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Washburn University
School of Business
1700 SW College Ave.
Topeka, KS 66621
785-670-1308
www.washburn.edu/sobu

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* Robert Hull is Clarence W. King Chair of Finance, School of Business, Washburn University, Topeka, KS. Sungkyu Kwak is professor of economics, School of Business, Washburn University, Topeka, KS. Rosemary Walker is professor of economics, School of Business, Washburn University, Topeka, KS. Comments should be directed to Robert Hull, School of Business, Washburn University, 1700 SW College Ave. Topeka, Kansas 66621, 785-670-1600, rob.hull@washburn.edu.

Hedge Fund Attributes, Insider Behavior, and IPO Volatility

Robert M. Hull, Sungkyu Kwak, and Rosemary Walker (Corresponding Author)[1]

Abstract

In this paper, we explore the influence of hedge fund attributes and insider ownership on volatility in the excess stock returns for 707 initial public offerings (IPOs) occurring from 2004-2010. Our sample period covers the subprime mortgage crisis where the number of hedge funds rose 36% for the years 2007-2009 even though the overall size of hedge fund assets fell 38% during these same years. We discover the following when we test IPO volatility during the month of the IPO. We find an increase in the number of hedge funds decreases volatility and this is true for both of our volatility measures: idiosyncratic volatility (*IVOL*) and systematic volatility (*SVOL*). We document that an increase in leverage and equity hedge strategies intensifies *IVOL* and to a lesser degree *SVOL*. We discover an increase in relative (arbitrage) value and event-driven strategies amplifies *SVOL* and to a lesser degree *IVOL*. We provide evidence that greater hedge fund returns lessens IPO volatility, especially for *SVOL*. We find greater IPO volatility during the subprime meltdown and also show that greater assets under management during this period reduce volatility. We find larger insider ownership proportions after the IPO are associated with higher volatility. Finally, we discover greater declines in insider ownership due to the IPO are associated with lower *IVOL* and to a lesser extent with *SVOL*.

Keywords: Volatility · Initial Public Offerings · Hedge Fund Attributes · Insider Ownership

JEL Classification: G11 · G14 · G32

1. Introduction

In this paper, we study the role of hedge fund attributes and insider ownership on volatility in excess stock returns using a sample of 707 initial public offerings (IPOs). In contrast to Hull et al. (2014) who used data from 1999–2005 covering the dot-com bubble collapse to study volatility for seasoned equity offerings (SEOs), our IPO study utilizes data from 2004–2010 encompassing the subprime mortgage failure. While both of these two periods of study undergo market turbulence, the 2004-2010 period stands alone in that assets under management of hedge funds declined during the subprime meltdown from December 2007 to June 2009. This decline contrasts with the dot-com collapse of 2000-2001 where Hull et al. document a continuous increase in hedge fund assets.

Before the decline in assets during the subprime crisis, hedge funds had manifested significant growth in assets. King and Maier (2009) document over a ten-fold increase in hedge fund assets from 1998 through the end of 2007. Our hedge fund data from Hedge Fund Research (HFR) database reveals the average hedge fund assets reached a peak during 2007. The decline in assets was the beginning of a decline in hedge fund performance. Denning (2013) notes the HFRX Global Hedge Fund Index fell 13.6% for the five years after its growth peaked with this fall occurring while equity indices were increasing. Unlike hedge fund assets, the number of hedge funds did not decline during the subprime mortgage crisis but continued to increase at a similar rate.[2]

In this study, we focus on the impact of hedge fund attributes and insider behavior on IPO volatility. Hedge fund managers are market timers buying undervalued securities and shorting overvalued securities. The buying of shares by hedge funds increases the demand and thus raises the price of undervalued stocks and,

[1] Robert M. Hull, King Endowed Professor of Finance, rob.hull@washburn.edu; Sungkyu Kwak, Professor of Economics, sungkyu.kwak@washburn.edu; Rosemary Walker, Professor of Economics, rosemary.walker@washburn.edu.

[2] From Table 3, the annual percentage increases in the number of hedge funds for 2004-2010 can be computed as 22%, 20%, 14%, 12%, 21% and 14% and those for hedge fund assets as 17%, 28%, 20%, -1%, -37% and 2%. These percentages can be compared with Hull et al. for 1999-2005 where the annual increases in the number of hedge funds can be computed as 22%, 25%, 27%, 28%, 25% and 25% and those for assets as 23%, 18%, 18%, 19%, 21%, and 18%.

concomitantly, the selling by hedge funds decreases the demand and thus lowers the price for overvalued stocks. This buying and selling can influence the volatility of securities. In this paper, we offer hypotheses to predict the direction of the volatility and these prediction include the attributes of hedge funds such as (1) the number and/or size of hedge funds that allow them to exercise a greater clout on prices, (2) the proportion of hedge funds using leverage where greater leverage can create greater resources to undertake trading strategies, and (3) the proportion of hedge funds using a certain trading strategy such as relative value, event-driven and equity hedge. In contrast to hedge funds that can simultaneously take opposite trading positions, insiders would tend to act in unison on the same private information by decreasing or increasing their ownership proportions.

With the above in mind, we regress independent variables on measures of volatility for various periods after the IPO. Independent variables of interest in our regression tests include hedge fund variables such as the number of hedge funds, hedge fund assets, various hedge fund strategies and hedge fund returns. Non-hedge fund variables of emphasis are inside ownership proportions and the change in these proportions caused by the IPO. We focus on reporting results for two measures for volatility: idiosyncratic volatility (*IVOL*) and systematic volatility (*SVOL*). *IVOL* measures the volatility in the firm-specific component of the excess return. *SVOL* assesses the portion of the volatility inherent in the market and outside the firm's control. We also tested total volatility (*TVOL*) that measures the total volatility in the excess returns during the period tested. However, we do not report *TVOL* results because they mirror those for *IVOL*. We focus our reporting on periods up to 50 days after the IPO. This is because we use hedge fund data for the month of the offering. Thus, reporting beyond 50 days is seen as less accurate since the composition of the hedge fund attributes are more apt to change as the period after the IPO lengthens.[3] Below we describe our findings.

First, we find the number of hedge funds is associated with lower volatility in the IPO market. *Second*, we discover an increase in the use of leverage increases *IVOL* but only somewhat for *SVOL*. *Third*, we document that an increase in the proportion of hedge fund managers using relative value, event-driven, and equity hedge strategies generally increases both *IVOL* and *SVOL*. *Fourth*, we find that greater positive hedge fund returns are associated with less volatility and this is especially true for *SVOL*. *Fifth*, during the subprime mortgage crisis, we find greater volatility compared to years outside this period. We also show that hedge funds with larger asset under management are associated with less volatility during this crisis. *Sixth*, we test non-hedge fund variables with a particular focus on insider ownership where we find that larger insider holdings are associated with greater volatility.

The remainder of the paper is organized as follows. Section two provides a literature review, while section three presents our hypotheses and regression model. Section four describes the data and presents descriptive statistics. Section five details the empirical results and section six offers conclusions.

2. Literature Review

In this section we review five strands of research related to our study. *First*, we look at IPO volatility. *Second*, we review the relation between *IVOL* and returns. *Third*, we overview the influence of hedge funds on market volatility. *Fourth*, we look at the impact of hedge fund characteristics on volatility. *Fifth*, we consider the role of hedge fund activism.

First, in regards to IPO volatility, Lowry et al. (2010) find the monthly volatility of IPO initial returns is substantial, fluctuates dramatically over time, and is considerably larger during strong IPO markets. Their results raise questions about the usefulness of the firm-commitment IPO underwriting process, as the volatility of the pricing errors reflected in initial IPO returns can be large. This is particularly true for firms with great information asymmetry and for IPOs that occur during hot market periods. Bruce and Thilakaratne (2015a) examine the initial returns volatility of IPOs using the OLS and GARCH models to show that fraud tendency via underpricing and overpricing accounts for highly volatile returns during the first-day, first-month and first-year of IPO trading. Bruce and Thilakaratne (2015b) examine the initial returns volatility of IPOs by

[3] As mentioned in the concluding section, testing longer run periods after IPOs is a task for future research.

determining whether mispricing actually takes place during and after IPOs in Nigeria and Sri Lanka and if mispricing constitutes corporate fraud inclinations. They find the fraud via underpricing and overpricing causes volatile returns. Leong and Sundarasen (2015) investigate the impact of firm characteristics, signaling variables and financial variables on IPO initial returns and the volatility of initial returns. They suggest that oversubscription of IPOs has a positive impact on the initial returns, while prospective dividend yield has a negative impact on the volatility of initial IPO returns.

