Leveraged Speculators and Asset Prices

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ABSTRACT

I test the hypothesis that the use of leverage by market speculators can increase the likelihood and magnitude of a crash in asset prices. Using a novel leverage measure derived from public filings, I find that stocks held by highly-levered hedge funds subsequently have more negatively skewed returns than stocks held by less highly-levered funds. This finding extends to the aggregate U.S. market index and is economically significant. I relate this effect to financial distress and find evidence that highly-levered funds are more likely to fire sell long positions when experiencing adverse economic events, including negative fundamental shocks to the assets they hold and funding liquidity shocks.

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I. Introduction

The excessive use of leverage by speculators can greatly amplify market crashes. During the stock market collapse in the summer of 1998, for example, Long-Term Capital Management (LTCM) was blamed for taking an extremely high level of leverage and consequently being vulnerable to adverse economic shocks. To meet margin calls, LTCM was forced to sell a large fraction of its holdings, including stocks. It is widely believed that this pushed the stock market lower and induced selling by other leveraged institutions, causing further market declines and a downward spiral.[1] In the view of chairpersons of major U.S. regulatory agencies (Rubin, Greenspan, Levitt, and Born, 1999), "excessive leverage can greatly magnify the negative effects of any event or series of events on the financial system as a whole ... [and] can increase the likelihood of a general breakdown in the functioning of financial markets."

A similar destabilizing effect of leverage has also been recognized in other events, including the stock market crashes in 1929 and 1987, the quant crisis in 2007, and the financial crisis in 2007 to 2008.[2] In all of these events, regulators regarded leverage as an important factor in the crises and strongly recommended policies to constrain excessive leverage in order to lower systemic risk.[3] Motivated by the common interpretation of these events, a large body of theoretical literature points out the potentially negative impact of leverage on asset prices and financial stability (e.g., Shleifer and Vishny (1992), Gromb and Vayanos (2002), Geanakoplos (2003), and Brunnermeier and Pedersen (2009)).[4]

The link between theory and evidence, however, remains a challenge. There has been limited empirical analysis of speculators' leverage and its relation to asset prices and systemic risk. The main obstacle is the lack of data. In recent decades, hedge funds have played a dominant role as speculators in public equity markets. At the same time, they have been exempt from regulatory disclosures that would allow for direct calculations of leverage. Several papers attempt to address

[1] For more details about this event, see Rubin et al. (1999), Edwards (1999), and Lowenstein (2000).

[2] For the stock market crash in 1929, see Kindleberger (1978) and White (1990). For the "Black Monday" stock market crash in October 1987, see Presidential Task Force on Market Mechanisms and Brady (1988). For the quant crisis in August 2007, see Khandani and Lo (2011). For the recent financial crisis in 2007 to 2008, see Greenlaw et al. (2008) and Brunnermeier (2009). In addition, Frehen et al. (2013) analyze several early financial bubbles in 1720 and show that leverage played a critical role during the build-up and bursting of the bubbles.

[3] For example, as put in Rubin et al. (1999), "the principal policy issue arising out of the events surrounding the near collapse of LTCM is how to constrain excessive leverage."

[4] For more papers in this vein, see Shleifer and Vishny (1997, 2010, 2011), Kyle and Xiong (2001), Xiong (2001), Fostel and Geanakoplos (2008), Geanakoplos (2010), Acharya and Viswanathan (2011), among many others.

this issue by using indirect measures of leverage. For example, Schwert (1989), Hsieh and Miller (1990), and Hardouvelis (1990) examine how changes in regulatory margin requirements influence stock volatility but reach very different conclusions.

In this paper, I develop a direct measure of hedge fund leverage, and use it to explore whether and how hedge fund leverage increases the chance of a crash in individual stocks and in the aggregate market. I start by constructing a novel dataset of U.S. hedge funds' leverage based on regulatory disclosures required by the Dodd-Frank Act.[5] This leverage data is only available from 2011 to 2013. However, it provides a basis for estimating leverage over a much longer sample period. Specifically, I find that a hedge fund's leverage is highly predictable from its trading style and level of portfolio diversification. I use these predictors, which are observable in the pre-reporting period, to estimate hedge funds' leverage before 2011. I show that this extrapolated leverage matches well with the aggregate time-series of actual leverage calculated by Ang, Gorovyy, and van Inwegen (2011), who have access to proprietary data on a subset of hedge funds.

Theoretical work mentioned above argues that leveraged speculators are vulnerable to adverse shocks to their asset value or to their funding activities, and thus are more likely to become financially distressed and to be forced to sell assets, thereby amplifying and transmitting the negative shocks to the prices of the assets they hold. Price declines and fire sales can be mutually reinforcing, leading to a crash. In the long run, prices gradually revert to fundamental value. This intuition can be applied to the cross-section of individual stocks: stocks held long by highly-levered hedge funds will be more subject to crashes in prices than stocks held by funds using little leverage, all else equal.

To test this prediction, I use skewness as the primary measure of the asymmetry of a stock's return distribution – a stock with more negatively skewed returns is more likely to experience a dramatic price drop. The explanatory variable I am interested in is "stock-level leverage", i.e., the average (extrapolated) leverage of all hedge funds holding the stock. Specifically, I regress a stock's future skewness on the recent deviation of stock-level leverage from its trend, i.e., from its moving average over the past eight quarters. This specification is meant to remove unobservable firm or fund fixed effects that are correlated with leverage and return skewness. I also control for the

[5]The full name is "Dodd-Frank Wall Street Reform and Consumer Protection Act." Most regulations regarding the hedge fund industry are in Title IV, or "Private Fund Investment Advisers Registration Act of 2010."

stock's current return skewness and a number of characteristics that are known to predict return skewness. I find that a stock whose hedge fund holders exhibit an increase in leverage relative to its trend is predicted to have more negatively skewed returns. This leverage effect is statistically and economically significant, and robust to several alternative specifications.

I conduct a similar test for the aggregate stock market index. Specifically, I run an analogous time-series regression to test whether an increase in aggregate hedge fund leverage forecasts more negatively skewed market returns. Although the statistical power of this time-series regression is lower due to the small number of observations, I nonetheless find an effect that is qualitatively similar to that in the cross-sectional regressions. The economic magnitude of the coefficient is sizable.

Next, I implement two event-study analyses to provide more direct evidence of the fire-sale mechanism. The ability to maintain a leveraged position depends on the position's market value. Following an adverse movement in asset prices, leveraged arbitrageurs can be forced to reduce positions to meet margin calls or internal risk management controls. These fire sales lead to low current returns and undervaluation for the asset being sold, but high subsequent returns as the price reverses to fundamental value in the long run (e.g., Shleifer and Vishny (1992, 2011), Geanakoplos (2003)).

My empirical results are consistent with these predictions. Using negative earnings surprises as a proxy for fundamental shocks, I find that stocks held by high-leverage hedge funds tend to experience larger price declines around the announcement of bad earnings, compared to stocks held by low-leverage funds, all else equal. Also, the subsequent long-run return for stocks held by high-leverage funds tends to be higher.

In addition to shocks to asset value, I conduct an analogous analysis using shocks to hedge funds' borrowing capacity. In particularly, when a leveraged hedge fund's broker is insolvent and has to reduce lending, the fund is forced to deleverage and to unwind holdings. The forced selling can transmit liquidity shocks into the price of assets held by distressed funds (Brunnermeier and Pedersen (2009)). To proxy for a liquidity shock to prime brokers, I use jumps in a composite index of the credit default swap (CDS) prices of all major U.S. investment banks. The evidence is consistent with my conjecture: the prices of stocks held by high-leverage hedge funds tend to decrease more than the prices of stocks owned by low-leverage funds during weeks in which there is an aggregate funding liquidity shock, and reverse after four weeks.

The findings of this paper are consistent with the evidence of market instability related to the use of debt by speculators. Brunnermeier, Nagel, and Pedersen (2009) find that high-interest rate currencies tend to have more negatively skewed returns as they are held long by leveraged carry traders. Rappoport and White (1994) find anecdotal evidence that the contraction of margin lending by brokers contributed to the subsequent stock market crash in 1929.[6] Mitchell and Pulvino (2012) document substantial mispricing of a few corporate securities normally traded by arbitrageurs when borrowing was extremely difficult during the crisis in 2008. By developing a direct measure of speculators' leverage and implementing a large-sample analysis, this paper provides more systematic evidence. Also, my novel measure of leverage overcomes the long-standing obstacle to empirical research on hedge fund leverage, namely the lack of data. My measure, derived from public mandatory disclosures, can be easily adopted in future research.

Coval and Stafford (2007) and Mitchell, Pedersen, and Pulvino (2007) document the price impact of fire sales caused by outflows from mutual funds and convertible bond hedge funds, respectively. Hong, Kubik, and Fishman (2012) find a similar price overshooting pattern driven by the forced-to-cover behavior of short sellers around positive fundamental news. Ellul, Jotikasthira, and Lundblad (2011) and Merrill, Nadauld, Stulz, and Sherlund (2012) find evidence of fire sales by insurance firms who are constrained by regulatory capital requirements. This paper investigates the speculator vulnerability that stems from debt financing and its impact on asset prices, and thereby complements the empirical literature on fire sales.

This paper is also closely related to the current literature on intermediary leverage and its implications for asset prices. Adrian and Shin (2010) document the pro-cyclicality of broker-dealers' leverage; I find a similar pro-cyclicality for hedge fund leverage. Using a proprietary dataset of hedge fund leverage, Ang, Gorovyy, and van Inwegen (2011, AGV hereafter) find that hedge funds lever up when funding costs are low and the stock market value is high. Adrian, Etula, and Muir (2014) and Adrian, Moench, and Shin (2013) show that the innovation to broker-dealer leverage is a useful pricing factor.

This paper is also related to the theoretical literature on the destabilizing role of intermediaries on asset prices and market stability through different amplification mechanisms. Gromb and

[6] Also see Voth (2003) for a similar case in Germany.

Vayanos (2002), for example, focus on borrowing constraints, while He and Krishnamurthy (2013) emphasize capital constraints. Xiong (2001) and Kyle and Xiong (2001) examine the role of wealth effects. Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) discuss the potential adverse effects of leverage on productivity and on the macroeconomy.

The paper proceeds as follows. Section II discusses the institutional background and develops testable hypotheses. Sections III and IV introduce the data and the method for extrapolating historical leverage. Section V analyzes the effect of leverage on return skewness. Section VI presents evidence of the amplification mechanism. Section VII concludes. Supplemental materials are included in an online appendix.

II. Institutional Background and Hypotheses

The primary focus of this paper is to investigate whether the leverage of speculating financial intermediaries affects the distribution of the returns of the assets they hold. In particular: does higher hedge fund leverage lead to a greater likelihood of dramatic price declines? As predicted by a number of the theoretical papers mentioned above (also see the survey by Gromb and Vayanos (2010)), leveraged arbitrageurs are vulnerable to a variety of adverse shocks, including shocks to asset value and shocks to their funding activities. In the presence of a negative shock, leveraged investors are more likely to become financially distressed than are investors using little leverage. The resulting fire sales can transmit and magnify the negative shock into the price of assets they hold. The decrease in price can trigger more selling by other leveraged investors, leading to further declines in asset prices. In the long run, the price of distressed assets gradually reverts to fundamental value.

