of Hedge Funds Using Leverage*. As seen in Table IV, *PLV* is very highly (negatively) correlated with *PED* and so is not used in regression tests as it would cause collinearity problems.

PED = *Proportion of Hedge Funds with an Event-Driven (Special Situations) Strategy*.

PRV = *Proportion of Hedge Funds with a Relative Value (Arbitrage) Strategy*. As seen in Table IV, *PRV* is almost perfectly (negatively) correlated with *PED* and so is not used in regression tests as it would cause collinearity problems.

PEH = *Proportion of Hedge Funds with Directional (Equity Hedge) Strategy*.

AHR = *Average Equal-Weighted Hedge Fund Return*.

***NFV* = *Non-Hedge Fund Variables* (the thirteen non-hedge fund variables are defined below)**

ILA = *Inside Ownership Proportion after SEO*: (Insider Shares after SEO) / (Shares Outstanding after SEO).

CIL = *Change in Inside Ownership Proportion*: *ILA* – *ILB* where *ILB* is *Inside Ownership Proportion before SEO* defined as: *ILB* = (Insider Shares before SEO) / (Shares Outstanding before SEO).

PRI = *Primary Shares as a Proportion of Total Shares Offered*.

UND = *Underpricing*: log of (Estimated Price / Offer Price) where Estimated Price is given by the *Investment Dealer's Digest*.

ITB = *Internet-Technology Bubble* dummy variable equals 1 if SEO occurs before 1/1/02; else *ITB* = 0.

POP = *Purpose of Proceeds* dummy variable equals 1 if major purpose is expansionary; else *POP* = 0.

TLQ = *Trading Liquidity* dummy variable equals 1 if NYSE/AMEX; else *TLQ* = 0.

FLQ = *Financial Liquidity Ratio*: (Cash and Other Short-Term Investments) / (Book Value of Equity).

GRO = *Growth Ratio*: Capital Expenditures / Total Assets.

LEV = *Leverage Ratio*: Total Liabilities / (Market Value of Common Stock + Total Liabilities).

PFT = *Profitability Ratio*: Operating Income before Depreciation / Total Assets.

TAN = *Tangible Assets Ratio*: Net Plant and Equipment / Total Assets.

TBQ = *Tobin's Q Ratio*: (Common Value + Total Asset – Book Value Equity) / Total Assets.

Table I (Click here to return to Insert Table I)

Descriptive Statistics for Independent Variables

This table reports means, medians, and standard deviations (StDev) for independent variables tested during regression analysis. Panel A gives statistics for nine "hedge fund" variables. Values for hedge fund variables are computed as follows. Data for "hedge fund" variables are collected from the HFR data base for each of the 651SEOs for the month corresponding to its public announcement month (event month 0). From these 651 values for each variable, the mean, median, and standard deviations (StDev) are computed. For example, consider the "*Average Hedge Fund Size*." For all hedge funds that are active during each event month 0, the "average hedge fund size" is taken for each of the 651 event months. From the 651 "average hedge fund size" values gathered, we compute a mean, median, and standard deviation of $366M, $370M, and $26M, respectively, as seen in the last three columns. Panel B gives statistics for "non-hedge fund" variables. The last six variables are computed from *Compustat* using data from the fiscal year ending closest to the registration date.

Panel A: Hedge Fund Variables	Mean	Median	StDev
Hedge Fund Assets under Management	$763B	$669B	$285B
Number of Hedge Funds where "B" stands for billions	2,551	2,038	1,241
Average Hedge Fund Size where "M" for millions	$366M	$370M	$26M
Median Hedge Fund Size where "M" for millions	$79M	$82M	$10M
Proportion of Hedge Funds Using Leverage	0.595	0.592	0.016
Proportion of Hedge Funds with an Event-Driven (Special Situations) Strategy	0.084	0.086	0.008
Proportion of Hedge Funds with an Relative Value (Arbitrage) Strategy	0.104	0.103	0.006
Proportion of Hedge Funds with an Directional (Equity Hedge) Strategy	0.131	0.132	0.007
Average Hedge Return	1.22%	0.90%	1.60%
Panel B: Key Non-Hedge Fund Variables	**Mean**	**Median**	**StDev**
Common Value: (Estimated Price) × (Shares Outstanding before SEO) where "B" stands for billions	$1.86B	$0.66B	$3.89B
Inside Ownership Proportion Before: (Insider Shares before SEO) / (Shares Outstanding before SEO)	0.492	0.470	0.216
Inside Ownership Proportion After: (Insider Shares after SEO) / (Shares Outstanding after SEO)	0.386	0.350	0.216
Change in Inside Ownership Proportion: Inside Ownership Proportion After – Inside Ownership Proportion Before	–0.106	–0.093	0.078
Primary Shares as a Proportion of Total Shares Offered	0.604	0.750	0.405
Underpricing: Logarithm of (Estimated Price / Offer Price) where Estimated Price is given by the *Investment Dealer's Digest*.	0.042	0.031	0.075
Financial Liquidity Ratio: (Cash and Other Short-Term Investments) / (Book Value of Equity)	0.271	0.139	0.290
Growth Ratio: Capital Expenditures / Total Assets	0.061	0.038	0.073
Leverage Ratio (day 0): (Total Liabilities) / (Common Value + Total Liabilities).	0.228	0.152	0.226
Profitability Ratio: Operating Income before Depreciation / Total Assets	0.031	0.103	0.244
Tangible Assets Ratio: Net Plant and Equipment / Total Assets	0.232	0.143	0.236
Tobin's Q Ratio: (Common Value + Total Liabilities) /Total Assets	6.998	2.849	11.591