Second, besides the IPO volatility research, there is a line of research that focuses on the relation between *IVOL* and returns in general. Ang et al. (2006) document that high *IVOL* predicts low returns. Similarly, Babenko et al. (2016) also obtain a negative relation between *IVOL* and expected stock returns. They state this is a puzzling empirical finding that seems to be at odds with risk-based explanations. Garbaravicius and Dierick (2005) suggest hedge fund trading can lessen volatility because it levies lengthier redemption horizons on investors, evades momentum trading, and tends to put capital at risk in volatile markets thus absorbing shocks. Hull et al. (2014) explore the potential influence of hedge fund attributes on *IVOL* in excess stock returns around SEOs. They discover that *IVOL* appears to decrease with greater hedge fund performance except when hedge funds are riding the pre-SEO stock price run-up. The downward shift in *IVOL* around SEOs is best explained by hedge fund attributes.

Third, pertaining to the general research on hedge fund influences on market volatility, there are different beliefs. Some researchers believe that hedge funds can have a major influence. For example, King and Maier (2009) contend hedge fund liquidation can indirectly increase market volatility as the hedge funds buy and sell in large volumes. In contrast to this belief, others argue that hedge funds, being a small percentage of the overall market, may not have a major role in impacting market volatility. To illustrate, Fung and Hsieh (2000) find mixed results as to whether hedge fund activity had an impact on the stock market crash of 1987, the Asian Currency Crisis, and the European bond market rally. While they did not rule out any hedge fund impact in the post-crisis markets, they conclude that hedge funds did not likely cause any initial turmoil in market volatility during these crises.

Fourth, concerning the role of hedge fund characteristics and volatility, Garbaravicius and Derick (2005) argue hedge fund managers can leverage their positions to take full advantage of market inefficiencies and arbitrage away price differences across the market. This creates the possibility of stable prices. King and Maier (2009) suggest greater hedge fund assets, as well as more leverage, can exercise a greater impact on volatility. This impact can arguably reduce volatility when hedge fund managers take opposite positions on a security with one fund buying while the other is selling. Hull et al. (2014) explore the downward trend in *IVOL* beginning in 2000. For their SEO sample, they find that the decline in *IVOL* is related to the rapid growth of the hedge fund industry and to a greater use of leverage by hedge fund managers. The downward shift in *IVOL* around SEO offering dates is better explained by hedge fund attributes than by non-hedge fund attributes. Their findings suggest that the rapid increase in the hedge fund industry offers an explanation for the mysterious decline in *IVOL* for their period of study. However, where applicable one must interpret their findings with caution when applied to the time period of our study and the differences between SEOs and IPOs as well as differences in the periods each study tested.

Fifth, in regards to hedge fund activism, it can be pointed out that this activism was prevalent for most of our period of study from 2004-2010. Prior to 2006, the study of hedge fund activism was largely non-existent until an active community of researchers brought the activism literature to the mainstream. Much of this hedge fund activism research centers on balance sheet outcomes and stock performance (Brav et al., 2008; Brav et al., 2009; Klein and Zur, 2011; Ang et al., 2011). Activist hedge funds take a more active role in determining the value of its investments. Most recently, Bessler et al. (2015) document that, on average, hedge funds increased shareholder value in the short-run and long-run, while Wang and Zhao (2015) find hedge funds enhance firm value by increasing the quantity and quality of patents. In this paper, we complement the hedge fund activism line of research by focusing on activism associated with security offerings by exploring active hedge fund strategy in relation to IPO volatility after the time of their offer dates. We do this by using regression tests that include active hedge fund strategies as the independent variables. Thus, this paper falls within the line of research that explores the empirical query as to whether hedge fund activities in general can have a significant impact on events regardless of whether they are major crisis events or company-specific events like IPOs.

3. Hypotheses and Model

3.1 Hypothesis

This paper examines the relation between IPO volatility and hedge fund and non-hedge fund attributes. In regards to hedge fund attributes, the research (Henry and Koski, 2010; Hull et al. 2014) finds that hedge funds influence stock returns and their volatility around security offerings. This finding should extend to IPOs given their greater information asymmetry that Lowry et al. (2010) discovers leads to greater IPO volatility. This raises questions as to what attributes can either increase or decrease IPO volatility. Our hypotheses presented in this section seek to answer such questions by testing hypotheses representing attributes that predict the direction of the IPO volatility. For this paper, as described Section 4.2, volatility is measured by idiosyncratic volatility (*IVOL*) and systematic volatility (*SVOL*). We now overview the attributes used in formulating our research hypotheses.

First, we consider hedge fund attributes hypothesized to reduce volatility in the IPO market. For example, consider the situation where more and more hedge funds enter the market. For this scenario, hedge fund managers will be challenged to find innovative approaches and employ diverse trading strategies to earn positive returns. King and Maier (2009) state that hedge funds use aggressive trading strategies designed to earn positive returns in all market environments such as short sales, leverage, program trading, arbitrage, and the use of derivatives. As the number of hedge funds increases, there should be more and more hedge fund managers seeking not only aggressive strategies but also taking opposite positions relative to other managers. The undertaking of aggressive strategies and opposite positions should be especially true for IPOs where there exists greater information asymmetry and uncertainty causing greater diversity of opinions on what strategy is best. A by-product of taking opposite positions is that volatility should be reduced because equilibrium in prices can be reached more quickly. This curtails, if not prevents, wide swings in prices. Besides the number of hedge funds reducing volatility, we will also study the possible reduction in volatility related to greater hedge fund returns and to hedge funds that hold larger assets during the subprime mortgage crisis.

Second, we investigate hedge fund attributes predicated on increasing volatility in the IPO market. Consider the situation where hedge fund managers try to take advantage of inefficiently priced IPOs. Suppose shares of IPO are undervalued and there is general agreement on this undervaluation among hedge fund managers involved in trading shares for this IPO. This would lead to hedge fund managers pursuing strategies that attempt to buy shares as opposed to pursuing different strategies based on disagreement on whether the IPO is undervalued. To take full advantage of this undervalued situation, hedge fund manager would employ a tactic of leverage to increase their resources enabling them to purchase underpriced IPOs in large quantities. This would cause a rapid upward swing in the price leading to greater volatility. Similarly, if the IPO was overvalued, they would use leverage to pursue strategies to short the IPO. Once again, the end process can be increased volatility. Because leverage enhances the use of strategies (such as relative value, event-drive and equity hedge), there would also be a positive relation between the use of these strategies and volatilities.

Third, we consider non-hedge fund variables with a focus on the role of insider behavior as it influences IPO volatility. We are able to perform a unique analysis of insider attributes from our hand-gathering of insider data from IPO prospectuses. Not only are we able to test to what extent the proportion of insider ownership after the IPO relates to volatility but we are also able to examine how the change in the proportion of inside ownership is associated with volatility. One possible reason for this greater volatility (when insiders are retaining large ownership proportions) is that greater ownership retainment signals greater confidence in the future earnings capability of the company. This could cause a flurry of buying with a swift upward swing in prices and thus greater volatility. However, a more likely reason is that the amount retained sends an ambiguous signal because those retaining larger amounts can also be lowering their ownership proportions. This ambiguity causes more uncertainty and more volatility. Leland and Pyle (1977) state it is not the proportion itself that signals news but how the proportion is changing. In terms of the change in ownership proportion, our sample is characterized by 99% of our IPOs lowering their ownership proportions.[4] Suppose there is a lot of information asymmetry over the value of the IPO. By the time of the offering, the market will know the extent of insider selling (or not buying) thus reducing any uncertainty in the market as to what insiders believe about the value of the IPO. Thus, the possibility exists that volatility can be reduced based on knowing what insiders have signaled through the change in their ownership proportions brought about by the IPO.

In view of the above considerations, we offer seven hypotheses predicting the relation between hedge fund and insider factors on IPO price volatility. While Hull et al. (2014) did not report detailed results for *SVOL* (it was very small for their SEO sample), we report *SVOL* results because its impact is five times greater for our IPO sample compared to the SEO study by Hull et al. Below we now describe our hypotheses.

Our first hypothesis (H-1) considers the possibility that the number of hedge fund can influence volatility in the IPO market. We hypothesize that the IPO market can become less volatile due to the sheer number of hedge funds that allow for a greater variety, diversity and volume of differing positions taken on a stock's price. Thus, we have:

H-1: We predict less volatility in IPO price behavior when the number of hedge funds are larger.

Our second hypothesis (H-2) looks at the relation between leverage and volatility. Leverage is a tactic used by hedge funds to increase their resources and thus invest more in long or short positions. The ability to use large resources can cause a greater shock and increase volatility as hedge fund trading strategies can be used to a greater extent. Hence, we have:

H-2: We predict greater volatility in the IPO market when a greater proportion of hedge funds are using leverage.

Our third hypothesis (H-3) considers the notion that managers look to apply a variety of strategies to make profits especially when opportunities exist for mispriced IPOs. H-3 can be intertwined with H-2 in that leverage can increase the use of strategies. The increased use of these strategies can cause a larger swing in IPO stock prices creating greater volatility. Thus, we have:

H-3: We predict greater volatility in IPO price behavior when a greater proportion of hedge funds are utilizing relative value, event-drive and equity hedge strategies.