This intuition can be applied to the cross-section of individual stocks and motivates the first testable hypothesis. For stocks held long by highly-levered hedge funds, prices tend to be more sensitive to negative economic shocks and are more likely to experience sharp declines, compared to prices of stocks held by funds using little leverage. Thus, I have Hypothesis 1 below.

HYPOTHESIS 1: *Stocks held by hedge funds that are highly levered are more likely to experience price crashes in the next period, compared to stocks held by hedge funds that use little leverage, all else equal.*

The intuition can be also applied at the level of the aggregate stock market, leading to Hypothesis 2 below.

HYPOTHESIS 2: *When aggregate hedge fund leverage is high, the aggregate stock market tends to be more crash-prone.*

The intuition relies on fire sales as a key amplifying force in causing dramatic price declines. In the rest of this section, I discuss the institutional background of hedge funds' debt financing and how it contributes to the financial fragility of leveraged speculators. Specifically, I focus on two types of adverse shocks, i.e., shocks to the value of speculators' holdings and shocks to speculators' borrowing capacity, and develop more testable hypotheses.[7]

A. Collateralized borrowing and pro-cyclical leverage

An important source of leverage for equity hedge funds is collateralized financing from prime brokers via margin debt or security lending. For example, suppose that a hedge fund plans to buy shares with a value of $100 using a leverage ratio of 2. The hedge fund would buy the shares with $50 of its own capital and $50 borrowed from the broker, and post the stock as collateral against the loan.[8] To limit the excessive use of credit when investors purchase and hold securities, U.S. regulatory agencies set the minimum initial margin to be 50%, a rule known as Reg T.[9] Reg T is often referred to as a position-based margining system, which does not take into account hedges or other offsets between different positions.

In practice, however, most prime brokers use a risk-based or "portfolio margining" system, which relies on proprietary risk models and determines the margin requirement based on the overall risk of a portfolio. As a result, portfolio margining substantially reduces the margin requirements for

[7]Another type of adverse shock that would be interesting to examine is outflows of hedge funds. Unfortunately, for most hedge funds in my sample, I do not have information on their fund flows.

[8]The case for a short position is similar; the hedge fund borrows $100 in shares from the broker to sell short, and to achieve the same leverage level the fund posts $50 cash as collateral to the broker. In practice, the financing process can sometimes be done through an over the counter (OTC) derivative contract, such as a total return swap, which is economically equivalent to margin financing. Hedge funds that trade other asset classes may use other sources of financing. For example, fixed income funds often use different types of bonds as collateral and borrow in the repo market. Also, hedge funds may occasionally employ long-term debt.

[9]Reg T is on the basis of Section 7 of the Security Exchange Act of 1934, which authorizes the Federal Reserve to set the minimum requirement for the initial margin and the securities' self-regulatory organizations to govern the amount of margin that must be maintained for open positions. NYSE Rule 431 accordingly establishes a minimum 25% maintenance margin requirement for long positions and a 30% requirement for short positions.

hedge funds compared to Reg T.[10] Moreover, it means that hedge funds with a more diversified portfolio can obtain more leverage. This observation motivates the use of portfolio diversification measures as a predictor of hedge fund leverage in Section IV.

Several features regarding the collateralized borrowing arrangement contribute to the fragility of leveraged hedge funds. First, collateral value is marked to market. When the asset price falls, the loss in the value of the collateral is immediately reflected in the fund's account. If the collateral value drops below the minimum margin requirement for maintaining the leveraged position, the fund has to put up additional capital to avoid forced liquidation. This is known as a margin call, and generates fire sales by distressed funds when prices fall.

Second, the "portfolio margining" scheme often requires a higher margin when the asset value falls. This is because the risk model on which the scheme relies usually assumes that uncertainty and asset volatility increase following negative shocks (see, e.g., Geanakoplos (2003)). As lenders increase the margin, some leveraged funds, who would not otherwise have received margin calls, are forced to liquidate shares.

In addition to the forced selling, leveraged hedge funds may also voluntarily unwind long positions following bad news or trading losses. This may be driven by hedge funds' internal risk management controls, which assume higher uncertainty following bad news. Hedge funds thereby tend to deleverage and lower their risk exposure (See Adrian and Shin (2013)). Another reason might be a wealth effect, i.e., a hedge fund's risk-bearing capacity may decrease after losses (Kyle and Xiong (2001), Xiong (2001)), or agency issues such as managerial career concerns (Brown, Goetzmann, and Park (2001)).

Higher margin and voluntary deleveraging following adverse shocks to the value of a hedge fund's total assets contribute to the pro-cyclicality of leverage. Adrian and Shin (2010) first document the pro-cyclicality of leverage used by broker-dealers; they plot annual changes in total assets owned by broker-dealers, both in aggregate and by individual firms, against changes in leverage, and find a robust positive relation. Following Adrian and Shin (2010), in my analysis I use individual fund

[10] In an effort to legalize the use of the portfolio margining system, regulators amended Reg T in 1998 and accordingly NYSE Rule 431 in 2005 and 2006. But they require broker-dealers to use exchange-approved "portfolio margining" programs and to limit it to certain types of assets. In practice, it is now common to apply risk-based margining to an equity portfolio, or even to a portfolio across asset classes. Prime brokers can get around regulations by arranging trades off-shores or writing synthetic total return swaps. See, e.g., Berman (2009) and Brunnermeier and Pedersen (2009) for more details.

leverage and find that hedge fund leverage is pro-cyclical as well; see Figure B.

[**Place Figure B about here**]

Note that leverage is mechanically increased as the value of total assets decreases, as shown in the definition below.

$$Leverage = \frac{TotalAssets}{TotalAssets - Debt} \tag{1}$$

In this sense, the pro-cyclical leverage implies stronger selling following a drop in the asset value, compared with the case of constant leverage/margin. The selling leads to further price declines and amplifies the adverse shock. Anecdotal evidence supports this argument; as tools for pro-cyclically adjusting risk exposure, the "stop-loss" orders and portfolio insurance widely used in the 1980s are thought to have contributed to the stock market crash in 1987 (see, e.g., Shiller (1988) and Roll (1988)).

The forced or pro-cyclical selling by leveraged funds highlights the cost of using leverage, as it may force them to liquidate at fire-sale prices, which are lower than the asset's long-term value (Shleifer and Vishny (1992, 1997)). When an asset is in distress, the demand for it on the market can be limited. This is because the assets are sold to low-valuation buyers; high-valuation buyers (normally ones using high leverage) are wiped out. Also, as uncertainty is higher during shock periods, demand is reduced (Geanakoplos (2003)). However, the buying of distressed assets is profitable as the asset price returns to its fundamental value in the long run.

In short, following an adverse shock to an asset's value, the leveraged hedge funds who are holding the asset may experience fire sales, amplifying the negative effect on the asset's price in the short run. This conjecture is testable by comparing the prices of stocks held by high-leverage funds to the prices of stocks held by low-leverage funds around an adverse event. This is Hypothesis 3.

HYPOTHESIS 3: *When there is a negative shock to a stock's value, for stocks held by hedge funds that use higher leverage, the price will drop more around the event date but will reverse in the long run, all else equal.*

B. Prime brokerage and funding liquidity

Prime brokerage provides many services that hedge funds need for their growth and operations.[11] In particular, prime brokers, directly or indirectly, serve as the counterparty for hedge funds' trading and borrowing activities. Broker-dealers typically employ much higher leverage than hedge funds and rely on external financing through interbank loans, the repo market, and other sources. A negative shock to a broker's lending capacity can force its clients to deleverage and liquidate holdings, transmitting funding liquidity shocks into asset prices (Brunnermeier and Pedersen (2009)).

Broker-dealers may decrease their total lending when they perceive higher risk and uncertainty in asset markets. Rappoport and White (1994) provide anecdotal evidence that the contraction of brokers' loans to market speculators contributed to the stock market crash in 1929. They show that, right before the crash in October, brokers sharply increased both the interest rate and haircut on margin loans due to a fear of a crash.

In addition, shocks to brokers' solvency can also impact their lending and hence hedge funds' access to leverage. Moreover, the use of rehypothecation introduces additional counterparty risk to a hedge fund. Rehypothecation refers to the industry practice whereby prime brokers use assets that have been posted as collateral by hedge funds to back their own transactions and trades.[12] As seen during the episode of Lehman's failure, when a broker is insolvent, the broker's rehypothecation lenders may liquidate a hedge fund's assets without notifying the fund, and, depending on the nature of the broker's failure, the hedge fund may have difficulty reclaiming its assets or cash from the broker.[13] Aragon and Strahan (2012) show that stocks owned by Lehman-connected hedge funds experienced larger declines in market liquidity.

In sum, leveraged hedge funds are also vulnerable to changes in their brokers' lending capacity. Around an adverse shock on funding liquidity, distressed funds may experience forced deleveraging

[11]These services include trade execution, clearance and settlements, asset custody, securities' lending and borrowing, margin lending, consolidated reporting, risk management advice, and even capital introduction. See Berman (2009) for more discussion of the relationship between hedge funds and prime brokers.

[12]In the U.S., rehypothecation of collateral by broker-dealers is limited to 140% of the loan amount to a client, under Rule 15c3-3 of the SEC. In Europe and Asia, there is no such limit, and the range can be anywhere from 100% to full access to the long side of the book. According to Singh and Aitken (2010), as of the end of 2007, approximately $4.5 trillion of collateral (largely owned by hedge funds) at the seven largest U.S. investment banks was rehypothecated.

[13]See, e.g., the story of the Oak Group mentioned in Aragon and Strahan (2012), p.572.

and selling of assets whose fundamental value is unchanged. Unlike shocks to an asset's value which are normally idiosyncratic, shocks to borrowing are often systematic. As a result, after a shock to borrowing, most buyers in the market are likely to have much less purchasing power, so that fire-sale price will be lower than the asset's fundamental value. In the long run, the asset's price should revert. This is Hypothesis 4.

HYPOTHESIS 4: *When there is a shock to dealer-brokers' lending capacity, for stocks held by hedge funds that use higher leverage, prices will fall around the event date but will reverse in the long run, all else equal.*

III. Data

The primary data source in this paper is Form ADV, an SEC regulatory filing that is required for all investment managers who qualify as an "investment adviser" under the Investment Advisers Act of 1940. Before the passage of the Dodd-Frank Act, hedge funds were exempt from registration with the SEC and from filing Form ADV.[14] The Dodd-Frank Act, signed on July 21, 2010, however, imposed a significant regulatory reform on the hedge fund industry. In particular, starting from fiscal year 2011, the SEC required *all* U.S. hedge fund advisers with more than $150 million in assets under management (AUM) to register with the SEC and to file Form ADV annually.[15]

Under the Dodd-Frank Act, the SEC also adopted several crucial amendments to Form ADV and imposed substantially more disclosure requirements on investment advisers. I use these additional disclosures to develop a novel method of measuring the level of leverage used by hedge fund advisers.