Table II (Click here to return to Insert Table II)

Descriptive Statistics for Dependent Variables

This table presents means and standard deviations (abbreviated as StDev) for two measures of volatility in daily excess returns: the idiosyncratic volatility (*IVOL*) and the systematic volatility (*SVOL*). These two measures are used as dependent variables in regression tests. See Section II.B for more information on both measures including computational details. Volatility results are reported in two panels. Panel A gives volatility statistics for seven short-run periods, Panel B provides volatility statistics for six long-run periods, and Panel C offers parametric *t* and nonparametric (Wilcoxon signed rank) *z* statistics when comparing the two short-run before and after volatility measures and the two long-run measures. The "difference" consists of the post-SEO volatility minus the pre-SEO volatility. Statistical significance at the 1% and 5% levels are denoted by ** and *, respectively.

Panel A: Volatility Statistics for Short-Run						
	Idiosyncratic Volatility			Systematic Volatility		
Time Frame	Mean	Median	StDev	Mean	Median	StDev
Days –20 to 0	0.0429	0.0379	0.0232	0.0021	0.0017	0.0017
Days –10 to 0	0.0432	0.0373	0.0252	0.0021	0.0016	0.0018
Days +1 to +10	0.0377	0.0313	0.0275	0.0021	0.0015	0.0020
Days +1 to +20	0.0391	0.0326	0.0258	0.0022	0.0016	0.0020
Days –2 to 0	0.0415	0.0340	0.0319	0.0019	0.0013	0.0020
Days –10 to +10	0.0419	0.0359	0.0241	0.0022	0.0017	0.0019
Days –20 to +20	0.0418	0.0364	0.0230	0.0023	0.0018	0.0019
Panel B: Volatility Statistics for Long-Run						
	Idiosyncratic Volatility			Systematic Volatility		
Time Frame	Mean	Median	StDev	Mean	Median	StDev
Days –520 to 0	0.0469	0.0435	0.0207	0.0035	0.0031	0.0019
Days –260 to 0	0.0453	0.0426	0.0189	0.0057	0.0055	0.0019
Days +1 to +260	0.0432	0.0388	0.0217	0.0031	0.0026	0.0018
Days +1 to +520	0.0424	0.0365	0.0218	0.0038	0.0035	0.0019
Days –260 to +260	0.0450	0.0408	0.0208	0.0037	0.0034	0.0019
Days –520 to +520	0.0454	0.0410	0.0199	0.0049	0.0047	0.0020

Panel C: Test for Differences in Volatilities around SEOs				
	Idiosyncratic Volatility		Systematic Volatility	
Comparison Test	Difference	*t (z)*	Difference	*t (z)*
+1 to +10 minus –10 to 0	–0.0055	–5.52**(–7.90**)	–0.0000	–0.18(–1.64)
+1 to +20 minus –20 to 0	–0.0038	–4.97**(–7.22**)	0.0001	2.51**(2.16*)
+1 to +260 minus –260 to 0	–0.0021	–4.51**(–5.06**)	–0.0026	–42.7**(–22.0**)
+1 to +520 minus –520 to 0	–0.0045	–6.96**(–8.06**)	0.0003	4.05**(–5.77**)

Table III (Click here to return to Insert Table III)

Means by Year for Hedge and Volatility Variables

This table presents means by year for nine hedge fund variables and two volatility variables for four periods surrounding SEOs. As described previously, the means for hedge variables were taken from SEO announcement month (event month 0). The letter "*n*" refers to the sample size or number of SEOs during the year in question. "B" refers to billions and "M" refers to millions. The abbreviations for the twelve variables and their descriptions are:

AUM = *Hedge Fund Assets Under Management*;
NHF = *Number of Hedge Funds*;
AHS = *Average Hedge Fund Size*;
MHS = *Median Hedge Fund Size*;
PLV = *Proportion of Hedge Funds Using Leverage*;
PED = *Proportion of Hedge Funds with a Event-Driven (Special Situations) Strategy*;
PRV = *Proportion of Hedge Funds with a Relative Value (Arbitrage) Strategy*;
PEH = *Proportion of Hedge Funds with a Directional (Equity Hedge) Strategy*;
AHR = *Average Equal-Weighted Hedge Fund Return*;
IVOL = Idiosyncratic volatility in the excess returns as given by equation (3) for the period in question; and,
SVOL = Systematic volatility in the excess returns as given by equation (5) for the period in question.