Our fourth hypothesis (H-4) examines the association between hedge fund returns during the month of the IPO and volatility in the post-offering IPO market. Hedge funds are distinguished by their capacity to make profits in all markets. This means they can take contrarian strategies involving opposite positions that lead to profits based on their superior skill and knowledge. This also means their profit-making can lead to a quicker equilibrium being achieved with one end product being reduced volatility. Therefore, we have:

H-4: We predict less volatility in the IPO market when hedge funds perform better during the month of the IPO.

Our fifth and sixth hypotheses (H-5 and H-6) considers the subprime mortgage and two aspects. H-5 looks at the first aspect, which examines if there is greater volatility during the subprime mortgage period as crisis periods are believed to have more volatility. H-6 centers on the second aspect, which investigates the decline in hedge fund assets that occur during this period where there were fewer hedge funds that were large in size. For H-5, we have

H-5: We predict greater volatility in the IPO market during the subprime mortgage crisis.

Suppose those hedge funds that survived (and even grew) during the subprime meltdown are stronger hedge funds. These stronger and larger hedge funds could convey more information about the value of the IPO. This would lower any information asymmetry and thus lower volatility. Thus, we have:

[4] As will be seen in Table 1, our IPO sample is characterized by decreases in insider ownership proportions. In fact, 702 of our 707 IPOs have a decrease in their insider ownership proportion.

H-6: We predict less IPO price volatility during the subprime mortgage crises when hedge funds have greater assets under management.

Our seventh and eight hypotheses (H-7 and H-8) consider the relation of IPO market volatility and two inside ownership attributes where these attributes are confirmed in the final IPO prospectus. H-7 focuses on the first attribute, which is the proportion of ownership retained by insiders after the IPO. H-8 concentrates on the second attribute, which is the change in the ownership proportion brought about by the IPO. It can be argued that any signal related to greater retainment of ownership is not clear because these owners can also be lowering their ownership proportion. Thus, a higher insider ownership (albeit a positive signal) is clouded in uncertainty when insiders are also lowering their ownership proportions which is true of our IPO sample. This uncertainty can increase volatility and lead to a positive relation between the proportion of inside ownership after the IPO and volatility. Thus, we have:

H-7: We predict greater IPO volatility for higher insider ownership proportions.

Leland and Pyle (1977) demonstrate that decreases in ownership proportions signal negative news. It is the change in the ownership proportion as opposed to the proportion itself that is the clearer insider signal. As applied to IPOs where little is known, the greater decreases in ownership proportions reveal not only greater news (albeit negative news) but also resolve the asymmetric information problem inherent in valuing IPOs. It follows that there would be a positive association since greater decreases in ownership proportions lead to greater decreases in volatility. Consequently, we have:

H-8: We predict less IPO volatility for greater decreases in insider ownership proportions.

3.2 Regression Model

Our regression model used in testing our hypotheses borrows largely from the recent volatility research of Hull et al. (2014) which is influenced by the research of Black (1976), Christie (1982), Kawawini and Keim (1995), Xu and Malkiel (2003) and Clayton et al. (2005). Our model also considers variables used by Hull et al. (2012) who offer a regression model that performs favourably compared to other similar studies (Asquith and Mullins, 1986; Hull and Moellenberndt, 1994; Kahle, 2000; Errunza and Miller, 2003) in explaining stock price behavior.

Our model is:

$$VOL = \beta_0 + \sum_{h\in H} \beta_h HFV_h + \sum_{n\in N} \beta_n NHV_n + \varepsilon \;(1)\,.$$

As will be described in Section 4.2, *VOL* can be represented by three volatilities for a period of choice that for our study involves periods from the offer date (day 0) up to 50 days later.[5] The three volatilities are: idiosyncratic or firm-specific volatility (*IVOL*), market or systematic volatility (*SVOL*), and total volatility (*TVOL*). *HFV* and *NFV* refer respectively to hedge fund and non-hedge fund variables. All *HFVs* values are retrieved during the month of the offering as described in Section 4.1. They are:

AUM = Average (or mean) asset for hedge funds in HFR (in millions of dollars)
NUM = Number of hedge funds
PUL = Proportion of hedge funds using leverage
PRV = Proportion of hedge funds with a relative-value strategy
PED = Proportion of hedge funds with an event-driven strategy
PEH = Proportion of hedge funds with an equity hedge strategy
AHR = Average monthly hedge fund return for month of the IPO

The non-hedge fund variables (*NHVs*) for regression tests are:

[5] Our periods are chosen to represent a variety of periods to track any change in volatility and how it might be impacted by our explanatory variables. As mentioned previously, we use monthly hedge fund data for the month of the offering such that going past 50 days poses problems as the hedge fund attributes are more apt to change as the period after the IPO lengthens.

CRI = Mortgage Crisis: *CRI* = 1 if the IPO occurred during the recession resulting from the subprime mortgage crisis (December 2007 to June 2009); else 0[6]

ILA = Inside ownership proportion after the IPO

CIL = Change in inside ownership proportion: (Inside ownership proportion after the IPO) minus (Inside ownership proportion before the IPO)

PRI = Proportion of primary shares: (Primary shares offered) / (Total shares offered)

UND = Underpricing: (Closing price day 0 – Offer price) / Offer price

DBT = Debt purpose: *DBT* = 1 if the major purpose of the offering was to pay off debt; else 0

CLA = Class variable: *CLA* = 1 if more than one class of shares was offered; else 0

FLQ = Financial liquidity measure: Cash and short-term investments / Total assets

In our regression tests, we also use an interaction variable, *IAC*, composed of both a hedge fund variable and a non-hedge fund variable:

IAC = *CRI* × *AUM*: measures the effect of the interaction between the mortgage crisis and hedge fund assets.

H-1 predicts negative coefficients for the number of hedge funds (*NUM*). H-2 hypothesizes the coefficient for leverage (*PUL*) will be positive. H-3 suggests positive coefficients for relative value (*PRV*), event-driven (*PED*), and equity hedge (*PEH*) strategies. H-4 predicts the coefficient for average hedge fund return (*AHR*) will be negative. H-5 predicts a positive coefficient for the crisis period dummy variable (CRI). H-6 advocates a negative coefficient on the interaction term (*IAC*). H-7 predicts a positive coefficient for the insider ownership proportion after the IPO (ILA) and H-8 suggests the change in the insider ownership brought about the by the IPO (*CIL*) will also have a positive coefficient.

While not presented as a formal hypothesis we can offer general predictions for the five non-hedge fund variables. We expect positive coefficients for *PRI*, *UND* and *FLQ* to the extent a larger number of primary shares issued, greater underpricing, and surplus liquidity create more asymmetric information and thus greater volatility. We predict negative coefficient for *DBT* to the extent debt reduction resolves uncertainty than just stating the proceeds will be used for a number of general purposes. It also lowers agency costs and thus resolves uncertainty about the firm squandering cash flows. Finally, a negative coefficient for CLA is expected because the 65 IPOs having multiple share classes are firms three times larger than those without multiple classes. Larger IPOs will have less asymmetric information and thus less volatility.

4. Sample, Data, Methodology

4.1 Sample and Data

Our initial sample of IPOs was identified from the *Investment Dealers' Digest* (IDD) for the seven-year period from January 2004 to December 2010. Limiting our time frame to these years is one screening criterion that makes our study more manageable because of the time-consuming process of hand-gathering prospectus data used for this study. We next screened out all observations that did not have adequate data supplied by our sources. Besides *IDD*, other major sources are final prospectuses, Compustat, Capital IQ and the Center for Research in Security Prices (CRSP).

The IPO process formally starts when the company files with the SEC. The SEC reviews the filing and sends back exhaustive comments that must be answered in an amendment. This process is typically repeated several times and ends with a preliminary prospectus and the roadshow to find buyers. The offer price is set in the final IPO prospectus with the IPO occurring the next business day. Besides the offer price, major details from the final prospectus include the number of primary and secondary shares being issued, shares outstanding, issue costs, purpose of proceeds, and data to compute the change in proportional share ownership by insiders. The latter is calculated by subtracting the insider ownership proportion before the offering from the insider ownership proportion after the offering. This computation typically creates negative values because the

[6] We use a period where the crisis affected the economy and the market as this period is deemed the best for our purposes.

volume of non-insiders buying new shares is often greater than current insiders. Insiders include (1) directors and officers, D&O, as a group and (2) any beneficial owner who controls 5% or more of the outstanding shares but who is not in the D&O group. Our final sample includes 707 IPOs.