A. Constructing hedge fund samples

This first step is to obtain a list of hedge fund advisers who filed the amended Form ADV. Form ADV filings include investment advisers of all types, such as mutual funds, pension funds, private equity funds, and hedge funds. However, this paper focuses on hedge funds, as they are the category that extensively uses leverage to implement their trading strategies. To screen out those advisers whose major line of business is not hedge fund management, I require an adviser to

[14] Filing was voluntary except for a single year, 2006. See Brown et al. (2008) for details.

[15] In this paper, I use "hedge fund adviser", "hedge fund management company", and "hedge fund" interchangably.

have more than 80% of AUM from its hedge funds. The procedure is in the spirit of the method developed by Brunnermeier and Nagel (2004) and Griffin and Xu (2009).[16] From 2011 to 2013, the list includes 983 unique hedge fund advisers. I label it as Sample A.

The second step is to identify equity hedge funds in Sample A. The term "equity hedge fund" here refers to funds that invest in U.S. public stocks as at least one of their major strategies. Since this paper focus primarily on stock prices, the leverage ratio of funds that mostly invest in non-equity securities, such as fixed income funds, is less relevant to my analysis. I apply two criteria to identify equity hedge funds. First, I keep advisers that regularly file Form 13F.[17] Since 1978, all institutions with more than \$100 million AUM are required to file Form 13F quarterly for all U.S. equity long positions worth over \$200,000 or consisting of more than 10,000 shares. I manually merge hedge fund advisers in Sample A with 13F via the advisers' names. Second, I drop hedge funds with a self-reported investment strategy of fixed income, global macro, real estate, or fund of funds. My final sample thus consists of equity long-short, event-driven, relative value, and multi-strategy hedge funds. Information about each hedge fund's strategy is hand-collected from its client brochure in Part 2B of Form ADV.[18] I label this equity fund subset of Sample A as Sample B; it contains 448 unique hedge fund advisers.

Sample B is only available from 2011 to 2013, and for hypothesis testing may lack sufficient power. To resolve this issue, I extend Sample B backwards for ten years.[19] In order to address possible survivorship bias when doing so, the third step is to create a supplementary hedge fund list which contains funds that went out of business before 2011. Following the method used in Griffin and Xu (2009), I start with a list of all investment management companies who reported to two commercial hedge fund databases, i.e., Lipper TASS or Morningstar CISDM, from 2001 to 2010. Similar to before, I first keep investment companies whose primary business lies in hedge fund management.[20] Second, I keep hedge funds who have records in 13F filings and whose primary in-

[16] In their papers, they used a 50% cutoff. As the amended version of Form ADV provides a more accurate estimate of the fraction, to be conservative, I increase the cutoff to 80%. Details are in the online appendix.

[17] All 13F filings are downloaded through Thomson Reuters on Wharton Research Data Services (WRDS).

[18] The description of each investment strategy is listed in Appendix B.

[19] Ten years is arbitrary. Since my sample includes much fewer hedge funds in the earlier period, I start my sample period in 2001 to be conservative. The results are robust to starting the sample in 1996 and are reported in the online appendix.

[20] Here I follow Griffin and Xu (2009)'s criteria, which include 1) a company has over 50% of its investments listed as "other pooled investment vehicles" (private investment companies, private equity, and hedge funds) or over 50% of its clients as "high net worth individuals", 2) the company charges performance-based fees, and 3) the company does not manage any mutual funds.

vestment strategy is classified as equity long-short, event-driven, relative value, or multi-strategy.[21] Finally, I add hedge funds in this list to Sample B, and label the combined sample as Sample C.[22]

Panel A of Table I reports the number of hedge funds in Samples A, B, and C in each year. In 2001, Sample C consists of 152 hedge funds and grows quickly to 395 funds in 2008. Over the financial crisis, the number drops to 374 in 2009, before rebounding to 439 by the end of 2013.[23] Sample C contains 621 unique funds, 439 (or 70.7%) of which remain in the sample by the end of 2013.

[**Place Table I about here**]

B. Calculating a hedge fund's leverage

Although the new Form ADV does not require hedge fund advisers to explicitly report their leverage, it provides sufficient information to calculate the leverage for *some* hedge funds. A brief summary of the method follows, and more details are in an online appendix.

In Form ADV, every investment adviser reports assets under management in Part 1A. To determine the asset value, the SEC adopted the *gross* asset value (GAV) as the unified method for the purpose of monitoring systemic risk. According to Form ADV instructions, the asset value is calculated without deduction of "any outstanding indebtedness or other accrued but unpaid liabilities".[24] That is, the amount should include the value of securities purchased on margin or value of securities borrowed to sell short. Also, in Part 2B, investment advisers need to upload a copy of a client brochure as an attachment. The brochure aims to provide clients with general business information, including the adviser's total AUM. The adviser has discretion on how to calculate asset value here.[25] To reflect their true size, some advisers disclose the *net* asset value

[21] For details on how to categorize hedge fund advisers by investment strategy based on information in TASS or CISDM, see Appendix B.

[22] Note that this procedure may not completely eliminate survivorship bias. Because TASS and CISDM are based on voluntary reports, hedge funds that have never appeared in these databases but went out of business before 2011 are not included in Sample C.

[23] Sample C contains slightly more funds than Sample B in 2011 to 2013. This is because the cutoff used to screen out non-hedge-fund advisers when constructing Sample B and the supplementary list is different. The former is 80%, while the latter is 50% due to the data limitation of the old version of Form ADV.

[24] See amended Form ADV: Instruction for Part 1A, instr. 5.b., available at http://www.sec.gov/about/forms/formadv-instructions.pdf

[25] See General Instructions for Part 2 of Form ADV, page 2, available at http://www.sec.gov/about/forms/formadv-part2.pdf

(NAV).

For advisers who do report NAV, I define their LEVERAGE as the ratio of GAV to NAV. For those who do not report NAV, the observation of leverage is missing. Like most variables in Form ADV, this leverage measure is at the investment company level. As shown in Panel A of Table I, for 250 of 790 hedge fund advisers in Sample A, their leverage ratio in 2013 is observed using this methodology. The reporting rate is higher for Sample B – it is possible to calculate leverage ratios for approximately 40% of fund-year observations.

Two points regarding this leverage measure are particularly noteworthy. First, this definition of leverage is best interpreted as the "gross leverage" (or "book leverage", or "balance-sheet leverage") that is widely used by industry professionals. It accounts for leverage obtained through explicit borrowing, but does not capture the implicit leverage that funds exploit when investing in financial instruments such as derivatives. This may lead to an under-estimation of a hedge fund's real economic exposure, particularly for funds with strategies focused on derivatives, such as global macro funds. However, if gross leverage correlates with overall leverage, my measure can still effectively capture the impact of leverage. In another chapter of my dissertation (Jiang (2014)), I show that gross leverage is indeed strongly correlated with other widely-used risk-taking measures.

Second, the leverage data are based on mandatory disclosures which promote quality and availability. The leverage variables in commercial databases only provide a summary of a hedge fund's whole leverage history and thus are not time-varying.[26] One exception to this is the leverage data used in AGV (2011). Unfortunately, their data are from a proprietary source and are not accessible to the public.

C. Summary statistics of hedge fund leverage

Panel B of Table I presents summary statistics of leverage of reporting hedge funds in Samples A and B. The term "reporting hedge fund" refers to those with sufficient information in Form ADV to allow their leverage to be directly calculated. One concern is that these reporting hedge funds may not be representative of the population. In this section, I alleviate this concern by comparing

[26]For example, TASS contains three variables regarding leverage for each hedge fund: a dummy variable indicating whether a fund uses leverage, the average leverage a fund employed since it opened, and the maximum leverage a fund has ever taken.

my summary statistics to those reported in the SEC's Annual Staff Report on Form PF.[27]

The Dodd-Frank Act requires hedge funds to directly report their book leverage in Form PF. Although all filings in Form PF are highly confidential, the SEC discloses some summary statistics in this annual staff report, which I use to verify my estimates. According to the report, the average leverage of hedge funds with more than $500 million AUM is 1.72 in 2012, versus 1.98 for funds with comparable size in my sample.[28]

Two characteristics of the distribution of hedge fund leverage are worth discussing. First, while the average level is modest, there is considerable dispersion in hedge fund leverage. The 25th percentile of Sample A funds is 1.29 and the 75th percentile is 1.92. In the extreme, the 99th percentile reaches 8.81. The distribution is strongly right-skewed. The skewness of leverage of hedge funds in Sample B, for example, is 4.28.

Second, there is a strong strategy fixed effect. Among the four categories in Sample B, event-driven funds have the lowest average leverage, 1.39, while relative value funds have the highest, 3.21. Since leverage is the tool by which funds reach their volatility targets, hedge funds tend to lever up most on low-volatility assets, consistent with the strategy effect. This finding also motivates me to use strategy dummies as predictors of hedge fund leverage in Section IV.

D. *Other data sources*

This paper also obtains U.S. stock return and trading information from the Center for Research in Security Prices (CRSP), accounting variables from Compustat, and analyst forecasts records from Institutional Brokers' Estimate System (IBES). All variables are constructed following the standard methods in the empirical asset pricing literature. Details are in Appendix A.

[27] In the online appendix, I address this selection issue more carefully. I develop an instrument variable and implement the two-stage Heckman model. It turns out that the corrected mean is very close to the unadjusted average and the correction term (i.e., Heckman's lambda) is insignificant.

[28] The SEC's Annual Staff Report on Form PF is available at http://www.sec.gov/news/studies/2013/im-annualreport-072513.pdf. On page 2 of the Appendix of the report, it shows that the "Aggregated Net Asset Value of All Qualifying Hedge Funds reported on Form PF" is $1.47 trillion, and on page 3 it reports that the "Aggregated Dollar Amount of Borrowings of Qualifying Hedge Funds reported on Form PF" is $1.06 trillion. Qualifying hedge fund refers to those with "$500 million or more in net assets" (page 4). Thus, the average leverage is $(1.47 + 1.06)/1.47 = 1.72$.

IV. Extrapolating Hedge Funds' Leverage

In this section, I first attempt to find predictors of hedge fund leverage. Specifically, I use the reporting hedge fund sample in 2011 to 2013 and project leverage onto funds' characteristics that are observable in the pre-reporting period. Then, I use the coefficients and fund characteristics that exhibit strong correlation with leverage to extrapolate hedge funds' historical leverage. Finally, I conduct several robustness tests and show that the extrapolated measure of leverage matches well with the actual hedge fund leverage in a proprietary database.