Panel A: Hedge Variables

Year	*n*	*AUM*	*NHF*	*AHS*	*MHS*	*PLV*	*PED*	*PRV*	*PEH*	*AHR*
1999	130	$448B	1,306	$385M	$92M	0.579	0.093	0.097	0.312	2.18%
2000	130	$552B	1,589	$394M	$86M	0.584	0.092	0.098	0.324	1.21%
2001	92	$654B	1,983	$379M	$83M	0.596	0.086	0.103	0.330	0.90%
2002	72	$771B	2,509	$361M	$77M	0.592	0.084	0.104	0.326	0.35%
2003	72	$918B	3,215	$343M	$73M	0.592	0.078	0.108	0.321	1.49%
2004	90	$1,007B	4,028	$337M	$67M	0.611	0.074	0.111	0.317	0.77%
2005	65	$1,311B	5,045	$325M	$61M	0.630	0.070	0.115	0.327	1.07%

Panel B: Selected Volatility Variables Before and After SEOs

		Days –20 to 0		Days +1 to +40		Days –520 to 0		Days +1 to +520	
Year	*n*	*IVOL*	*SVOL*	*IVOL*	*SVOL*	*IVOL*	*SVOL*	*IVOL*	*SVOL*
1999	130	0.0460	0.0022	0.0422	0.0023	0.0516	0.0030	0.0585	0.0041
2000	130	0.0683	0.0036	0.0665	0.0041	0.0608	0.0038	0.0601	0.0063
2001	92	0.0413	0.0020	0.0364	0.0019	0.0479	0.0046	0.0424	0.0040
2002	72	0.0362	0.0016	0.0320	0.0017	0.0427	0.0056	0.0313	0.0021
2003	72	0.0329	0.0014	0.0274	0.0014	0.0423	0.0025	0.0273	0.0018
2004	90	0.0287	0.0015	0.0248	0.0015	0.0363	0.0019	0.0268	0.0035
2005	65	0.0258	0.0016	0.0223	0.0015	0.0323	0.0031	0.0257	0.0031

Panel C: Selected Volatility Variables Around SEOs

		Days –10 to +10		Days –20 to +20		Days –260 to +260		Days –520 to +520	
Year	*n*	*IVOL*	*SVOL*	*IVOL*	*SVOL*	*IVOL*	*SVOL*	*IVOL*	*SVOL*
1999	130	0.0440	0.0023	0.0449	0.0023	0.0544	0.0034	0.0561	0.0040
2000	130	0.0680	0.0038	0.0688	0.0041	0.0646	0.0047	0.0607	0.0057
2001	92	0.0397	0.0020	0.0396	0.0023	0.0452	0.0061	0.0456	0.0074
2002	72	0.0352	0.0018	0.0346	0.0018	0.0374	0.0030	0.0377	0.0056
2003	72	0.0326	0.0014	0.0308	0.0014	0.0344	0.0019	0.0359	0.0024
2004	90	0.0282	0.0015	0.0275	0.0015	0.0294	0.0023	0.0323	0.0038
2005	65	0.0254	0.0016	0.0247	0.0016	0.0283	0.0038	0.0303	0.0054

Table IV (Click here to return to Insert Table IV)

Correlation Results

This table provides correlation coefficients for variables tested for use in regression analysis. Pearson correlations coefficients are presented in the upper right-hand half of the table, while the Spearman correlation coefficients are reported in the lower left-hand half of the table. All variables are defined previously and can also be found in the Appendix. Pairs of variables with correlation coefficients greater than 0.30 are marked in bold print because they offer the most potential for collinearity problems and thus their variance inflation factors should be checked to help determine potential collinearity problems. Those pairs of variables with coefficients over 0.08 are significant at the 5% level and beyond, while those with coefficients over 0.10 are significant at the 1% level and beyond.