We use the Hedge Fund Research (HFR) database to get monthly hedge fund data.[7] The most important month is month 0 or the offering month for the IPO. When getting hedge fund data for month 0 for each of our 707 IPOs, we match these 707 IPO announcement months with the same month in HFR. We then use these HFR months to get data for hedge fund variables. To illustrate, consider the hedge fund variable for an event-driven strategy (*PED*). From all of the hedge funds in the HFR database for month 0, HFR will report what number uses an event-driven strategy for month 0. This number is divided by the number of hedge funds in HFR for month 0 to give the proportion of all hedge funds claiming to use the event-driven strategy for month 0. Thus, for our 707 IPO announcement months, we get 707 *PED* values. From these values, we can get descriptive statistics (mean, median and standard deviation) for *PED* using all of these 707 values. Similarly, all other hedge fund variables including our hedge fund return variable are derived in this fashion. Thus, our average hedge fund return for month 0 (*AHR*) is an equal-weighted average monthly return.

4.2 Methodology

In this paper, we follow the methodology presented by Hull et al. (2014).[8] This process involves computing expected returns as given in Fama and French (2009) that are used as needed when computing our three volatility variables: total volatility (*TVOL*), idiosyncratic volatility (*IVOL*) and systematic volatility (*SVOL*). The steps in computing values for these variables are described below when using our IPO data gotten from CRSP.

First, we compute *TVOL* for each of the 707 IPOs. This is accomplished by using our daily IPO stock returns to compute volatility in excess daily stock returns (*ER*) defined as

$$ER_{i,\tau} = R_{i,\tau} - r^f_\tau \qquad (2)$$

where $ER_{i,\tau}$ is the IPO's daily excess return for stock *i* for day τ; $R_{i,\tau}$ is the IPO's daily raw return for stock *i* for day τ; and, r^f_τ is the risk-free return for day τ given by the one-day T-bill. Volatility in excess returns can be computed for chosen *t* periods. $TVOL_{i,t}$ is the standard deviation of $ER_{i,\tau}$ given in (2). Using logarithmic returns to lessen the mechanical effect from skewness due to large positive returns, we have

$$TVOL_{i,t} = \sqrt{\frac{\sum_{\tau \in t} (r_{i,\tau} - \overline{r_{i,t}})^2}{n_t - 1}} \qquad (3)$$

where $r_{i,\tau}$ is the natural logarithm of $(1 + ER_{i,\tau})$; $\overline{r_{i,t}}$ is the mean of all $r_{i,\tau}$ values during period *t*; and, n_t is the number of non-missing returns during period *t*.

Second, we compute *IVOL* which is the firm-specific component of total volatility. $IVOL_{i,t}$ is calculated for stock *i* for period *t* as

$$IVOL_{i,t} = \sqrt{\frac{\sum_{\tau \in t} \varepsilon^2_{i,\tau}}{n_t - 1}} \qquad (4)$$

where $\varepsilon_{i,\tau}$ is the Fama and French residual for day τ and is calculated from the following regression:

[7] For this paper's time period of study, we estimate the HFR database has about 2/3 of all hedge funds. Fung and Hsieh (2006) describe the potential biases in the commercial databases like HFR. By using the HFR database, this paper avoids survivorship bias as this data base keeps hedge funds that have ceased to exist. Malkiel and Saha (2005) discuss the biases in reported hedge fund returns.

[8] Besides our description here, these volatility variables are also described in the standard volatility research (Duffee, 1995; Grullon et al., 2012; Ang et al., 2009).

$$\varepsilon_{i,\tau} = ER_{i,\tau} - [\alpha + \beta 1_{i,t}(MKT_\tau - r^f_\tau) + \beta 2_{i,t}(HML_\tau) + \beta 3_{i,t}(SMB_\tau)] \quad (5)$$

where $ER_{i,\tau}$ and r^f_τ were given in (2); α is the intercept of the regression line representing the average excess return; the three $\beta_{i,t}$ values are the three sensitivity factors for stock i for period t; MKT_τ is the return on the value-weighted CRSP index for day τ; HML_τ is the average return for day τ for value portfolios minus the average return for day τ for growth portfolios; SMB_τ is the average return for day τ for small-sized portfolios minus the average return for day τ for large-sized portfolios; and, the last part of the equation inside [·] is the expected return. For the latter, we have: expected return = $\alpha + \beta 1_{i,t}(MKT_\tau - r^f_\tau) + \beta 2_{i,t}(HML_\tau) + \beta 3_{i,t}(SMB_\tau)$.

Third, we calculate $SVOL$ which is the market or systematic component of total volatility. $SVOL_{i,t}$ is computed for stock i for period t as

$$SVOL_{i,t} = \sqrt{\frac{\sum_{\tau \in t}(R_{i,\tau} - \varepsilon_{i,\tau} - \overline{R_{i,t}})^2}{n_t - 1}}. \quad (6)$$

where $\overline{R_{i,t}}$ is the mean of all $R_{i,\tau}$ during period t where $R_{i,\tau}$ is the raw return for stock i for day τ found in (2).[9]

4.3 Descriptive Statistics

The descriptive statistics from Hedge Fund Research (HFR) are presented in Panel A of Table 1 with all statistics computed for the month of the offering (month 0). Hedge funds average $338 million in assets. When we average the 707 median hedge fund sizes, we get only $73 million, which signifies that the average fund size is skewed to the right with lots of small hedge funds. On average, there are 3,663 hedge funds from the HFR data base. For our sample period, 0.527 of the hedge funds used leverage in their investment portfolio; 0.114 of the hedge funds are operating under a relative-value investment strategy; 0.077 are using an event-driven strategy; and, 0.347 are using an equity-hedge strategy. Hedge funds averaged a 1.00% return (equivalent to an APY of 12.71%). This return is net of fees.

Panel B of Table 1 gives the descriptive statistics for the non-hedge fund variables used as independent variables in our regression tests. The low mean of 0.061 for CRI (which is a dummy variable used in our regression tests) reflects the fact that only 43 of our 707 IPOs occur during the subprime mortgage crisis period (0.061 × 707 = 43). The average common stock value prior to the IPO is $648 million with a much lower median of $280 million. Insiders owned an average of 0.869 common shares prior to the IPOs and retained an average of 0.620 shares after the IPOs. There is an average reduction in insider ownership proportions of 0.249 that results from the IPO. Panel B also reports that 0.861 of the shares offered are primary shares implying that 0.139 is the proportion of secondary shares. The mean underpricing of 0.151 indicates that the offering price is set over 15% below its first day (or day 0) closing price. The median of 0.050 is much lower and consistent with the well-known skewness in IPO underpricing. The panel adds that 0.181 of the IPOs have a primary purpose to reduce debt while 0.092 have more than one class of common shares. Like the underpricing variable, the financial liquidity variable has a mean (0.873) much higher than its median (0.161) indicating its mean is highly influenced by positive outliers.

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[9]When computing a standard deviation, the standard deviation is computed as $\sqrt{\sum(Statistic - Mean\,of\,Statistic)^2/(n-1)}$. In this case, we have the "statistic" = (Raw Return – Fama-French residual) = $R-\varepsilon$ with "mean of statistic" = $\overline{R-\varepsilon}$ = $\overline{R}$ since the mean of ε is 0. Thus, we have $SVOL$ as found in (6). Because we use the log in (3) for $TVOL$, the expression of $TVOL$ = $SVOL$ + $IVOL$ does not hold.

Table 1

Descriptive Statistics of Independent Variables

This table reports descriptive statistics for means, medians, and standard deviations (StDev). Panel A gives statistics for seven hedge fund variables (*HFVs*) computed from data collected from Hedge Fund Research (HFR) as described in Section 4.1. The last row in Panel A gives the average hedge fund return based on 707 monthly returns and is thus an equal-weight return. Hedge fund returns are computed with fees considered. Panel B gives statistics for non-hedge fund variables (*NHV*) used in regression tests. Prospectuses, Compustat, Capital IQ, Investment Dealers' Digest, and CRSP supply data for *NHVs*. The financial liquidity ratio (*FLQ*) is computed using data from the fiscal year ending closest, yet prior, to the offer date. $M stands for millions of dollars.