A. Predictors of hedge fund leverage

To find predictors, I restrict my analysis to variables constructed based on hedge funds' 13F filings for several reasons. First, both 13F and Form ADV are filed at the management company or adviser level. Variables from one source can match well with the other. Also, the 13F data is available back to 1980 and is filed every quarter, making it possible to extrapolate leverage not only in a longer sample period but also at a higher frequency. Further, as a mandatory disclosure, 13F filings have fairly high data quality, as compared to commercial hedge fund databases which are based on voluntary reports and suffer from some quality issues.[29]

One caveat about 13F filings is worth mentioning: they only contain information on long positions in U.S. equities and lack short positions and holdings of other asset classes. However, despite this disadvantage, the literature shows that the information provided in 13F filings can, to a large extent, capture hedge funds' trading behavior and performance (see, e.g., Griffin and Xu (2009) and Ben-David et al. (2012)). This paper focuses on identify the leverage effect on long positions.

The first set of predictors is motivated by the widely used "portfolio margining" system. Under this metric, hedge funds can benefit from a more diversified portfolio, i.e., obtain higher leverage from brokers. To measure the degree of diversification, I follow Goetzmann and Kumar (2008)

[29]By merging Form ADV with TASS and CISDM, I find that there are two kinds of selection bias: 1) some hedge fund advisers (likely successful ones) in Form ADV never show up in TASS or CISDM, and 2) for funds which are reporting to TASS or CISDM, they typically do not file *all* hedge funds they manage. Thus, variables computed by aggregating individual funds' information in TASS or CISDM may not be available or reliable. Moreover, the literature on hedge fund performance uncovers several kinds of selection bias from these commercial databases, including TASS, CISDM, and others. For survivorship bias, selection bias, and back-filling bias present in these databases, see Brown et al. (1992), among others. Also, see Stulz (2007) for a survey. Further, several recent papers, e.g., Aiken et al. (2013), Bhardwaj et al. (2014), illustrate that hedge funds' performance shown in these voluntarily-reported databases are largely over-estimated. In addition, Bollen and Pool (2009) and Patton et al. (2012) find there exists manipulation in reporting and manual revision to historical underperformance in these commercial databases.

and construct two variables. The first one is the log of one plus the number of stocks in a hedge fund's 13F portfolio, denoted as LNNSTK. A higher number of stocks indicates a more diversified portfolio. The second measure is the sum of squares of each stock's portfolio weight, denoted as SSPW. SSPW ranges from 0 to 1, where 1 represents the most concentrated portfolio. Of course, this does not capture offsetting long-short positions.

In addition, I consider the active share measure (denoted as ACTSHARE, Cremers and Petajisto (2009)), which equals $\frac{1}{2}\sum_i |w_i - w_{mkt,i}|$, where w_i is the weight of stock i in the fund's portfolio and $w_{mkt,i}$ is the weight of stock i in the market portfolio. It measures the degree to which a fund's long-side portfolio deviates from the market portfolio; a lower value of ACTSHARE means that the long-side portfolio is closer to the market.

As the distribution of leverage is positively skewed, I use the log of LEVERAGE, denoted as LNLEV, in regressions to eliminate the potential impact of outliers. The regression is specified as

$$LNLEV_{j,t} = \alpha + \beta_1 LNNSTK_{j,t} + \beta_2 SSPW_{j,t} + \beta_3 ACTSHARE_{j,t} + \epsilon_{j,t} \tag{2}$$

for reporting hedge fund j in Sample B at year $t \in \{2011, 2012, 2013\}$. All variables on the right-hand side are calculated using the 4th quarter 13F filing in each year.

Panel A of Table II presents summary statistics. Comparing them to similarly measured values for mutual funds, hedge funds are much less diversified. The number of stocks in long positions, for example, has a median of 35. Also, the average active share is 84%, compared to approximately 60% reported in Cremers and Petajisto (2009) for mutual funds.

I start by running univariate regressions using each measure to see whether the relationship between diversification and leverage, if any, can be captured by all the measures. As shown in columns (1) - (3) in Panel B of Table II, the coefficient on each diversification measure is significant, and the signs all indicate that funds with a more diversified long portfolio tend to have higher leverage. Further, comparing the adjusted R^2, we find that the log of the number of stocks in the portfolio, LNNSTK, stands out and has the strongest explanatory power (with a R^2 of 31%). In column (4), I include the quadratic term of LNNSTK and find that this non-linear specification fits the leverage distribution better as the R^2 increases 37%. This captures the well-known non-linear relationship between the number of stocks and diversification of idiosyncratic risk. Finally, I run a horse race by including all the diversification variables in a single regression. According to the results in column (5), the R^2 stays almost the same as in column (4), and the coefficients of SSPW and ACTSHARE become insignificant, indicating that LNNSTK, i.e., the number of stocks held long, is the main driver in predicting leverage.

[Place Table II about here]

The second set of variables aims to comprehensively describe a hedge fund's investment strategy and trading style. This is motivated by the literature on hedge fund performance: Brown and Goetzmann (2003) and Fung and Hsieh (1997), for example, find that hedge fund styles persistently contribute to the cross-sectional variability of performance. Given that hedge funds use leverage to magnify expected returns and target volatility, leverage ought to have strong correlation with a fund's style and strategy.

The most straightforward variables in this set are the strategy dummies. As shown in the bottom of Panel B of Table I, we indeed find significant strategy fixed effects on leverage. However, strategy dummies are too coarse to comprehensively describe a fund's style. Thus, I also include portfolio turnover, denoted as PORTTURN. It equals the minimum of the value of selling and buying within a quarter scaled by the total portfolio value at the beginning of the quarter, as in Griffin and Xu (2009). The mean turnover rate in our sample is 26%, and there is a sizable heterogeneity (with a standard deviation of 16%).

Column (6) shows the result of regressing LNLEV on strategy dummies, and we can see that all coefficients are statistically significant and the R^2 is 17%. Meanwhile, as shown in column (7), PORTTURN also exhibits a positive correlation with LNLEV.[30]

For my final backcast model, I only employ significant predictors, i.e., LNNSTK, LNNSTK^2, PORTTURN, and strategy dummies. The estimation is shown in column (8). The magnitude of coefficients before strategy dummies and PORTTURN goes down, indicating that part of the style effect is captured with the diversification effect. However, all coefficients are still statistically

[30] In untabulated analysis, I also attempt to categorize a fund's style by looking at the characteristics of stocks in the fund's long portfolio. For example, funds trading the value strategy ought to long value stocks. The characteristics that I consider include beta, size, book-to-market, momentum, prior return, volatility, liquidity, turnover, and institutional ownership. However, the regression results show that these variables have very marginal explanatory power (with a R^2 of 4%). I also look at some fund characteristics available in Form ADV, such as hedge fund age and clientele information. They all have nearly zero correlation with leverage. To save space, I omit the discussion of this analysis here. Results are available upon request.

significant, and the R^2 is as high as 47%.

The final version of the backcast model is the following: for a hedge fund j in Sample C at quarter t, the log of its extrapolated leverage (denoted as $LN(XLEV_{j,t})$) is given by the following equation:

$$\begin{aligned} LN(XLEV_{i,t}) = .733 - .28LNNSTK_{i,t} + .046LNNSTK_{i,t}^2 + .28PORTTURN_{i,t} \\ -.096\ \text{EVENT-DRIVEN}_i + .069\ \text{MULTI-STRATEGY}_i \\ +.28\ \text{RELATIVE VALUE}_i \end{aligned} \tag{3}$$

where $LNNSTK_{j,t}$ and $PORTTURN_{j,t}$ are calculated using the 13F filing by fund j for quarter t. Strategy dummies are fixed for each fund j over the whole sample. In the following analysis, I use the extrapolated leverage variable, i.e., XLEV, in levels.

B. Robustness check

First, I run a cross-validation test to assess the robustness of the leverage backcast model (Eq.(3)). All reporting hedge funds in Sample B are randomly split into two half-samples, a *training* sample and a *test* sample. Next, I run the same regression as in column (8) of Panel B, Table II, with the *training* sample, and then use the coefficients to extrapolate leverage for hedge funds in the *test* sample. Then, I compare the extrapolated leverage (denoted as $\hat{L}$) with a fund's real leverage (labeled as L). Specifically, two measures are constructed to evaluate the model's fit over the *test* sample. The first one is $R^2(test) = Var(\hat{L_j})/Var(L_j)$ for all hedge funds j in the *test* sample; the other one is $RMSE = \sqrt{\frac{1}{N_{test}} \sum_{j \in test} (\hat{L_j} - L_j)^2}$, where N_{test} is the number of funds in the *test* sample. I repeat this procedure 400 times and the average of these statistics is shown in Panel A of Table III. The model fits the *test* sample data well with $R^2(test)$ of 0.48 and RMSE of 0.30.

In addition, I run an OLS regression of L on $\hat{L}$ on the *test* sample. Panel B reports the average of the coefficient b of $\hat{L}$ and the R^2. I find that the extrapolated leverage is a statistically powerful predictor of actual leverage. The coefficient on $\hat{L}$ equals 0.98, which is close to one, and the R^2 equals 0.44. In sum, the result of cross-validation tests eliminates the concern of overfitting.

[Place Table III about here]

There is another methodological concern with the extrapolated measure of leverage (i.e., XLEV). The backcast model Eq.(3) is estimated in 2011 to 2013, but the relation may not be the same before this period. To address this, I compare XLEV with actual leverage reported in AGV (2011). As noted above, AGV (2011) obtain a proprietary dataset of leverage from a large fund of hedge funds. Their sample contains 208 unique hedge funds and spans the period from December 2004 to October 2009. AGV (2011) show that their sample is representative of the whole hedge fund industry.

I first run a contemporaneous time-series regression of the mean leverage reported in AGV (2011) on the mean of XLEV in both levels and first differences.[31] As shown in Panel B of Table III, the coefficients on the mean of XLEV are significantly positive with a t-statistic of 5.8 in levels and 2.5 in first differences. The effect is also economically meaningful – the R^2 is 70% for the regression in levels and 29% in first differences. In addition, I run the same regression but use the dispersion of leverage rather than the mean. That is, I regress the interquartile of AGV's leverage on the interquartile of XLEV. Columns (3) and (4) present the result: the coefficients on the interquartile of XLEV are significantly positive with a t-statistic of 5.2 using variables in levels and 5.3 in first differences. The R^2 is 38% in both specifications. Figure 2 plots the time series of XLEV and the leverage reported in AGV (2011). To sum up, XLEV is plausibly measuring the actual leverage used by hedge funds.

V. Leverage and Return Skewness

A. *Empirical specification*

In this section, I test Hypothesis 1. My sample consists of all common stocks (i.e., with share code of 10 or 11 in CRSP) in NYSE, AMEX, and NASDAQ from January 1996 to December 2013, except those with prices less than \$5 at the end of each quarter. The key variable of interest is average leverage of a stock's hedge fund holders. I denote it as SXLEV, for "stock-level extrapolated leverage". In addition, in most of my analysis, I consider two weighting schemes in calculating the variable. One is equal-weighted and defined as below,

[31] AGV's data are obtained from Figure 4 and 6 in the original paper and transformed from monthly data into quarterly data.

$$SXLEV\_EW_{i,t} = \frac{1}{N_i}\sum_{j}^{N_i} XLEV_{j,t},\ j = 1, ..., N_i \tag{4}$$

where j refers to hedge funds holding stock i at the end of quarter t, and N_i is the total number of hedge funds holding stock i. If $N_i = 0$, I assume that other categories of investors do not take significant leverage and set SXLEV_EW= 1. The second measure is value-weighted by each hedge fund's ownership, $w_{i,j,t}$, of the stock,

$$SXLEV\_VW_{i,t} = \frac{1}{W_{i,t}}\sum_{j}^{N_i} w_{i,j,t} XLEV_{j,t},\ j = 1, ..., N_i \tag{5}$$

where $W_{i,t} = \sum_j^{N_i} w_{i,j,t}$, i.e., the total ownership by all hedge fund holders. Similarly to before, if $W_{i,t} = 0$, I assume that SXLEV_VW= 1. In most of my analyses, I use both specifications and reach similar results.