	AUM	*NHF*	*AHS*	*MHS*	*PLV*	*PED*	*PRV*	*PEH*	*AHR*	*ILA*	*CIL*	*PRI*	*UND*	*ITB*	*POP*	*TLQ*	*FLQ*	*GRO*	*LEV*	*PFT*	*TAN*	*TBQ*
AUM		**0.99**	**-0.86**	**-0.98**	**0.90**	**-0.97**	**0.97**	**0.33**	-0.22	-0.12	-0.14	-0.14	0.02	**-0.87**	-0.18	-0.18	-0.17	-0.17	0.27	0.13	0.04	-0.30
NHF	**0.99**		**-0.90**	**-0.98**	**0.89**	**-0.98**	**0.97**	0.29	-0.19	-0.13	-0.14	-0.14	0.02	**-0.89**	-0.18	-0.19	-0.17	-0.17	0.27	0.13	0.04	**-0.31**
AHS	**-0.84**	**-0.84**		**0.89**	**-0.75**	**0.88**	**-0.89**	-0.09	0.03	0.12	0.13	0.13	0.00	**0.86**	0.15	0.18	0.19	0.14	-0.26	-0.14	-0.03	0.28
MHS	**-0.98**	**-0.98**	**0.83**		**-0.91**	**0.96**	**-0.96**	**-0.31**	0.20	0.13	0.12	0.13	-0.02	**0.86**	0.17	0.18	0.16	0.16	-0.25	-0.13	-0.04	0.29
PLV	**0.89**	**0.89**	**-0.68**	**-0.87**		**-0.90**	**0.91**	**0.34**	-0.19	-0.12	-0.11	-0.13	0.01	**-0.65**	-0.16	-0.16	-0.14	-0.13	0.21	0.13	0.01	-0.26
PED	**-0.96**	**-0.96**	**0.81**	**0.95**	**-0.91**		**-0.98**	-0.25	0.19	0.14	0.16	0.15	-0.01	**0.86**	0.18	0.18	0.18	0.16	-0.28	-0.15	-0.04	**0.32**
PRV	**0.95**	**0.95**	**-0.86**	**-0.93**	**0.88**	**-0.96**		**0.32**	-0.14	-0.13	-0.15	-0.15	0.01	**-0.83**	-0.19	-0.17	-0.16	-0.16	0.27	0.13	0.02	-0.30
PEH	**0.36**	**0.36**	-0.04	**-0.36**	**0.42**	**-0.31**	0.30		-0.22	-0.02	0.01	0.02	0.00	-0.10	-0.08	-0.03	-0.05	-0.04	0.08	0.05	0.02	-0.07
AHR	-0.12	-0.12	-0.06	0.11	-0.16	0.09	-0.02	-0.20		0.07	0.01	0.01	-0.05	0.18	0.03	0.04	0.05	0.10	-0.09	-0.02	-0.01	0.16
ILA	-0.11	-0.11	0.11	0.11	-0.11	0.12	-0.11	-0.02	0.02		-0.18	-0.09	0.13	0.10	-0.03	-0.01	0.08	0.12	-0.07	-0.07	0.01	0.20
CIL	-0.12	-0.12	0.11	0.11	-0.13	0.14	-0.15	0.00	-0.03	-0.28		0.29	-0.04	0.14	0.16	0.05	0.15	-0.04	-0.14	-0.18	-0.08	0.14
PRI	-0.10	-0.10	0.10	0.10	-0.13	0.11	-0.12	0.01	-0.01	-0.10	**0.33**		0.12	0.13	**0.32**	0.29	0.16	-0.02	-0.05	**-0.32**	-0.03	0.03
UND	-0.01	-0.01	0.03	0.01	-0.01	0.02	-0.02	-0.04	-0.08	0.10	-0.01	0.09		0.01	0.01	0.03	0.07	0.00	-0.05	-0.13	0.05	0.08
ITB	**-0.86**	**-0.86**	**0.85**	**0.86**	**-0.65**	**0.84**	**-0.84**	-0.07	0.08	0.09	0.13	0.10	0.03		0.15	0.21	0.20	0.15	**-0.32**	-0.15	-0.07	**0.31**
POP	-0.18	-0.18	0.14	0.18	-0.16	0.17	-0.19	-0.08	0.02	-0.03	0.17	0.28	0.02	0.15		0.12	0.05	0.02	-0.06	-0.03	-0.02	0.10
TLQ	-0.18	-0.18	0.18	0.18	-0.16	0.19	-0.17	-0.04	-0.01	0.00	0.08	0.25	0.10	0.21	0.12		0.44	0.00	**-0.47**	-0.30	-0.28	0.27
FLQ	-0.16	-0.16	0.18	0.16	-0.15	0.18	-0.16	-0.08	0.00	0.07	0.14	0.12	0.14	0.19	0.09	0.48		-0.16	**-0.59**	**-0.61**	**-0.43**	**0.49**
GRO	-0.25	-0.25	0.20	0.25	-0.20	0.23	-0.24	-0.08	0.07	0.07	-0.02	-0.05	0.04	0.21	0.07	0.02	-0.11		-0.08	0.10	**0.60**	0.04
LEV	**0.32**	**0.32**	**-0.32**	-0.30	0.30	**-0.35**	**0.33**	0.08	-0.06	-0.10	-0.18	-0.07	-0.09	**-0.36**	-0.08	**-0.48**	**-0.72**	-0.05		0.28	0.28	**-0.43**
PFT	0.12	0.12	-0.13	-0.11	0.14	-0.14	0.12	0.04	-0.01	-0.06	-0.19	**-0.36**	-0.15	-0.14	-0.12	-0.28	**-0.44**	0.22	**0.31**		0.25	**-0.46**
TAN	-0.03	-0.03	0.02	0.03	-0.02	0.02	-0.04	-0.03	0.04	-0.01	-0.08	-0.06	0.01	-0.01	-0.01	-0.25	**-0.44**	**0.72**	0.30	**0.33**		-0.19
TBQ	**-0.34**	**-0.34**	**0.34**	**0.33**	-0.30	**0.37**	**-0.34**	-0.10	0.06	0.10	0.18	0.04	0.07	**0.39**	0.08	**0.45**	**0.67**	0.11	**-0.89**	-0.28	-0.21	