Variable	Description	Mean	Median	StDev
Panel A: Hedge Fund Variables (all are for month 0)				
AUM	Average (or mean) asset for hedge funds in HFR (in $M)	$338	$349	$73
AUD	Median asset for hedge funds in HFR (in $M)	$73	$77	$15
NUM	Number of hedge funds	3,663	3,415	1,065
PUL	Proportion of hedge funds using leverage	0.527	0.527	0.009
PRV	Proportion of hedge funds using a relative-value strategy	0.114	0.111	0.012
PED	Proportion of hedge funds using an event-driven strategy	0.077	0.076	0.003
PEH	Proportion of hedge funds using an equity-hedge strategy	0.347	0.346	0.004
AHR	Hedge fund return for month of IPO	1.00%	1.24%	1.56%
Panel B: Non-Hedge Fund Variables				
CRI	Crisis Period: CRI = 1 if IPO occurs during December 31, 2007 to June 30, 2009	0.061	0.000	0.239
COM	Common stock value: Offer price × Shares before the offering (in $M)	$648	$280	$1,320
ILB	Insider ownership proportion before: (Insider shares / Pre-IPO shares outstanding)	0.869	0.956	0.184
ILA	Insider ownership proportion after: (Insider shares / Post-IPO shares outstanding)	0.620	0.649	0.184
CIL	Change in insider proportion: *ILA* – ILB	-0.249	-0.220	0.165
PRI	Primary Shares: Primary shares offered / Total shares offered	0.861	1.000	0.232
UND	Underpricing: (Closing price day 0 – Offer price) / Offer price	0.151	0.050	0.547
DBT	Debt purpose: *DBT* = 1 if the major purpose of the offering was to pay off debt; else 0	0.181	0.000	0.385
CLA	Class of shares variable: *CLA* = 1 if more than one class of shares was offered; else 0	0.092	0.000	0.289
FLQ	Financial liquidity measure: Cash and short-term investments / Total assets	0.873	0.161	3.753

Table 2 presents descriptive statistics for the volatility variables described in the previous section. Panel A reveals that the mean *IVOL* for periods from day 0 up to day 50 ranges from 0.031 to 0.034 and averages 0.033 for all periods. *SVOL* is approximately one-third of *IVOL* and averages about 0.010 for all periods with little variation in its range of 0.090 to 0.110. The total volatility (*TVOL*) statistics are very similar to the *IVOL* statistics. The greatest standard deviations occur for the shorter periods for *IVOL* and *SVOL*. Compared to longer periods, there is a substantially greater standard deviation for *IVOL* for the shortest period of days 0 to 3 where the standard deviation is 0.037. This compares to 0.016 for days 0 to 50. Thus, a lot more variation in volatility occurs very shortly after day 0. Finally, Table 2 reveals that the standard deviations for *SVOL* are much smaller than *IVOL*.

Table 3 gives descriptive statistics by year. These statistics illustrate how hedge fund and volatility variables change over time or in some cases remain fairly constant. In Panel A of Table 3, we can see that the hedge fund assets are highest in 2007 with an average of $428 million just before the subprime mortgage crisis took full effect in 2008. The number of hedge funds is increasing over time and, unlike hedge fund assets, does not fall during the crisis period. Also increasing somewhat over time are: the proportion of hedge funds using leverage and a relative value strategy. The lowest average return for the hedge funds occurred during 2008 averaging -0.13% monthly or -1.55% annually. The highest occurred the following year at 1.83% monthly or 24.24% annually.

Table 2

Descriptive Statistics for Volatility Measures

This table presents means and standard deviations for the volatility measures described in Section 4.2 where *IVOL* = idiosyncratic volatility in the excess returns as given by equation (4) for the period in question; *SVOL* = systematic volatility in excess returns as given by equation (6) for the period in question; and, *TVOL* = total volatility in the excess returns as given by equation (3) for the period in question.

Periods	*IVOL*		*SVOL*		*TVOL*	
	Mean	StDev	Mean	StDev	Mean	StDev
Days 0 to 3	0.034	0.037	0.009	0.007	0.034	0.035
Days 0 to 5	0.034	0.031	0.010	0.007	0.034	0.029
Days 0 to 7	0.033	0.028	0.010	0.006	0.033	0.027
Days 0 to 10	0.032	0.024	0.010	0.006	0.032	0.023
Days 0 to 20	0.031	0.020	0.010	0.006	0.031	0.020
Days 0 to 30	0.032	0.018	0.010	0.006	0.033	0.018
Days 0 to 50	0.032	0.016	0.011	0.006	0.033	0.016

Panel B of Table 3 shows the volatility measures for each year. When looking at *IVOL*, we see a similar pattern for the various periods where the years 2005 and 2007 have relatively high *IVOL* values while 2010 is relatively low. For example, from day 0 to +3, we find that *IVOL* has a high of 0.041 in 2007 and a low of 0.029 in 2010. Prior to 2007, all the measures of *SVOL* range from 0.006 to 0.009. After 2007, the *SVOL* range increases from 0.010 to 0.014. Unlike the values for *IVOL* in year 2010, the lowest values for *SVOL* do not occur for this year but for the year 2005.

5. Empirical Results

This section gives our empirical results. In general, we show that most of our hypothesis cannot be rejected. We first report our correlation findings followed by regression results for both *IVOL* and *SVOL*. We close this section with a review of the main robust tests that we conducted.

5.1 Correlation Results

Before running the regressions presented in equation (1), we computed a correlation matrix that is given in Table 4. The upper right portion of this matrix presents the Pearson's correlation coefficients. The lower left portion provides Spearman's rank correlation coefficients. The variables described below suggest the greatest potential for multicollinearity problems when interpreting regression tests.

First, the crisis period dummy variable (*CRI*) and interaction term of *IAC* (*CRI* × *AUM*) have the highest correlation of 1.00 for both the Pearson and Spearman tests. However, this high correlation always results for the correlation between an interaction term and one of its components especially when a small sample size is involved. As mentioned earlier, the crisis period (*CRI*) has only 43 IPOs. In brief, researchers do not have to worry about multicollinearity problems for variables with high correlation that are caused by the inclusion of a product as is the situation for *CRI* and *IAC* where *IAC* includes the product *CRI*.

Second, all *HFVs*, except hedge fund returns (*AHS*), are highly correlated. Among the *HFVs*, the highest correlation of 0.94 for the Pearson test (0.98 for the Spearman test) is between the proportion of hedge funds using a relative value strategy for month 0 (*PRV*) and the number of hedge funds for month 0 (*NUM*). The high correlation is explained by the fact that both are continually increasing as shown previously in Table 3. Eliminating *PRV* from the regression equation does not cause significant changes in the coefficients on *NUM*, which is a variable that involves H-1. However, we can see changes for some tests in the coefficients for *PRV* when we eliminate *NUM* from the regression equation as it becomes negative. However, we believe this sign change occurs because of a misspecification problem caused by eliminating *NUM* from our model. Of importance, for most of the cases where *PRV* is significant in the regression models, eliminating *NUM* doesn't cause the *PRV* coefficients to become negative. Whereas *PRV* is used in H-3, it is not the sole variable used there as this hypothesis includes two other strategy variables (*PED* and *PEH*).

Table 3
Mean Statistics by Year

This table presents mean statistics by years. The letter "n" refers to the sample size or number of IPOs for each year from 2004 through 2010. Panel A gives means by year for hedge fund variables taken from Hedge Fund Research (HFR) database as described in Section 4.1. These means are taken from the IPO announcement month. The description for the variables associated with the abbreviations in Panel A is given in Table 1. Panel B provides means by year for the volatility variables described in Section 4.2 where *IVOL* = idiosyncratic volatility in the excess returns as given by equation (4) for the period in question and *SVOL* = systematic volatility in excess returns as given by equation (6) for the period in question.

		2004 n=69	2005 n=53	2006 n=152	2007 n=201	2008 n=31	2009 n=61	2010 n=140
Panel A: Hedge Fund Variables								
AUM		$238	$278	$356	$428	$423	$267	$273
AUD		$64	$73	$78	$90	$88	$55	$53
NUM		2,075	2,525	3,026	3,457	3,877	4,706	5,365
PUL		0.504	0.526	0.526	0.527	0.531	0.539	0.535
PRV		0.101	0.103	0.103	0.111	0.114	0.127	0.134
PED		0.080	0.074	0.075	0.075	0.077	0.081	0.081
PEH		0.343	0.340	0.345	0.350	0.355	0.347	0.348
AHR		0.55%	1.41%	1.09%	0.88%	-0.13%	1.83%	1.05%
Panel B: Volatility Variables								
IVOL	Days 0 to 3	0.035	0.040	0.030	0.041	0.032	0.031	0.029
	Days 0 to 5	0.035	0.037	0.031	0.039	0.033	0.033	0.031
	Days 0 to 7	0.034	0.033	0.030	0.038	0.032	0.032	0.031
	Days 0 to 10	0.033	0.032	0.029	0.036	0.032	0.031	0.030
	Days 0 to 20	0.034	0.031	0.029	0.035	0.031	0.029	0.029
	Days 0 to 30	0.035	0.000	0.029	0.036	0.033	0.029	0.031
	Days 0 to 50	0.036	0.033	0.028	0.036	0.037	0.028	0.030
SVOL	Days 0 to 3	0.009	0.006	0.008	0.010	0.010	0.011	0.010
	Days 0 to 5	0.009	0.007	0.008	0.011	0.011	0.012	0.011
	Days 0 to 7	0.009	0.007	0.008	0.011	0.012	0.012	0.011
	Days 0 to 10	0.009	0.007	0.009	0.011	0.011	0.012	0.011
	Days 0 to 20	0.009	0.007	0.009	0.011	0.012	0.011	0.012
	Days 0 to 30	0.009	0.007	0.009	0.012	0.012	0.011	0.012
	Days 0 to 50	0.009	0.007	0.009	0.012	0.014	0.011	0.012

In conclusion, while the high correlation coefficients appear to pose a problem, we found that deleting a highly correlated variable did not generally change coefficient signs for the remaining variables. Furthermore, omitting highly correlated variables that are significant can cause a biased estimate of the coefficient of the included variable that is forced to play a double role. Regardless, caution should be used when interpreting the results for our highly correlated variables and we find that *PRV* is the most problematic to interpret. Finally, heteroscedasticity is not a concern since our regression tests use robust standard errors corrected for heteroscedasticity.