I follow the literature (e.g., Chen, Hong, and Stein (2001), Bris, Goetzmann, and Zhu (2007), and Brunnermeier, Nagel, and Pedersen (2009)) and use return skewness as my primary measure for "chance of crash". More precisely, SKEW for stock i over quarter t is defined as

$$SKEW_{i,t} = \frac{n(n-1)^{3/2}\sum_d r_{i,d}^3}{(n-1)(n-2)(\sum_d r_{i,d}^2)^{3/2}} \tag{6}$$

where $r_{i,d}$ is the de-meaned log daily returns for all days d in quarter t, and n is the number of total return observations in that quarter.[32] I require a stock to have at least 50 observations during a quarter to calculate SKEW.

As the baseline measure, SKEW is calculated using market-adjusted returns, i.e., the return of a stock minus the value-weighted average return of all CRSP stocks. However, I also run all regressions with two variations of SKEW based on 1) beta-adjusted returns, and 2) returns in excess of the risk-free rate.

In addition to SKEW, I also use an alternative measure, i.e., up-to-down volatility (denoted as UDVOL), which is the log of the ratio of the standard deviation of returns on up days to the standard deviation on down days during a quarter. Up (down) days refer to days with returns

[32] Results using percentage returns are very similar.

above (below) the quarter mean. Thus we have,

$$UDVOL_{i,t} = log\left(\frac{(n_d - 1)\sum_{UP} r_{i,d}^2}{(n_u - 1)\sum_{DOWN} r_{i,d}^2}\right) \tag{7}$$

where n_u and n_d are the number of up and down days, respectively. A higher value of UDVOL corresponds to a more right-skewed distribution. All versions of SKEW and UDVOL generate quite similar results.

Here I set up the baseline cross-sectional regression specification. I regress $\text{SKEW}_{i,t+1}$ on $\text{DSXLEV}_{i,t}$ and on several control variables. $\text{DSXLEV}_{i,t}$ refers to detrended $\text{SXLEV}_{i,t}$, which is equal to $\text{SXLEV}_{i,t}$ minus a moving average of its value over the prior eight quarters. The rationale for doing so is to eliminate stock or fund fixed effects that could drive the correlation between stock-level leverage and skewness. For example, it could be that more aggressive funds take on more leverage, but also hold more negatively skewed stocks. I also control for the stock's current skewness and other firm characteristics that are known to forecast skewness, in an effort to alleviate the concern that aggressive funds prefer to hold stocks that are predicted to be left-skewed. The regression can be interpreted as a cross-sectional prediction of skewness over quarter $t + 1$ based on available information at the end of quarter t.

Thus, the regression is

$$SKEW_{i,t+1} = \alpha + \beta_1 SKEW_{i,t} + \beta_2 DSXLEV_{i,t} + \beta_3 HFHOLD_{i,t} + \gamma' \mathbf{X_{i,t}} + \epsilon_{i,t} \ , \tag{8}$$

where $\text{HFHOLD}_{i,t}$ is total hedge fund ownership and $\mathbf{X}_{i,t}$ is the vector of control variables. I control for book-to-market ratio ($\text{BM}_{i,t}$) and past returns going back up to four quarters ($\text{RET}_{i,t}, ..., \text{RET}_{i,t-3}$) to capture the effect of possible overpricing on increasing crash probability. I also control for firm characteristics correlated with return skewness, including firm size ($\text{LOGCAP}_{i,t}$), volatility ($\text{SIGMA}_{i,t}$), and turnover ($\text{DTURN}_{i,t}$). In a robustness test, I further add analyst coverage ($\text{LNCOV}_{i,t}$), the liquidity ratio ($\text{LNLIQ}_{i,t}$), and institutional ownership ($\text{IO}_{i,t}$) to the right-hand side. The construction of each variable is standard in the literature and details are in Appendix A. All variables are winsorized at the 1% and 99% level by quarter. Dummy variables for each quarter t are included in all regressions. Standard errors are double clustered by stock and by quarter, as suggested by Petersen (2009).[33]

Table IV reports summary statistics and the correlation matrix for all variables. First, both SKEW and UDVOL are larger than zero, indicating that individual stock returns are right-skewed, the opposite of market returns. The means of SXLEV_EW and SXLEV_VW are 2.45 and 2.65, respectively, and the cross-sectional variation is significant with a standard deviation of approximately 1 for both variables. As expected, SXLEV_EW and SXLEV_VW are highly correlated with a correlation coefficient of 0.87. Also, SXLEV is strongly associated with firm size, i.e., LOGCAP.

[Place Table IV about here]

B. *Forecasting return skewness of individual stocks*

According to Hypothesis 1 developed in Section II, I expect β_2 in the regression in Eq.(8) to be negative. Table V reports the results. Columns (1) to (3) present results using equal-weighted SXLEV. In column (1), the dependent variable is SKEW calculated using market-adjusted returns. The coefficient on DSXLEV_EW is -0.018 and is statistically significant (with a t-statistic of 2.9). It indicates that, when a stock is held by hedge funds with higher leverage, the stock's return is predicted to be more negatively skewed, i.e., to be more crash-prone, all else equal. Interestingly, the coefficient of HFHOLD is significantly positive, indicating that stocks heavily held by hedge funds tend to exhibit right-skewed returns. This finding is possibly due to hedge funds' superior skills in acquiring private information and picking stocks. The coefficients on turnover and past returns are significantly negative while the coefficient on book-to-market ratio is significantly positively, consistent with the findings in previous literature (e.g., Harvey and Siddique (2000) and Chen et al. (2001)).

[Place Table V about here]

In columns (2) and (3), the dependent variables are now SKEW computed using beta-adjusted returns and excess returns, respectively. The coefficients on DSXLEV_EW are quite similar to that reported in column (1) and are still significantly negative. In Columns (4) to (6), value-weighted SXLEV is used in regressions; the results are virtually unchanged.

[33] In the online appendix, I also run a Fama-MacBeth regression with the same specification and obtain very similar results.

I gauge economic significance of the leverage effect following the option price approach of Chen et al. (2001). That is, I am interested in how the price of an out-of-the-money put would change with a two standard deviation shock to DSXLEV_EW, all else equal. To calculate the hypothetical price of put options, I use the model developed by Corrado and Su (1997), which extends the Black-Scholes model by taking into account skewness and kurtosis of underlying asset returns.[34] This model gives the same value as the Black-Scholes model when skewness is 0 and kurtosis is 3.

Consider a stock with current price of $100, annualized volatility of 36%, and skewness of 0. Assume a zero dividend yield and a zero risk-free rate. According to the estimation shown in column (1), a two standard deviation increase in a stock's DSXLEV_EW corresponds to a decrease in skewness from 0 to -0.028 during the next quarter.[35] Suppose that there is an out-of-money European put option on this stock with strike price of $70 and time-to-maturity of 3 months; in this case, the shift in skewness would raise the put's price from $0.134 to $0.154, an increase of 15.1%. The effect becomes smaller as strike prices go up; the increase in the price of a put with strike of $75, for example, is 3.6%.

[Place Table VI about here]

C. Robustness tests

Next, I conduct several robustness checks to validate my findings. The estimations in Table VI are based on equal-weighted stock-level XLEV and skewness calculated with market-adjusted returns. The results using the value-weighted stock-level XLEV and other risk-adjusted returns are very similar and are reported in the online appendix.

In column (1), I include additional covariates on the right-hand side and examine whether the leverage effect uncovered in Table V is robust. The variables include the log of one plus analyst coverage (LNCOV), the log of one plus the liquidity ratio (LNLIQ), and institutional ownership (IO). All of these variables exhibit strong unconditional correlation with stock-level leverage; thus, to be conservative, I add them on the right-hand side. According to the point estimate of the

[34] Brown and Robinson (2002) correct an error in Corrado and Su (1997). The program used here is based on the corrected version of Corrado and Su (1997) and is available to download at http://investexcel.net/option-pricing-skew-kurtosis/

[35] -0.028=2*0.79*(-0.018).

coefficient on DSXLEV_EW (-0.018 with a t-statistic of 3.0), the leverage effect documented in the baseline regression is almost the same after including additional controls.[36]

In column (2), I test an auxiliary prediction of Hypothesis 1. That is, the leverage effect ought to be stronger among stocks with higher hedge fund ownership, because fire sales, if any, would be larger relative to total shares outstanding for these stocks. As the same time, the effect should be insignificant when the levered hedge funds own only a tiny fraction of shares outstanding, as the fire sale of those shares are more likely to be accommodated by other traders. To test this prediction, I add a term that interacts detrended stock-level leverage with hedge fund ownership (i.e., DSXLEV_EW*HFHOLD) to the regression of Eq.(8); I expect its coefficient to be negative. The result, reported in column (2), shows that this is indeed the case. The coefficient on the interaction item is -0.57 and the t-statistic is -3.6. The economic magnitude of the effect is also meaningful; moving from the 25th percentile (i.e., 1%) to the 75th percentile (i.e., 6%) of HFHOLD is associated with a change of -0.028 in the coefficient of DSXLEV_EW, compared with the coefficient of -0.018 in the baseline regression.

In the baseline regression, I only control for one lag of past return skewness and volatility. One concern is that this is insufficient to capture a stock's true average skewness and volatility, particularly since both measures are based on daily returns in just one quarter and may therefore be very noisy. In column (3), I control for lags of past skewness and volatility up to four quarters, and find that the coefficient of DSXLEV_EW remains negative (i.e., -0.017) and statistically significant (with a t-statistic of 2.7).

In column (4), I use an alternative measure of crash risk, up-to-down volatility (UDVOL), as the dependent variable. Given the high correlation between UDVOL and SKEW (the correlation coefficient is 0.93), it is not surprising that the coefficient on DSXLEV remains significantly negative (with a t-statistic of 2.5).