Table V (Click here to return to Insert Table V)

Predicted Coefficient Signs

This table gives predicted and actual coefficient signs of independent variables for the two volatility measures (*VOL*). If more than one actual sign is found for tests, then the sign that occurs most frequently is given. All variables are defined previously in Section I.B and can also be found in the Appendix.

Independent Variables	*Predicted Sign*	*Actual Sign*
AUM	–	–
NHF	–	–
AHS	+	+
MHS	+	+
PLV	–	–
PED	+	+
PRV	–	–
PEH	+	+
AHR	+	–
ILA	+	+
CIL	–	–
PRI	–	+
UND	+	+
ITB	+	+
POP	+	+
TLQ	+	+
FLQ	+	+
GRO	+	+
LEV	–	–
PFT	–	–
TAN	–	–
TBQ	+	+

Table VI (Click here to return to Insert Table VI)

Regression Results for Short-Run Volatility

The regression model used is $VOL = \beta_0 + \beta_i\, HFV + \beta_j\, NFV + \varepsilon$ where the volatility variables (*VOL*), the hedge fund variables (*HFV*) and non-hedge fund variables (*NFV*) are defined in the Appendix with these additions: *PED* and *ITB* are replaced with PED^R and ITB^R, respectively, where PED^R and ITB^R are each uncorrelated with *AUM*. *TBQ* is replaced with TBQ^R where TBQ^R is uncorrelated with *LEV*. We indicate significance at the 1% and 5% levels by ** and *, respectively. The last column reports the R^2 value with the *F* value below it. *Adjusted* R^2 values are very similar to R^2 values and so are not reported.