5.2 Idiosyncratic Volatility Results

Table 5 presents the idiosyncratic volatility (*IVOL*) regression results.[10] The regression results show highly significant negative coefficients for *NUM* for all tests. For days 0 to 3, we find a 1% increase in the number of hedge funds during the month of the offering has a 2.27% reduction in *IVOL*. Whereas this percentage reduction diminishes for longer periods tested, it picks up and achieves a 1.87% reduction in *IVOL* for the longest period

[10] For what follows, the results expressed in term of percent change come (where applicable) from the formula: [exp(b/100)-1]×100% where "exp" means exponential function and "b" is the coefficient of interest.

of days 0 to 50. The average reduction for all seven tests is 1.54%. These results supports H-1 that predicts a greater number of hedge funds will be associated with less *IVOL* in the IPO market.

Table 4

Correlation Results

This table provides correlation coefficients for the independent variables used in regression analysis. Pearson coefficients are presented in the upper right-hand half of the table, while the Spearman coefficients are reported in the lower left-hand half. All variables were defined previously in Table 1. Pairs of variables with correlation coefficients greater than 0.50 are marked in bold print. These all involved hedge fund variables. For one-tailed tests, those pairs of variables with coefficients over 0.08 are generally significant at the 5% level and beyond, while those with coefficients over 0.10 are significant at the 1% level and beyond.

	AUM	*NUM*	*PUL*	*PRV*	*PED*	*PEH*	*AHR*	*CRI*	*IAC*	*ILA*	*CIL*	*PRI*	*UND*	*DBT*	*CLA*
AUM		-0.03	0.14	-0.29	**-0.70**	**0.56**	-0.05	0.13	0.14	-0.04	-0.04	0.03	0.10	0.08	0.06
NUM	0.09		**0.85**	**0.94**	0.48	0.54	0.08	0.12	0.12	0.03	-0.09	-0.12	-0.02	0.09	0.08
PUL	-0.06	**0.83**		**0.70**	0.11	0.38	0.14	0.16	0.16	-0.01	-0.13	-0.13	-0.02	0.08	0.06
PRV	0.06	**0.98**	**0.82**		**0.69**	0.41	0.07	0.06	0.05	0.04	-0.07	-0.11	-0.05	0.05	0.08
PED	**-0.57**	0.49	0.37	0.47		0.04	-0.06	0.05	0.04	0.04	-0.02	-0.04	-0.07	-0.02	0.02
PEH	**0.59**	**0.66**	0.46	**0.62**	0.07		-0.06	0.42	0.42	0.00	-0.05	-0.06	0.06	0.07	0.08
AHR	0.05	0.05	0.11	0.10	-0.11	-0.05		-0.05	-0.06	-0.04	-0.04	-0.06	0.01	0.00	0.01
CRI	0.09	0.18	0.23	0.14	0.08	0.36	-0.06		**1.00**	-0.03	-0.04	-0.05	-0.03	0.04	-0.04
IAC	0.10	0.18	0.23	0.14	0.08	0.36	-0.06	**1.00**		-0.03	-0.04	-0.05	-0.03	0.04	-0.04
ILA	-0.04	0.07	0.03	0.07	0.06	0.02	-0.02	-0.02	-0.02		0.45	-0.06	0.11	0.05	0.09
CIL	-0.06	-0.04	-0.05	-0.05	0.01	-0.02	-0.03	-0.02	-0.02	0.28		0.00	0.10	-0.08	0.12
PRI	0.00	-0.10	-0.13	-0.10	0.01	-0.08	-0.04	-0.03	-0.03	-0.04	0.05		-0.02	0.06	-0.02
UND	0.07	-0.08	-0.11	-0.07	-0.09	-0.02	0.09	-0.08	-0.08	0.09	0.12	-0.22		-0.09	-0.01
DBT	0.07	0.09	0.03	0.06	0.00	0.08	0.00	0.03	0.04	0.04	-0.12	0.01	-0.10		0.04
CLA	0.07	0.09	0.06	0.10	0.03	0.10	0.03	-0.04	-0.04	0.09	0.13	0.02	0.02	0.04	
FLQ	0.05	-0.04	-0.05	-0.01	-0.06	0.00	0.10	-0.03	-0.03	0.04	0.05	-0.02	0.21	-0.24	-0.11

For our leverage variable (*PUL*), we find our predicted positive coefficients. Furthermore, all coefficients are highly significant, thus offering strong support for H-2. We find that a 1% increase in the proportion of hedge funds using leverage is associated with increases in *IVOL* that ranges from 14.3% for days 0 to 20 to as high as 33.9% for days 0 to 3. The average increase in *IVOL* for all seven tests is 21.3%.

The three hedge fund strategy variables have their predicted positive coefficients for all tests. These variables also manifest some statistical significance for 12 of the 21 tested and this is particularly true for the equity hedge strategy (*PEH*) where all seven tests are significant beyond the 1% level. For days 0 to 3, we find a 1% increase in *PEH* increases *IVOL* by about 113.4% with the average for all seven periods at 67.1%. The largest percentage for the relative value strategy (*PRV*) and the event-drive strategy (*PED*) are, respectively, 27.5% for days 0 to 50 and 29.9% for days 0 to 50. A 1% change in all three of these strategy variables cause, on average, an increase in *IVOL* of 100.7%. Collectively, these results render support for H–3 that asserts the increase in hedge fund strategies increases *IVOL*.

Table 5

Idiosyncratic Volatility Results

The regression model found in Section 3.2 is $\text{Ln}(IVOL) = \beta_0 + \sum \beta_i\, HFV + \sum \beta_j\, NHV + \varepsilon$ where the hedge fund variables (*HFVs*) and non-hedge fund variables (*NHVs*) are defined in Table 1. *IVOL* is idiosyncratic volatility in the excess returns as given by equation (4) for the period in question. Logs are not only used for *IVOL* but also for *AUM* and *NUM*. *IAC* is an interaction variable equal to *CRI* × *AUM*. All columns report results for the robust residuals. The first row for each test gives coefficients and the second row reports robust standard errors. We indicate significance at the 1%, 5% and 10% levels by ***, ** and *, respectively, for the one-tailed *t* test as all coefficients have expected signs.

Days	0 to 3	0 to 5	0 to 7	0 to 10	0 to 20	0 to 30	0 to 50
AUM	-0.411	-0.386	-0.337	-0.151	0.046	0.295	0.413**

	(0.479)	(0.402)	(0.363)	(0.326)	(0.280)	(0.258)	(0.221)
NUM	-2.269***	-1.374**	-1.203**	-1.267***	-1.252***	-1.565***	-1.874***
	(0.783)	(0.646)	(0.586)	(0.524)	(0.470)	(0.428)	(0.382)
PUL	29.206***	21.333***	21.389***	19.444***	13.367**	14.249***	15.063***
	(9.985)	(8.655)	(7.973)	(7.106)	(5.865)	(5.457)	(4.982)
PRV	18.63	6.286	2.086	7.276	11.407	20.873**	26.137***
	(16.848)	(14.156)	(12.653)	(11.520)	(10.331)	(9.392)	(8.316)
PED	0.996	9.406	19.873	21.568	20.020*	24.017**	24.302**
	(26.472)	(22.397)	(20.478)	(18.126)	(15.405)	(13.980)	(12.451)
PEH	75.791***	61.801***	62.670***	50.018***	41.302***	28.389***	29.773***
	(19.368)	(16.478)	(14.898)	(13.526)	(11.223)	(10.639)	(9.313)
AHR	-2.564	-1.140	-2.451*	-2.727**	-2.673**	-2.616***	-2.017**
	(2.064)	(1.726)	(1.580)	(1.387)	(1.217)	(1.116)	(1.002)
CRI	6.446**	5.233**	4.804**	4.360**	3.685**	3.094*	1.838
	(2.938)	(2.472)	(2.325)	(2.186)	(2.122)	(2.081)	(1.881)
IAC	-1.114**	-0.903**	-0.845**	-0.759**	-0.647**	-0.534*	-0.311
	(0.500)	(0.421)	(0.394)	(0.371)	(0.360)	(0.350)	(0.317)
ILA	0.767***	0.525***	0.461***	0.399***	0.403***	0.501***	0.473***
	(0.197)	(0.161)	(0.148)	(0.133)	(0.120)	(0.110)	(0.102)
CIL	0.718***	0.930***	1.000***	0.984***	0.841***	0.757***	0.678***
	(0.237)	(0.206)	(0.188)	(0.171)	(0.161)	(0.148)	(0.127)
PRI	-0.021	0.106	0.104	0.079	0.092	0.121*	0.126**
	(0.125)	(0.115)	(0.103)	(0.094)	(0.082)	(0.076)	(0.070)
UND	0.181*	0.148*	0.124	0.111	0.112	0.132*	0.104*
	(0.111)	(0.110)	(0.109)	(0.110)	(0.108)	(0.089)	(0.073)
DBT	-0.146*	-0.171***	-0.186***	-0.170***	-0.170***	-0.186***	-0.209***
	(0.090)	(0.071)	(0.064)	(0.056)	(0.049)	(0.046)	(0.042)
CLA	0.112	-0.042	-0.035	-0.085	-0.147***	-0.175***	-0.217***
	(0.100)	(0.088)	(0.079)	(0.070)	(0.062)	(0.056)	(0.051)
FLQ	0.021*	0.022**	0.017**	0.016**	0.018***	0.015**	0.016***
	(0.013)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.005)
Constant	-27.032***	-24.515***	-26.764***	-22.558***	-17.970***	-14.285***	-13.963***
	(7.297)	(6.343)	(5.746)	(5.207)	(4.324)	(4.078)	(3.706)
F Statistic	7.07***	7.26***	8.38***	8.73***	11.41***	13.89***	19.92***
Adjusted R^2	0.140	0.154	0.175	0.186	0.203	0.237	0.284