One may also be concerned that the extrapolated measure of hedge fund leverage simply cap-

[36] Another interesting point emerging from column (1) lies in the coefficient of LOGCAP. The literature (e.g., Harvey and Siddique (2000), Chen et al. (2001)) documents that small stocks' returns are more positively skewed. This is clearly the case as shown Table V that the coefficients of LOGCAP are significantly negative. In column (2) of Table VI, however, after adding IO and LNCOV, the coefficient of LOGCAP becomes insignificant. The coefficients of IO and LNCOV are both significant. This finding is consistent with Chen et al. (2001)'s discretionary-disclosure hypothesis that managers of small companies have more discretion to quickly release good news but dribble out bad news slowly. Having more institutional investors or higher analyst coverage can strengthen governance and prevent managerial manipulation in information releases. Of course, more work is needed to draw a firm conclusion.

tures the effects of diversification and trading frequency given in Eq.(3). Although I have shown that extrapolated leverage matches actual hedge fund leverage in Section IV, here I adopt alternative approach to address this concern. That is, I construct a "placebo leverage" measure (denoted as PLEV) for mutual funds by inputting LNNSTK and PORTTURN based on *mutual* funds' quarterly holdings into Eq.(3). Then, I follow the same procedure above to define detrended stock-level placebo leverage (denoted as DSPLEV) and run the regression of Eq.(8) with DSPLEV instead.

Since mutual funds typically do not use leverage to implement their trading strategies, a negative coefficient on DSPLEV would indicate that the previous results using DSXLEV may not be truly related to a leverage effect. However, the result, in column (5), shows that this is not the case. The coefficient on DSPLEV is significantly *positive* with a t-statistic of 3.2. In sum, this result does not support the conjecture that the negative correlation between extrapolated leverage and return skewness is driven by portfolio diversification and trading style.

The baseline result is also robust to several alternative specifications and is robust in sub-periods. For brevity, I include these analyses in the online appendix.

D. Forecasting return skewness of the aggregate stock market

In this subsection, I examine Hypothesis 2, i.e., whether the relationship between hedge fund leverage and future return skewness exists at the *aggregate* market level. Since hedge fund leverage can only be estimated once a quarter and since the hedge fund industry was small before the late 1990s, the statistical power of this test may be low. All the same, one would hope to see results that are qualitatively consistent with those from the cross-sectional regressions.

I stay with the baseline panel specification and apply it to the aggregate time series. The left-hand-side variable, MKTSKEW_{t+1}, is the skewness of (daily) returns of the market in excess of risk-free rate in quarter $t+1$. The market return is defined as the value-weighted return of all common stocks in the NYSE, AMEX, and NASDAQ.[37] On the right-hand side, the variable of interest is Agg.DSXLEV_EW_t, which is the equal-weighted average of all stocks' $\text{DSXLEV\_EW}_{i,t}$.[38] In addition, I control for average hedge fund ownership (HFHOLD_t), average book-to-market ratio (BM_t) and average detrended turnover (DTURN_t), as well as market return skewness (MKTSKEW_t),

[37] The data on daily market returns and risk-free rate are downloaded from Ken French's website.

[38] Alternatively, one can also use $\text{DSXLEV\_VW}_{i,t}$ to form the aggregate leverage measure, or even use the simple average of hedge funds' $\text{XLEV}_{j,t}$. Both generate qualitatively similar results to those reported here.

market volatility (MKTSIGMA$_t$), and past market returns (MKTRET$_t$ through MKTRET$_{t-3}$).

[Place Table VII about here]

Regression estimations are reported in Table VII. In column (1), the market skewness is regressed on its own lag and Agg.DSXLEV_EW from 2001 to 2013. The point estimate of the coefficient on Agg.DSXLEV_EW, consistent with what I found in the cross-sectional analysis, is -0.79 with a t-statistic of 1.7. Next, I include all other controls and find that, as shown in column (2), while the t-statistic becomes less significant, the coefficient's magnitude increases to -0.99.

In light of this power issue, I extend the time series five years back to 1996. Some caution is needed here: the extended sample of hedge funds may not be representative of market speculators in early sample years.[39] The results are reported in columns (3) and (4). The coefficient of Agg.DSXLEV_EW in both columns becomes statistically significant at 5% level. In column (4), for example, the point estimate of Agg.DSXLEV_EW is -0.85 (with a t-statistic of 2.2), which is comparable to that estimated over a shorter sample period in column (2).

In terms of economic magnitude, the effect in the time-series is much stronger than that in the cross section. Following the same option approach, assume an aggregate stock market with current price of $100, annualized volatility of 20%, and skewness of 0. To be conservative, based on the smallest point estimate shown in Table VII, a two standard deviation increase in Agg.DSXLEV_EW is associated with a drop in skewness of -0.187.[40] All else equal, this would cause the price of a European put option on the market with a strike of $85 and a time-to-maturity of three months to increase from $0.202 to $0.267, or by 33.4%. The increase for a put with strike of $90 is 3.8%. In summary, the results in Table VII are supportive of Hypothesis 2.

VI. Amplification Mechanism

In this section, I provide evidence of fire sales, the amplification mechanism through which hedge fund leverage can propagate asset price crashes. As discussed in Section II, I focus primarily on the effect of fire sales caused by shocks to asset value and shocks to brokers' lending capacity.

[39]The hedge fund sample in 1990s may not be representative because TASS and CISDM had a much smaller sample size then. In 1996, the sample includes 43 hedge funds.

[40]The standard deviation of Agg.DSXLEV_EW is 0.11. Thus, we have -0.187 =2*0.11*(-0.85).

A. Fundamental shocks

I use fundamental shocks, measured by negative earnings surprises, as a proxy for negative changes in asset value. This approach is guided by theory. Xiong (2001), for example, shows that negative fundamental shocks unambiguously lead to fire sales, while other types of shocks, such as supply shocks from noise traders, may make arbitrageurs purchase additional distressed assets to bet on a subsequent reversal, rather than liquidate their shares at a discounted price. Also, following the standard method in the literature, fundamental shocks can be easily measured by earnings surprises.

One might be concerned that the adverse effect of a fundamental shock on a stock may be fully offset by a fund's other positions, such as a covered call. Unfortunately, I do not observe the whole portfolio of each hedge fund; 13F typically only contains long positions of U.S. stocks. However, for a hedge fund that does not fully hedge the risk *ex ante*, a negative earnings surprise to a stock in the fund's long portfolio should cause the fund to incur losses and may thereby trigger fire sales. Thus, at the stock level, to the extent that at least some hedge fund holders do not fully hedge *ex ante*, a negative earnings surprise is valid in identifying the effect of fire sales.

My empirical strategy follows Hong, Kubik, and Fishman (2012), who investigate the price impact of the forced-to-cover behavior by short sellers following a *positive* price movement. They find that the prices of highly shorted stocks overshoot upon the announcement of positive earnings surprises compared to stocks with little short interest. I run an analogous test by comparing the price reaction to a *negative* earnings surprise of stocks with high leverage and of stocks with low leverage.

The left-hand-side variable, denoted $\text{CAR}[\text{-}1,1]_{i,t+1}$, is the cumulative abnormal return over trading days -1 to +1 relative to the announcement for stock i's earnings report during quarter $t+1$. CAR_i equals stock i's raw return minus its benchmark's return over the same window. Each stock is assigned to one of 18 benchmark portfolios based on the stock's size, book-to-market ratio, and prior 12-month return at the beginning of each year. The 18 benchmark portfolios are based on the intersection of two size-based groups, three book-to-market based groups, and three momentum groups.

To calculate unexpected earnings (denoted as UE), I use the summary file from IBES. $\text{UE}_{i,t+1}$

equals the difference between stock i's actual quarter $t+1$ earnings and the consensus forecast provided by IBES in the last month before the announcement date scaled by its past price. In the regression, I only consider extreme cases: I define $\text{UELO}_{i,t+1}$, a dummy variable which equals one if stock i's UE for quarter $t+1$ is lower than the bottom tercile of the sample distribution. My sample includes all NYSE, AMEX, and NASDAQ stocks with prices higher than \$5 and available analyst forecasts in IBES from 2001 to 2012.

To test the first part of Hypothesis 3, we check whether the sensitivity of price to extremely negative unexpected earnings (i.e., UELO=1) is stronger for stocks with higher leverage. The regression is specified as

$$CAR[-1,+1]_{i,t+1} = \alpha + \beta_1 UELO_{i,t+1} + \beta_2 SXLEV_{i,t} + \beta_3 UELO_{i,t+1} * SXLEV_{i,t} + \gamma' \mathbf{X_{i,t}} + \epsilon_{i,t} \ , \quad (9)$$

where β_1 estimates the overall sensitivity of price to earnings surprises, and β_3 measures how the sensitivity varies with leverage, i.e., SXLEV. β_3 is expected to be negative, as stocks held by more levered funds should underperform more. $\mathrm{X}_{\mathbf{i,t}}$ represents the vector of controls, including firm size (LOGCAP), book-to-market ratio (BM), momentum (MOM), hedge fund ownership (HFHOLD), institutional ownership (IO), return volatility (SIGMA), turnover (TURN), analyst coverage (LNCOV), liquidity ratio (LNLIQ), and dummies for each quarter. The controls are in line with those used in Hong et al. (2012) and include variables that significantly forecast return skewness in cross-sectional regressions. Except for UELO, all the right-hand-side variables are observed at the beginning of each announcement quarter. Standard errors are clustered by stock.

The most distinctive implication of the amplification theory is that the prices of stocks with previously high SXLEV will gradually reverse in the long run after a poor earnings surprise. That is, the subsequent returns for these stocks should be higher than for others. To check if this is the case, I replace the dependent variable in Eq.(9) with $\text{CAR}[2,126]_{i,t+1}$, the cumulative abnormal return over trading days +2 through +126 relative to the announcement day for stock i's earnings report during quarter $t+1$. The right-hand side is kept the same. The regression is given by Eq.

(10), where β_3 is expected to be positive:

$$CAR[+2,+126]_{i,t+1} = \alpha + \beta_1 UELO_{i,t+1} + \beta_2 SXLEV_{i,t} + \beta_3 UELO_{i,t+1} * SXLEV_{i,t} + \gamma' \mathbf{X_{i,t}} + \epsilon_{i,t} \ . \tag{10}$$

Table VIII presents the regression results. In Panel A, I use equal-weighted SXLEV. In column (1), I run the regression in Eq. (9) but omit the interaction term of UELO and SXLEV_EW. Under this specification, the coefficient on UELO represents the overall return sensitivity to extreme negative earnings surprises. Stocks with UELO of 1 decrease by 2.96% on average from day -1 to +1 around the announcement date. In column (2), the interaction term is added, and its coefficient equals -0.63 with a t-statistic of 8.6. In terms of economic magnitude, a two standard deviation increase in SXLEV_EW is associated with a 1.36% drop in CAR[-1,+1].[41] This finding is consistent with Hypothesis 3. In column (3), I also include the interaction terms of UELO with all control variables, to allow the return-to-earnings sensitivity to vary with stock characteristics. In column (4), I show that the coefficient on UELO*SXLEV_EW is almost unchanged and strongly significant in the presence of time-varying industry effects.