	CON	*AUM*	PED^R	*PEH*	*AHR*	*ILA*	*CIL*	*PRI*	*UND*	ITB^R	*POP*	*TLQ*	*FLQ*	*GRO*	*LEV*	*PFT*	*TAN*	TBQ^R	R^2/F
Panel A: Volatility before and including Day 0: Days –20 to 0																			
IVOL	10.993	-0.614	51.863	6.737	-1.770	0.004	-0.709	0.123	1.244	0.042	0.089	0.285	0.069	0.598	-0.268	-0.058	-0.279	0.004	0.56
	8.72**	-13.36**	6.57**	2.72**	-1.91	0.06	-3.55**	2.86**	6.38**	0.65	2.40*	7.53**	0.89	2.27*	-3.01**	-0.72	-3.21**	2.23*	47.7**
SVOL	-0.397	-0.259	70.145	1.923	2.468	0.389	0.514	-0.004	1.208	0.234	0.052	0.265	0.268	1.396	-0.172	-0.093	-0.279	0.006	0.30
	-0.18	-3.19**	5.03**	0.44	1.51	3.17**	1.46	-0.06	3.52**	2.07*	0.79	3.98**	1.94	3.00**	-1.09	-0.66	-1.82	2.20*	15.9**
Panel B: Volatility before and including Day 0: Days –10 to 0																			
IVOL	10.343	-0.578	48.920	5.504	-1.999	0.009	-0.703	0.103	1.157	-0.028	0.100	0.302	0.155	0.374	-0.173	-0.042	-0.234	0.003	0.47
	7.05**	-10.80**	5.33**	1.91	-1.85	0.12	-3.03**	2.07*	5.11**	-0.37	2.32*	6.87**	1.70	1.22	-1.67	-0.45	-2.32*	1.72	32.3**
SVOL	-0.445	-0.249	72.148	0.748	0.125	0.494	0.555	0.035	1.345	0.078	0.049	0.301	0.365	1.175	-0.135	-0.036	-0.229	0.007	0.29
	-0.19	-2.88**	4.86**	0.16	0.07	3.78**	1.48	0.43	3.67**	0.64	0.71	4.24**	2.48*	2.37*	-0.81	-0.24	-1.40	2.19*	15.0**
Panel C: Volatility after Day 0: Days +1 to +10																			
IVOL	10.446	-0.588	47.327	5.440	-1.960	-0.060	-0.382	0.070	1.816	0.090	0.048	0.271	0.405	0.946	-0.172	0.046	-0.304	0.005	0.46
	6.25**	-9.65**	4.52**	1.66	-1.59	-0.65	-1.44	1.24	7.04**	1.06	0.97	5.41**	3.90**	2.71**	-1.46	0.44	-2.65**	2.36*	31.9**
SVOL	2.532	-0.338	73.730	-0.788	-4.488	0.345	-0.205	0.043	1.062	0.092	0.042	0.283	0.324	1.365	-0.216	-0.029	-0.326	0.010	0.27
	1.01	-3.70**	4.70**	-0.16	-2.43*	2.50*	-0.52	0.50	2.74**	0.72	0.57	3.77**	2.08*	2.61**	-1.22	-0.19	-1.89	3.03**	14.1**
Panel D: Volatility after Day 0: Days +1 to +20																			
IVOL	11.331	-0.649	51.908	8.050	-0.536	-0.034	-0.429	0.095	1.453	0.051	0.052`	0.302	0.309	0.731	-0.241	-0.007	-0.235	0.007	0.58
	8.12**	-12. 8**	5.94**	2.94**	-0.52	-0.44	-1.94	2.00*	6.74**	0.71	1.25	7.21**	3.56**	2.51*	-2.45*	-0.08	-2.45*	4.29**	50.6**
SVOL	4.224	-0.403	89.404	0.105	-2.096	0.275	-0.116	0.051	0.785	0.143	0.005	0.270	0.222	1.321	-0.234	-0.080	-0.264	0.009	0.33
	1.95	-5.12**	6.60**	0.03	-1.32	2.31*	-0.34	0.69	2.35*	1.30	0.08	4.17**	1.66	2.92**	-1.54	-0.58	-1.77	3.26**	18.5**
Panel E: Volatility around Day 0: Days –2 to 0																			
IVOL	8.251	-0.562	30.809	9.351	-2.119	0.185	-0.895	0.149	1.077	-0.265	0.071	0.459	0.083	0.148	0.116	-0.357	-0.281	0.002	0.24
	3.07**	-5.73**	1.83	1.77	-1.07	1.25	-2.10*	1.63	2.59**	-1.94	0.89	5.70**	0.50	0.26	0.61	-2.09*	-1.52	0.61	11.6**
SVOL	2.160	-0.244	86.123	-8.015	-4.214	0.398	0.980	0.087	-1.381	0.246	0.039	0.360	0.292	1.428	-0.034	-0.167	-0.349	0.009	0.19
	0.65	-2.00*	4.11**	-1.22	-1.71	2.16*	1.85	0.77	-2.67**	1.45	0.39	3.59**	1.40	2.04*	-0.15	-0.79	-1.52	2.07*	8.9**
Panel F: Volatility around Day 0: Days –10 to +10																			
IVOL	10.815	-0.587	51.107	4.816	-2.002	-0.005	-0.614	0.099	1.460	0.050	0.089	0.267	0.221	0.619	-0.181	-0.021	-0.276	0.004	0.56
	8.57**	-12.8**	6.47**	1.94	-2.15*	-0.07	-3.07**	2.30*	7.49**	0.78	2.39*	7.05**	2.82**	2.35*	-2.04*	-0.26	-3.18**	2.42*	47.6**
SVOL	1.956	-0.347	76.651	2.093	-1.666	0.421	0.183	0.045	1.254	0.127	0.038	0.270	0.258	1.058	-0.201	-0.076	-0.211	0.007	0.31
	0.89	-4.31**	5.55**	0.48	-1.03	3.47**	0.53	0.60	3.68**	1.14	0.58	4.09**	1.89	2.30*	-1.29	-0.55	-1.39	2.68**	17.1**
Panel G: Volatility Days –20 to +20																			
IVOL	11.402	-0.626	53.716	6.214	-1.375	0.000	-0.633	0.118	1.341	0.067	0.078	0.295	0.164	0.620	-0.255	-0.028	-0.255	0.005	0.65
	10.2**	-15.3**	7.64**	2.82**	-1.66	0.01	-3.56**	3.09**	7.73**	1.18	2.34*	8.77**	2.36*	2.64**	-3.22**	-0.40	-3.30**	3.91**	67.8**
SVOL	2.866	-0.396	81.508	3.930	0.843	0.341	0.096	0.043	1.076	0.291	0.011	0.241	0.167	1.144	-0.224	-0.082	-0.229	0.006	0.36
	1.47	-5.55**	6.65**	1.02	0.58	3.16**	0.31	0.64	3.56**	2.92**	0.18	4.10**	1.37	2.80**	-1.63	-0.66	-1.70	2.65**	20.9**

Table VII (Click here to return to Insert Table VII)

Regression Results for Long-Run Volatility

The regression model used is $VOL = \beta_0 + \beta_i HFV + \beta_j NFV + \varepsilon$ where the volatility variables (*VOL*), the hedge fund variables (*HFV*) and non-hedge fund variables (*NFV*) are defined in the Appendix with these additions: *PED* and *ITB* are replaced with PED^R and ITB^R, respectively, where PED^R and ITB^R are each uncorrelated with *AUM*. *TBQ* is replaced with TBQ^R where TBQ^R is uncorrelated with *LEV*. We indicate significance at the 1% and 5% levels by ** and *, respectively. The last column reports the R^2 value with the *F* value below it. *Adjusted* R^2 values are very similar to R^2 values and so are not reported.