The negative coefficients for *AHR* in Table 5 are consistent with H-4 that predicts greater hedge fund returns will lead to less *IVOL*. However, only for the five longer period tests do we find significant support for H-4. These results lend general support for the notion that hedge fund profit-making is associated with lower *IVOL*. On average, a 1% increase in *AHR* reduces IVOL by 88.2%.

Consistent with H-5, we find positive coefficients for the crisis period dummy variable (*CRI*) with six of the seven tests significant. This renders support for the notion that crisis periods will have higher *IVOL* since we have verified it for the subprime mortgage crisis period. We provide support for H-6 from the negative coefficients for the interaction term between the subprime mortgage crisis and assets under management (*IAC*) with significance for six of the seven coefficients. This indicates that larger hedge funds have lower *IVOL* during the subprime crisis even though the period itself has higher volatility. To illustrate for days 0 to 3, we find a 1% increase in average hedge fund assets under management during the subprime mortgage crisis is associated with a reduction in *IVOL* of about 1.11%. However, this percentage reduction diminishes as the period increases. For example, for days 0 to 50, we find only a 0.31% fall in *IVOL*. The average reduction in *IVOL* is 0.73%. The latter average is greater than the reduction for the non-crisis period months where the average reduction in *IVOL* is miniscule.

Consistent with H-7, we find positive coefficients for the insider ownership proportion after the IPO (*ILA*). These coefficients are all highly significant beyond the 1% level for all tests. These results support the argument that higher insider ownership proportions can cause greater information asymmetry when insiders are also lowering their ownership proportions (which is what is happening with our IPO sample). This greater asymmetric information explains the greater *IVOL*. To illustrate using days 0 to 3, we find a 1% increase in *ILA* results in a 0.77% increase in *IVOL*. The average for all seven tests is 0.51%. Consistent with H-8, we show the change in the ownership proportion brought about by the IPO (*CIL*) has significant positive coefficients beyond the 1% level for all tests. These results suggest greater decreases in insider ownership (that is known prior to the IPO) will resolve information asymmetry and lead to less *IVOL*. To illustrate using days 0 to 3, we discover a 1% decrease in *CIL* causes a 0.72% fall in *IVOL*. The average for all seven tests is 0.85%.

All of the other five non-hedge fund variables are significant for at least two periods tested. The latter occurs for the proportion of primary shares offered divided by the total shares offered (*PRI*) where a greater value for *PRI* indicates greater *IVOL*. The results for underpricing (*UND*) are significant for four of the seven tests. These positive coefficients for all tests are consistent with prior IPO volatility research and supports the notion that greater underpricing is associated with more asymmetric information and thus more *IVOL*. If the purpose of the offering is to reduce debt (*DBT* = 1), we discover a significant reduction in *IVOL* for all tests. This is consistent with the belief that reducing debt lowers agency costs and thus resolves the uncertainty about squandering cash flows. With uncertainty reduced, *IVOL* is lowered. There is evidence for the three longer periods tested that IPOs with two classes of shares have lower *IVOL*. The findings for financial liquidity (*FLQ*) indicate that firms with greater cash and short-term assets have greater *IVOL* with all tests being significant. This is consistent with the notion that high and unused cash flows create uncertainty as to how these short-term assets might be used and when they will be used.

5.3 Systematic Volatility Results

The systematic volatility (*SVOL*) regression results are presented in Table 6. In contrast to the *IVOL* tests in Table 5, assets under management (*AUM*) and the event-driven strategy (*PED*) now manifest greater significance for the *SVOL* tests. This is also true for the non-hedge fund variable for the proportion of primary shares issued (*PRI*). Additionally, the leverage (*PUL*) and equity hedge strategy (*PEH*) are significant for fewer periods in the *SVOL* tests compared to the *IVOL* tests. The latter is also true for the change in insider ownership proportion (*CIL*) and underpricing (*UND*). Thus, we do find some differences in the results for the *IVOL* and *SVOL* tests even though similarities dominate. We also computed each change in volatility when an independent variable changes by 1% (or 1 unit if applicable) and found that it was pretty even in terms of whether *IVOL* and *SVOL* showed a greater change.

The negative coefficients for *NUM* support H-1 in that *SVOL* falls as the number of hedge fund increases. We can note that the increase in the number of hedge funds reduces *SVOL* in a magnitude smaller than that found for *IVOL*. For example, when averaging all seven tests, we find a 1% increase in *NUM* results in a 1.54% decrease in *IVOL* but only a 0.99% decrease in *SVOL*. The positive coefficients for leverage (*PUL*) support H-2 as leverage increases *SVOL* but the coefficients are only significant for periods up to days 5.

We find support for H-3, especially for the event-driven strategy (*PED*) where six of the sevens tests are significant. The results for *PEH* are the weakest as one can notice the wrong sign for the days 0 to 30 and days 0 to 50 test. However, collectively, we can say there is support for the notion that the greater use of the three strategies by hedge fund managers collectively increases *SVOL*. A 1% change in all three of these strategy variables causes, on average, an increase in *SVOL* of 92.6% that is slight below the 100.7% mentioned above for *IVOL*. Like the *IVOL* tests, the *SVOL* tests show support for H-4. However, this support is now stronger as all negative coefficients for *AHR* are significant at the 1% level and beyond. Thus, greater hedge fund returns during the offering month reduces *SVOL*. Thus, we have strong support for the premise that market volatility will decrease when hedge funds achieve greater returns. Of importance, these results are consistent with the notion that hedge funds can make profits when the general market is not performing well.

Table 6

Systematic Volatility Results

The regression model is Ln(*SVOL*) = $\beta_0 + \sum \beta_i HFV + \sum \beta_j NHV + \varepsilon$ where the volatility variables, the hedge fund variables (*HFVs*) and non-hedge variables (NHVs) are defined in Table 1. *SVOL* is systematic volatility in excess returns as given by equation (6) for the period in question. Logs are not only used for *SVOL* but also used for *AUM* and *NUM*. *IAC* is an interaction variable equal to *CRI* × *AUM*. All columns report results for the robust residuals. The first row for each test gives coefficients and the second row reports robust standard errors in parenthesis. We indicate significance at the 1%, 5% and 10% levels by ***, ** and *, respectively, for the one-tailed *t* test as all coefficients have expected signs.