In columns (5) to (8) of Panel A in Table VIII, the dependent variable is replaced with long-term subsequent returns, i.e., CAR[+2,+126]. Hypothesis 3 predicts that the coefficient on UELO*SXLEV_EW will be positive. In column (5), I run the regression in Eq. (10) without the interaction term of UELO and SXLEV_EW. The point estimate of the coefficient on UELO, -1.31, indicates that stocks with poor earnings surprises continue to underperform from day +2 to +126. This is the post-earnings announcement drift effect as documented by Bernard and Thomas (1989). The interaction term is added in column (6), and its coefficient is significantly positive with a t-statistic of 3.6. As shown in columns (7) and (8), the finding is robust to controlling for interaction terms of UELO with other stock characteristics and quarter-industry fixed effects. The economic magnitude of the effect is large. In column (8), for example, a two standard deviation increase in SXLEV_EW is associated with a 1.84% increase in subsequent returns.[42]

[Place Table VIII about here]

In Panel B, I re-run all regressions but use value-weighted stock-level leverage (SXLEV_VW).

[41] 1.36=0.63*1.08*2.

[42] 1.84=0.72*1.08*2.

The results are consistent with those in Panel A. All coefficients on the interaction term of UELO and SXLEV_VW are statistically significant, though the economic effect implied by the coefficients is weaker. Figure 3 illustrates the effect graphically. At the beginning of each quarter, stocks are equally divided into HI SXLEV and LO SXLEV groups based on SXLEV_EW. The figure plots CAR (in percent) from trading days -5 to +30 relative to the earnings release for each group. One can see that the prices of HI SXLEV stocks decrease by about 50 basis points more by the first day after the announcement than the prices of LO SXLEV stocks. The gap persists until day 10, and almost converges after approximately a month (or 20 trading days). In sum, I find supportive evidence for Hypothesis 3.[43]

[Place Figure 3 about here]

B. Funding liquidity shocks

In this section, I test Hypothesis 4; I investigate whether leveraged hedge funds transmit funding liquidity shocks into stock prices. To proxy for the shock in brokers' lending capacity, I focus on variation in broker-dealers' solvency, measured by a value-weighted index of all U.S. major investment banks' CDS, denoted as IBCDS index.[44] The CDS data is available from September 2001 to December 2013.

Figure 4 plots the weekly IBCDS index over the sample. I focus on extreme jumps in the index to capture aggregate funding liquidity shocks. I define a dummy variable, IBCDS_HI_t, which equals one if the IBCDS index increases by over 20% within week t.[45] The red bars in Figure 4 represent weeks with IBCDS_HI_t of one; these event weeks make up approximately 5% of all weeks in the sample. As expected, a majority of them occurred during the financial crisis between 2007 to 2008.

[Place Figure 4 about here]

I start by checking the empirical premise that broker-dealers' solvency influences hedge funds' borrowing. If this is true, then IBCDS should be negatively correlated with aggregate hedge fund

[43] An important prediction of the fire sales hypothesis is that distressed funds liquidate holdings. Although the holdings data in 13F are only available at the quarterly level, I find that hedge funds using high leverage are more likely to sell stocks that have experienced negative earnings reports than funds using low leverage. Results are in the online appendix.

[44] I follow AGV (2011) to construct the index. Details are in Appendix A.

[45] The 20% cutoff is arbitrary, but the main result is robust to changing the cutoff from 15% to 30%.

leverage. I regress the quarterly change of average XLEV (i.e., ΔHFXLEV) on the contemporaneous quarterly change of IBCDS (i.e., ΔIBCDS). The results are summarized in Table IX. In column (1), the point estimate from the univariate regression is negative with a t-statistic of 3.2. Further, in column (2), after controlling for the return and volatility of the aggregate stock market (MKTRET and MKTSIGMA, respectively), and for the risk-free rate (RF), the coefficient on ΔIBCDS remains significantly negative. This suggests that hedge funds tend to deleverage when brokers are financially distressed.

[Place Table IX about here]

As shown in Eq.(11) and Eq.(12) below, the main regressions in this section adopt the same specification as Eq.(9) and Eq.(10) with two exceptions. First, the shock indicator is now IBCDS_HI_t rather than $\text{UELO}_{i,t}$. Second, the time frequency changes from quarterly to weekly, as the liquidity shock is based on the movement of IBCDS within each week. Standard errors are clustered by week.

$$CAR[0]_{i,t+1} = \alpha + \beta_1 IBCDS\_HI_{t+1} + \beta_2 SXLEV_{i,t} + \beta_3 IBCDSHI_{t+1} * SXLEV_{i,t} + \gamma' \mathbf{X_{i,t}} + \epsilon_{i,t} \tag{11}$$

$$CAR[+1,+4]_{i,t+1} = \alpha + \beta_1 IBCDS\_HI_{t+1} + \beta_2 SXLEV_{i,t} + \beta_3 IBCDSHI_{t+1} * SXLEV_{i,t} + \gamma' \mathbf{X_{i,t}} + \epsilon_{i,t} \tag{12}$$

Here, $\text{CAR}[0]_{i,t+1}$ is the cumulative abnormal return for stock i in week $t+1$, and $\text{CAR}[+1,+4]_{i,t+1}$ is the cumulative abnormal return for stock i over week +1 to +4 relative to week $t+1$. The methods for calculating CAR and the variables in $\mathbf{X_{i,t}}$ are identical to the previous subsection. All stock characteristics, including $\text{SXLEV}_{i,t}$, are observed at the most recent quarter-end for stock i before the start of week $t+1$. According to Hypothesis 4, I expect β_3 to be negative in Eq.(11) but to be positive in Eq.(12).

[Place Table X about here]

In Table X, Panels A and B report the results using equal-weighted and value-weighted SXLEV, respectively. Column (1) of Panel A shows the regression estimation of Eq.(11) without the interaction term of IBCDS_HI and SXLEV_EW. The coefficient on IBCDS_HI is insignificantly different from zero. This is intuitive since the average abnormal return of all stocks in any week t should be close to zero. In column (2), the coefficient on the interaction term equals -0.31 with a t-statistic of 2.9. I include the interaction terms of IBCDS_HI with all other control variables in column (3) and find that the coefficient decreases to -0.15 but is still statistically significant (with a t-statistic of 2.4). This implies that a two standard deviation increase in SXLEV_EW is associated with a 32 basis points underperformance over one week.[46]

Columns (4) to (6) show the results from regression Eq.(12) in which CAR[+1,+4] is the dependent variable. The coefficient on the interaction term of IBCDS_HI and SXLEV_EW is positive and equal to 0.22 in column (5). After additional controls, the coefficient becomes 0.20 and significant with a t-statistic of 2.1. A two standard deviation increase in SXLEV_EW corresponds to a 42 basis points higher subsequent abnormal return over four weeks.[47]

The results in Panel B also support Hypothesis 4. As in Table VIII, the estimation using the value-weighted stock-level XLEV exhibits weaker economic effects, but is still statistically significant. Figure 5 demonstrates this effect graphically. At the beginning of each week, I split all stocks into two equal groups, labeled as HI SXLEV and LO SXLEV, respectively, based on SXLEV_EW observed at the most recent quarter-end before the week. Then, I plot abnormal CAR for each group over weeks -5 to +5 relative to the event week. Abnormal CAR equals the average CAR in event weeks (i.e., IBCDS_HI=1) minus average CAR in normal weeks (i.e., IBCDS_HI=0). As shown in the figure, HI SXLEV stocks underperform their benchmark during the event week while LO SXLEV stocks outperform. After approximately three weeks, the gap converges.

[Place Figure 5 about here]

VII. Conclusion

The effect of leverage on asset prices and financial markets has been extensively discussed, not only by academics but also by regulators and the media. This paper brings new large-sample evidence to the discussion. At both the firm and the aggregate stock market level, a rise in the leverage used by hedge funds is associated with a subsequent increase in the likelihood of a future

[46] 32bps = 0.15%*1.08*2.

[47] 42bps = 0.20%*1.08*2.

crash in asset prices. I further find evidence of fire sales related to the use of leverage. The prices of stocks owned by highly leveraged hedge funds overshoot around a negative fundamental shock and a funding liquidity shock.

By developing a novel measure of hedge fund leverage based on public filings, this paper opens a new door for empirical research on this topic. For example, one future question that could be addressed is whether the use of leverage amplifies investors' optimism, causing overpricing and initiating bubbles in asset markets. This is a key component of Kindleberger's (1978) narrative of bubbles and crashes and a clear prediction from several theoretical papers (e.g., Geanakoplos (2010)). Also, as addressed by Stein (2009), it is worth examining what determines a hedge fund's leverage choice, particularly when the fund manager is fully aware of the cost of using high leverage.

Appendix A. Variable definition

Notation	Description
	1. Hedge-fund-level Data
LEVERAGE	The ratio of gross asset value to net asset value of all discretionary assets managed by a hedge fund adviser. Gross asset value equals discretionary regulatory assets under management in Form ADV Part 1A, Item 5F(2)(a). Net asset value, if reported, is from Form ADV Part 2A Client Brochure, Item 4.
LNLEV	The natural logarithm of LEVERAGE
NSTK	The number of stocks reported in a hedge fund's 13F portfolio.
LNNSTK	The natural logarithm of one plus NSTK.
LNNSTK^2	The square of LNNSTK.
PORTTURN	A hedge fund's quarterly turnover rate of its 13F portfolio, as defined in Griffin and Xu (2009). It equals the minimum of the total value of stocks the hedge fund buys or sells during a quarter divided by the total value of the hedge fund's whole 13F portfolio at the beginning of the quarter.
SSPW	The sum of squares of portfolio weights, as defined by Goetzmann and Kumar (2008). It equals $\sum_i w_i^2$, where w_i is the value weight of stock i in a hedge fund's 13F portfolio.
ACTSHARE	The active share of a portfolio by Cremers and Petajisto (2009). It equals $\frac{1}{2}\sum_i \lvert w_i - w_{mkt,i}\rvert$, where w_i is the weight of stock i in the fund's portfolio and $w_{mkt,i}$ is the weight of stock i in the market portfolio.
XLEV	Extrapolated leverage, calculated by inputting a hedge fund's LNNSTK, LNNSTK^2, PORTTURN, and value of strategy dummies into Eq.(3).
	2. Stock-level Data
SKEW	The skewness of (daily) market-adjusted returns during a quarter.
UDVOL	The log of the ratio of up-day to down-day standard deviation of (daily) market-adjusted returns during a quarter.
SXLEV_EW	The equal-weighted average of extrapolated leverage of hedge funds holding the stock at the end of a quarter.
DSXLEV_EW	Detrended SXLEV_EW, obtained by subtracting SXLEV_EW from its moving average over the prior eight quarters.
SXLEV_VW	The value-weighted average of extrapolated leverage of hedge funds holders by each hedge fund's ownership of the stock at the end of each quarter.
DSXLEV_VW	Detrended SXLEV_VW, obtained by subtracting SXLEV_VW from its moving average over the prior eight quarters.
HFHOLD	The fraction of shares outstanding owned by hedge funds in Sample C at the end of a quarter.
IO	Institutional ownership at the end of a quarter, which equals the fraction of shares outstanding owned by all institutions in 13F filings.