	CON	*AUM*	PED^R	*PEH*	*AHR*	*ILA*	*CIL*	*PRI*	*UND*	ITB^R	*POP*	*TLQ*	*FLQ*	*GRO*	*LEV*	*PFT*	*TAN*	TBQ^R	R^2/F
									Panel A: Volatility before and including Day 0: Days –520 to 0										
IVOL	3.395	-0.369	6.176	9.537	-1.441	0.164	-0.469	0.105	0.916	-0.103	0.031	0.337	0.260	0.348	-0.190	-0.141	-0.125	0.003	0.60
	3.36**	-9.99**	0.97	4.80**	-1.93	2.95**	-2.93**	3.04**	5.86**	-2.01*	1.03	11.1**	4.13**	1.64	-2.66**	-2.20*	-1.79*	2.74**	56.3**
SVOL	-6.391	-0.578	-22.824	50.323	-0.816	0.117	-0.041	0.037	0.561	-0.530	-0.032	0.130	0.107	1.008	0.140	-0.000	-0.351	0.000	0.45
	-4.77**	-11.8**	-2.72**	19.1**	-0.83	1.59	-0.19	0.82	2.71**	-7.78**	-0.81	3.23**	1.29	3.60**	1.48	-0.01	-3.81**	-0.08	30.4**
									Panel B: Volatility before and including Day 0: Days –260 to 0										
IVOL	6.072	-0.367	9.430	1.086	0.381	0.092	-0.402	0.114	0.808	0.027	0.056	0.311	0.166	0.671	-0.179	-0.158	-0.192	0.003	0.63
	6.57**	-10.9**	1.63	0.60	0.56	1.82	-2.75**	3.63**	5.66**	0.58	2.07*	11.2**	2.89**	3.47**	-2.75**	-2.69**	-3.03**	2.96**	63.7**
SVOL	-9.155	-0.191	35.152	28.150	-0.457	0.096	-0.117	0.003	0.183	0.111	0.009	0.047	0.057	0.677	0.034	0.032	-0.233	0.001	0.52
	-10.8**	-6.21**	6.65**	16.97**	-0.74	2.07*	-0.87	0.12	1.40	2.59**	0.37	1.87	1.08	3.84**	0.58	0.59	-4.01**	1.42	39.5**
									Panel C: Volatility after Day 0: Days +1 to +260										
IVOL	13.673	-0.699	30.283	5.626	1.077	0.030	-0.398	0.123	0.612	0.114	0.080	0.279	0.147	0.850	-0.282	-0.092	-0.313	0.004	0.70
	13.4**	-18.8**	4.73**	2.80**	1.43	0.54	-2.46*	3.53**	3.88**	2.20*	2.65**	9.11**	2.32*	3.98**	-3.91**	-1.42	-4.45**	3.11**	85.5**
SVOL	4.709	-0.455	62.693	4.798	0.367	0.183	-0.088	0.022	0.537	0.877	0.011	0.153	0.126	0.805	-0.120	-0.054	-0.240	0.006	0.52
	3.37**	-8.93**	7.16**	1.75	0.36	2.38*	-0.40	0.47	2.49*	12.3**	0.26	3.65**	1.45	2.76**	-1.21	-0.61	-2.50*	3.20**	39.9**
									Panel D: Volatility after Day 0: Days +1 to +520										
IVOL	15.517	-0.689	16.039	-1.018	0.837	0.032	-0.387	0.108	0.607	0.229	0.086	0.284	0.078	1.064	-0.240	-0.203	-0.319	0.004	0.71
	15.4**	-18.8**	2.55*	-0.52	1.13	0.58	-2.43*	3.16**	3.91**	4.48**	2.89**	9.41**	1.25	5.07**	-3.38**	-3.18**	-4.62**	2.97**	89.1**
SVOL	7.925	-0.295	63.914	-17.579	-1.329	0.091	-0.128	-0.018	0.388	1.129	0.007	0.129	0.067	0.748	-0.202	-0.082	-0.163	0.005	0.57
	6.61**	-6.76**	8.52**	-7.47**	-1.51	1.38	-0.67	-0.45	2.09*	18.5**	0.20	3.59**	0.91	2.99**	-2.38*	-1.08	-1.98*	3.41**	49.8**
									Panel E: Volatility around Day 0: Days –260 to +260										
IVOL	10.509	-0.613	17.526	8.180	0.159	0.073	-0.462	0.136	0.843	0.039	0.067	0.303	0.195	0.601	-0.237	-0.113	-0.254	0.004	0.71
	11.3**	-18.1**	3.02**	4.49**	0.23	1.44	-3.15**	4.31**	5.88**	0.82	2.44*	10.9**	3.39**	3.10**	-3.62**	-1.92	-3.98**	3.18**	92.1**
SVOL	-2.272	-0.425	12.929	24.702	1.410	0.160	-0.116	-0.003	0.296	0.889	-0.003	0.106	0.084	0.814	0.046	-0.069	-0.249	0.002	0.56
	-1.89	-9.69**	1.72	10.47**	1.59	2.42*	-0.61	-0.06	1.59	14.6**	-0.08	2.95**	1.12	3.24**	0.54	-0.91	-3.02**	1.23	47.1**
									Panel F: Volatility around Day 0: Days –520 to +520										
IVOL	8.652	-0.495	9.750	4.010	0.020	0.094	-0.454	0.117	0.799	0.038	0.057	0.309	0.149	0.717	-0.208	-0.169	-0.232	0.004	0.68
	9.47**	-14.9**	1.70	2.23*	0.03	1.87	-3.13**	3.76**	5.66**	0.83	2.13*	11.3**	2.63**	3.75**	-3.22**	-2.90**	-3.69**	3.25**	78.4**
SVOL	-8.161	-0.237	24.550	28.353	-1.065	0.099	-0.136	-0.007	0.193	0.484	-0.001	0.070	0.072	0.885	0.130	0.005	-0.313	0.002	0.49
	-7.47**	-5.95**	3.59**	13.2**	-1.32	1.64	-0.78	-0.18	1.14	8.71**	-0.04	2.15*	1.06	3.87**	1.68	0.08	-4.16**	1.21	35.1