Days	0 to 3	0 to 5	0 to 7	0 to 10	0 to 20	0 to 30	0 to 50
AUM	0.348	0.297	0.560*	0.588*	0.957***	1.180***	1.464***
	(0.443)	(0.394)	(0.370)	(0.361)	(0.352)	(0.344)	(0.335)
NUM	-1.011*	-0.994*	-0.976*	-0.959*	-0.852*	-0.915**	-1.191**
	(0.751)	(0.656)	(0.607)	(0.589)	(0.565)	(0.556)	(0.547)
PUL	14.292*	12.724*	9.164	9.199	-3.283	-4.422	0.040
	(10.137)	(9.226)	(8.737)	(8.202)	(7.614)	(7.494)	(7.355)
PRV	12.681	13.692	18.400*	17.900*	30.286***	33.340***	36.579***
	(15.957)	(13.855)	(12.806)	(12.554)	(12.148)	(12.025)	(11.701)
PED	54.819**	47.908**	44.714**	43.767**	25.131	34.226**	48.509***
	(26.071)	(23.488)	(22.111)	(21.583)	(20.874)	(20.190)	(19.627)
PEH	36.441**	33.448**	17.343	17.566	-6.329	-13.110	-22.227*
	(18.546)	(17.201)	(16.433)	(15.971)	(15.303)	(14.755)	(14.443)
AHR	-10.560***	-11.050***	-9.578***	-9.194***	-8.778***	-6.155***	-3.856***
	(1.878)	(1.820)	(1.634)	(1.614)	(1.590)	(1.556)	(1.546)
CRI	15.098***	10.841***	11.032***	9.914***	8.426***	7.426***	5.617***
	(3.028)	(2.696)	(2.562)	(2.272)	(2.230)	(2.119)	(2.039)
IAC	-2.577***	-1.837***	-1.854***	-1.671***	-1.393***	-1.218***	-0.898***
	(0.514)	(0.455)	(0.433)	(0.385)	(0.379)	(0.361)	(0.348)
ILA	0.400**	0.441***	0.432***	0.415***	0.350**	0.325**	0.414***
	(0.185)	(0.172)	(0.162)	(0.154)	(0.152)	(0.150)	(0.149)
CIL	0.317*	0.249	0.270	0.283*	0.254	0.254	0.251
	(0.221)	(0.217)	(0.212)	(0.202)	(0.201)	(0.199)	(0.197)
PRI	-0.238**	-0.261**	-0.212**	-0.228**	-0.243***	-0.241***	-0.196**
	(0.133)	(0.114)	(0.108)	(0.105)	(0.095)	(0.092)	(0.089)
UND	-0.022	-0.010	-0.025	-0.030	-0.010	-0.007	-0.002
	(0.052)	(0.050)	(0.046)	(0.045)	(0.048)	(0.050)	(0.044)
DBT	0.192***	0.149**	0.093*	0.100*	0.097*	0.088*	0.079*
	(0.083)	(0.075)	(0.071)	(0.067)	(0.065)	(0.062)	(0.061)
CLA	0.152**	0.059	0.116**	0.086*	0.077	0.082	0.097*
	(0.090)	(0.081)	(0.069)	(0.066)	(0.064)	(0.065)	(0.064)
FLQ	-0.015***	-0.014***	-0.014***	-0.011***	-0.010***	-0.006*	-0.005*
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-24.545***	-21.967***	-16.452***	-16.664***	-4.699	-3.572	-3.736
	(7.214)	(6.702)	(6.454)	(6.147)	(5.739)	(5.592)	(5.435)
F Statistic	9.01***	9.06***	9.78	9.39***	8.59***	7.59***	7.01***
Adjusted R^2	0.134	0.148	0.143	0.140	0.139	0.129	0.125

We find strong support for H-5 as all coefficients for the dummy crisis variable (*CRI*) are positive and significant beyond the 1% level. Similarly, we demonstrate support for H-6 as all coefficients for the interaction term between the subprime dummy and average hedge assets (*IAC*) are negative and also significant beyond the 1% level. Thus, there was greater *SVOL* during the financial crisis period but with less *SVOL* when hedge funds have greater assets under management. Finally, like the *IVOL* tests, the insider ownership proportion after the IPO (*ILA*) was significantly positive for all *SVOL* tests. This offers strong support for H-7 and is consistent with the notion that IPOs with higher insider ownership are associated with greater *SVOL*. The change in ownership proportion variable (*CIL*) had all of their predicted positive coefficient signs offering support for H-8. While only three of these signs were significant, three more were significant near the 10% level. Thus, greater decreases in insider ownership proportions are associated with less *SVOL*, albeit not strongly associated. In terms of the other five non-hedge fund variables, three stand out with all coefficients significant indicating the following: a greater proportion of primary shares issued (*PRI*) and greater financial liquidity (*FLQ*) are associated with less *SVOL*, while a greater use of the proceeds to reduce debt (*DBT*) is associated with more *SVOL*. These *SVOL* results differ from the *IVOL* results for these three variables. The class variable (*CLA*) appears to have a modest positive association with *SVOL* and the underpricing (*UND*) has negative coefficients but none are significant. Once again these *SVOL* results differ from the *IVOL* results in that the coefficient signs tend to be the opposite.

5.4 Robustness and Other Tests

We tested total volatility (*TVOL*) and found their regression results mirror those for *IVOL*. To illustrate, we discovered that as the proportion of hedge funds using leverage increases by 1% there is an increase in total volatility of approximately 10.8% to 23.3% depending on the period tested. The range for the *IVOL* tests was higher at14.3% to 33.9%. Additionally we computed the volatility measures for longer periods past 50 days even though our independent monthly hedge fund variables are only for the month of the offering. The results for these tests change over time because the hedge fund attributes can change from year to year as indicated in Table 3 where the size and number of hedge funds changed in dramatic fashions. Two noteworthy exceptions were the two non-hedge fund variables for insider ownership that retained their significance for periods up to 750 days (or about three years after the IPO).

We tested mutual fund ownership from Capital IQ in our regression analysis. It was not included in our model because it was generally insignificant and does not change our regression results. We also tested different time periods for the subprime mortgage crisis but our regression results were robust for all periods tested. For example, we tested a period using the scholarly dating of the subprime mortgage crisis from June 2007 thru October 2009 and one using a dating of the subprime mortgage crisis that matched the impact of the subprime mortgage crisis on the hedge fund industry of August 2007 to April 2009. Since smaller hedge funds can increase their size through the use of leverage, we used an interaction variable using leverage and the number of hedge funds as a substitute for *AUM* within the interaction variable *IAC*. This new interaction variable performed similar to *IAC* as it was significantly negative indicating. Thus, when hedge funds have either greater assets under management or greater clout through greater leverage, they can be associated with reduced volatility during the subprime mortgage crisis.

6. Conclusions

Our first hypothesis (H-1) states that the increase in the number of the hedge funds will lead to less volatility in the IPO market. We offered strong evidence to support H-1 for both *SVOL* and *IVOL*. Our second hypothesis (H-2) predicts that the increased use of leverage will be associated with greater volatility. We found strong support for H-2 for *IVOL* and weaker support for *SVOL*. Our tests provide support for H-3 for both *IVOL* and *SVOL* as greater use of relative value, event-driven and equity hedge strategies collectively increased volatility. Our fourth hypothesis (H-4) states greater hedge fund returns will lead to less volatility. H-4 was supported especially for *SVOL*. Our fifth hypothesis (H-5) assert there will be greater volatility during the crisis period. We found strong support for this assertion. Our sixth hypothesis (H-6) advocates hedge funds with greater assets under management will be associated with reduced volatility even though the crisis period itself has higher volatility. This hypothesis was strongly supported. Our seventh hypothesis (H-7) was supported as higher insider ownership proportions were related to greater volatility. We attribute the greater volatility to our IPO sample where those with higher insider ownership proportions were also lowering their ownership proportions. This sends an unclear message that does not resolve uncertainty about the value of the IPO and thus leads to greater volatility. Finally, our eighth hypothesis (H-8) was supported as greater decreases in insider ownership proportions were linked to lower volatility, especially for *IVOL*. We interpret the latter insider finding as follows. A bigger decline in insider ownership is a clear signal (albeit a negative signal) lessening information asymmetry about the quality of the issuing firm. This decrease in information asymmetry is reflected in less volatility.

In conclusion, we have documented the important roles played by hedge fund attributes and insider ownership when accounting for volatility around IPOs. With the proper attributes in place, even an event surrounded with uncertainty like an IPO, can have the volatility in its price behavior curtailed. In particular, if there are a large number of hedge funds involved taking differing positions and the insider ownership proportional change is known, the extreme volatility in IPO price behavior can be minimized.

Future research needs to continue to explore volatility around equity offerings as well as other corporate events. The research can try to explain why the IPO results in this paper can differ from the SEO results of Hull et al. (2014). To illustrate using days 0 to 50 and *IVOL*, the proportion of hedge funds using leverage and the proportion of hedge funds using a relative-value strategy are negatively related for SEOs but positively for IPOs. Such differences can be puzzling and indicate that more research is needed to explain these dissimilarities in volatility when comparing SEOs and IPOs. Part of the exploration should focus on differences related to the crisis periods involved. For example, can differences in the IPO bubble period (2000-2001) and subprime mortgage crisis period (2008-2009) be the cause? To answer such questions, one would have to use a database covering both the IPO bubble and subprime crisis periods. Finally, for this study, we focused on testing periods up to only 50 days after the IPO. This is because we used hedge fund data for the month of the IPO. While this data is arguably the most important month to capture volatility, it is still important to know the volatility for longer periods. Future research can test longer periods by including monthly hedge fund data for more than just the month of the IPO (or whatever event other than an IPO is being studied). Research using longer periods would cover one year or more and have monthly data for twelve or more months.

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