Table VIII (Click here to return to Insert Table VIII)

Significant Independent Variables for Each SEO Period Tested

This table shows whether an independent variable is significant at the 5% level or better for a volatility test. If the coefficient signs agree for both the idiosyncratic volatility (*IVOL*) and systematic volatility (*SVOL*) tests, then only that sign is placed in the cell that corresponds with a variable and on its volatility test for that period. If the signs differ between the *IVOL* and *SVOL* tests, then the sign for *IVOL* is identified with an "i" while the sign for *SVOL* is accompanied with an "s." If both volatility tests are significant but with opposite signs, then an "i" for the *IVOL* test and an "s" for the *SVOL* test are both displayed with their corresponding signs.

	-20 to 0	-10 to 0	+1 to +10	+1 to +20	-2 to 0	-10 to +10	-20 to +20	-520 to 0	-260 to 0	0 to +260	0 to +520	-260 to +260	-520 to +520
AUM	–	–	–	–	–	–	–	–	–	–	–	–	–
NHF	–	–	–	–	–	–	–	–	–	–	–	–	–
AHS	+	+	+	+	+	+	+	+	+	+	+	+	+
MHS	+	+	+	+	+	+	+	+	+	+	+	+	+
PLV	–i	–i	–i	–i	–i	–i	–i	–	–i,+s	–i,+s	–i,+s	–i,+s	–i,+s
PED	+	+	+	+	+s	+	+	–s	+s	+	+	+i	+s
PRV	–	–	–	–	–i	–	–	–	–i	–i,+s	–i,+s	–i,+s	–i,+s
PEH	+i			+i			+i	+	+i	+i	+s	+	+
AHR			–s			–i							
ILA	+s	+s	+s	+s	+s	+s	+s	+s	+s	+s		+s	
CIL	–i	–i			–i	–i	–i	–i	–i	–i	–i	–i	–i
PRI	+i	+i			+i	+i	+i	+i	+i	+i	+i	+i	+i
UND	+	+	+	+	+	+	+	+	+i	+	+	+i	+i
ITB	+s						+s	–	+s	+	+	+s	+s
POP	+i	+i				+i	+i		+i	+i	+i	+i	+i
TLQ	+	+	+	+	+	+	+	+	+i	+	+	+	+
FLQ		+s	+	+i		+i	+i	+i	+i	+i		+i	+i
GRO	+	+i	+	+	+s	+	+	+s	+	+	+	+	+
LEV	–i			–i		–i	–i	–i	–i	–i	–	–i	–i
PFT					–i			–i	–i		–i		–i
TAN	–i	–i	–i	–i		–i	–i	–	–	–	–	–	–
TBQ	+	+s	+	+	+s	+	+	+i	+i	+	+	+i	+i