SIGMA	The standard deviation of daily market-adjusted returns during a quarter.
PRET	The market-adjusted return in the previous quarter.
LOGCAP	The log of market capitalization (in $million) measured at the end of a quarter.
BM	The ratio of most recent year-end book equity to market capitalization. The ratio is updated in July of every year.
TURN	The number of shares traded during a quarter scaled by the total number of shares outstanding at the end of the quarter.
DTURN	Detrended TURN, obtained by subtracting TURN from its moving average over the prior eight quarters
LNCOV	The log of one plus the number of analysts covering the stock at the end of each quarter.
LNLIQ	The log of one plus the ratio of total trading volume to the sum of the absolute value of daily raw returns during a quarter.
MOM	Cumulative return in prior 12 months skipping the most recent month.
UE	A stock's quarterly unexpected earnings, which equals the difference between the actual quarterly earnings and the mean forecast provided by IBES in the last month before the announcement date divided by past price.
UELO	A dummy variable which equals one if a stock's UE for a quarter is in the bottom tercile of the sample distribution of that quarter.
SPLEV_EW	The equal-weighted average of placebo leverage of mutual funds holding the stock at the end of a quarter. PLEV, placebo leverage of a mutual fund, is calculated by inputting the mutual fund's LNNSTK, LNNSTK^2, and PORTTURN into Eq.(3). LNNSTK and PORTTURN are calculated using mutual funds' quarterly holding data from CRSP.
DSPLEV_EW	Detrended SPLEV_EW, obtained by subtracting SPLEV_EW from its moving average over the prior eight quarters.

3. Aggregate Market Data

MKTSKEW	The skewness of (daily) market returns in excess of the risk-free rate during each quarter, where the market is defined as the value-weighted portfolio of all NYSE, AMEX, and NASDAQ stocks.
MKTSIGMA	The standard deviation of (daily) market returns in excess of the risk-free rate during each quarter.
MKTRET	The market return in excess of the risk-free rate during each quarter.
HFXLEV	The average of extrapolated hedge fund leverage, estimated at the end of each quarter.
RF	Quarterly risk-free rate.

IBCDS	The investment bank CDS index, constructed following the method in Ang, Gorovyy, and van Inwegen (2011). It equals the average of synthetic CDS spreads on long-term bonds of Bear Stearns, Citigroup, Credit Suisse, Goldman Sachs, HSBC, JP Morgan, Lehman Brothers, Merrill Lynch, and Morgan Stanley, weighted by each bank's market capitalization. Data on CDS prices are obtained from Bloomberg and market weights are taken from CRSP. See Ang, Gorovyy, and van Inwegen (2011) for more details.
IBCDS_HI	A dummy variable which equals one if the IBCDS increases by more than 20% during a week, otherwise zero.
Agg.DSXLEV_EW	The average of all stocks' DSXLEV_EW at the end of each quarter, value-weighted by each stock's market capitalization in the prior quarter.

Appendix B. Description of hedge funds' investment strategy

Hedge funds in Sample A are categorized by their self-descriptions of investment strategy in Item 8 of the client brochure in Part 2B of Form ADV. To group hedge funds by their strategies, I follow the method and definitions developed by Hedge Fund Research (HFR). The description of each strategy is listed below. For hedge fund advisers in Sample C but not in Sample B, I obtain their strategy information from TASS or CISDM. Because the strategy variable in both databases is at individual fund level, I aggregate it at the adviser level. That is, I define an adviser's major strategy as the strategy of the fund whose AUM makes up over 75% of the adviser's total AUM. If there is not any funds that consist of more than 75% of the adviser's total AUM, the adviser is categorized as a multi-strategy fund. For an adviser whose AUM information is missing in TASS and CISDM, its major strategy is that of the oldest, live fund managed by the adviser.

Strategy	Description
Equity long-short	Funds who primarily take long and short positions in publicly traded equities in the U.S. and global markets. They may use fundamental analysis or quantitative methods, and usually has directional exposure to the aggregate equity markets. It also includes long-only funds and short biased equity funds.
Event-driven	Funds who maintain positions in companies currently or prospectively involved in corporate transactions including mergers, restructurings, financial distress, shareholder buybacks, debt exchanges, security issuance or others. Security types can be equity, debt with all levels of seniority, and derivatives.
Relative value	Funds who maintain positions in which the investment thesis is predicated on realization of a valuation discrepancy in the relationship between multiple securities. Typical strategies include equity market neutral, convertible bond arbitrage, high-frequency trading, and statistics arbitrage.
Multi-strategy	Funds who employ more than one of strategies listed here as their primary strategy.
Fund of funds	Funds who primarily hold a portfolio of hedge funds and normally do not directly invest in asset markets.
Fixed income	Funds who primarily invests in one or multiple kinds of fixed income markets, including corporate bonds urities, mortgage loans and related securities, CDO, and others. They may take long-short positions or use relative value strategies.
Global macro	Funds whose investment is based on movements in underlying economic variables and the impact these have on equity, fixed income, currency and commodity markets. Funds may employ a variety of techniques, both discretionary and systematic analysis, top down and bottom up, quantitative and fundamental, and long and short term holding periods. It also includes managed future funds and commodity trading advisers (i.e., CTAs)).

REFERENCES

Acharya, Viral V., and S. Viswanathan, 2011, Leverage, moral hazard, and liquidity, *Journal of Finance* 66, 99–138.

Adrian, Tobias, Erkko Etula, and Tayler Muir, 2014, Financial intermediaries and the cross-section of asset returns, *Journal of Finance* 69, 2557–2596.

Adrian, Tobias, Emanuel Moench, and Hyun Song Shin, 2013, Leverage asset pricing, *Staff Report, Federal Reserve Bank of New York* .

Adrian, Tobias, and Hyun Song Shin, 2010, Liquidity and leverage, *Journal of Financial Intermediation* 19, 418–437.

Adrian, Tobias, and Hyun Song Shin, 2013, Procyclical leverage and value-at-risk, *Review of Financial Studies* .

Aiken, Adam L., Christopher P. Clifford, and Jesse Ellis, 2013, Out of the dark: Hedge fund reporting biases and commercial databases, *Review of Financial Studies* 26, 208–243.

Ang, Andrew, Sergiy Gorovyy, and Gregory B. van Inwegen, 2011, Hedge fund leverage, *Journal of Financial Economics* 102, 102–126.

Aragon, George O., and Philip E. Strahan, 2012, Hedge funds as liquidity providers: Evidence from the lehman bankruptcy, *Journal of Financial Economics* 103, 570–587.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2012, Hedge fund stock trading in the financial crisis of 2007–2009, *Review of Financial Studies* 25, 1–54.

Berman, Mark, 2009, *Hedge Funds and Prime Brokers* (Risk Books).

Bernanke, Ben, and Mark Gertler, 1989, Agency costs, net worth, and business fluctuations, *American Economic Review* 14–31.

Bernard, Victor L., and Jacob K. Thomas, 1989, Post-earnings-announcement drift: Delayed price response or risk premium?, *Journal of Accounting research* 1–36.

Bhardwaj, Geetesh, Gary B. Gorton, and K. Geert Rouwenhorst, 2014, Fooling some of the people all of the time: The inefficient performance and persistence of commodity trading advisors, *Review of Financial Studies* 27, 3099–3132.

Bollen, Nicolas P.B., and Veronika K. Pool, 2009, Do hedge fund managers misreport returns? evidence from the pooled distribution, *Journal of Finance* 64, 2257–2288.

Bris, Arturo, William N. Goetzmann, and Ning Zhu, 2007, Efficiency and the bear: Short sales and markets around the world, *Journal of Finance* 62, 1029–1079.

Brown, Christine A., and David M. Robinson, 2002, Skewness and kurtosis implied by option prices: A correction, *Journal of Financial Research* 25, 279–282.

Brown, Stephen, William N. Goetzmann, Bing Liang, and Christopher Schwarz, 2008, Mandatory disclosure and operational risk: Evidence from hedge fund registration, *Journal of Finance* 63, 2785–2815.

Brown, Stephen J., and William N. Goetzmann, 2003, Hedge funds with style, *Journal of Portfolio Management* 29, 101–112.

Brown, Stephen J, William N. Goetzmann, Roger Ibbotson, and Stephen A. Ross, 1992, Survivorship bias in performance studies, *Review of Financial Studies* 5, 553–80.

Brown, Stephen J., William N. Goetzmann, and James Park, 2001, Careers and survival: Competition and risk in the hedge fund and cta industry, *Journal of Finance* 56, 1869–1886.

Brunnermeier, Markus K., 2009, Deciphering the liquidity and credit crunch 2007-2008, *Journal of Economic Perspectives* 77–100.

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

Brunnermeier, Markus K., Stefan Nagel, and Lasse H. Pedersen, 2009, Carry trades and currency crashes, in *NBER Macroeconomics Annual 2008, Volume 23*, 313–347 (University of Chicago Press).

Brunnermeier, Markus K., and Lasse H. Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201–2238.

Chen, Joseph, Harrison Hong, and Jeremy C. Stein, 2001, Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices, *Journal of Financial Economics* 61, 345–381.

Corrado, Charles J., and Tie Su, 1997, Implied volatility skews and stock index skewness and kurtosis implied by s&p 500 index option prices, *The Journal of Derivatives* 4, 8–19.

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Cremers, K.J. Martijn, and Antti Petajisto, 2009, How active is your fund manager? a new measure that predicts performance, *Review of Financial Studies* 22, 3329–3365.

Edwards, Franklin R., 1999, Hedge funds and the collapse of long-term capital management, *Journal of Economic Perspectives* 189–210.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T. Lundblad, 2011, Regulatory pressure and fire sales in the corporate bond market, *Journal of Financial Economics* 101, 596–620.

Fostel, Ana, and John Geanakoplos, 2008, Leverage cycles and the anxious economy, *American Economic Review* 98, 1211–1244.

Frehen, Rik G.P., William N. Goetzmann, and Geert K. Rouwenhorst, 2013, New evidence on the first financial bubble, *Journal of Financial Economics* 108, 585–607.

Fung, William, and David A. Hsieh, 1997, Empirical characteristics of dynamic trading strategies: The case of hedge funds, *Review of Financial Studies* 10, 275–302.

Geanakoplos, John, 2003, Liquidity, default, and crashes endogenous contracts in general, in *Advances in economics and econometrics: theory and applications: eighth World Congress*, volume 170.

Geanakoplos, John, 2010, The leverage cycle, in *NBER Macroeconomics Annual 2009, Volume 24*, 1–65 (University of Chicago Press).

Goetzmann, William N., and Alok Kumar, 2008, Equity portfolio diversification, *Review of Finance* 12, 433–463.

Greenlaw, David, Jan Hatzius, Anil K. Kashyap, and Hyun Song Shin, 2008, Leveraged losses: Lessons from the mortgage market meltdown, *US Monetary Policy Forum Report No.2* .

Griffin, John M., and Jin Xu, 2009, How smart are the smart guys? a unique view from hedge fund stock holdings, *Review of Financial Studies* 22, 2331–2370.

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of financial Economics* 66, 361–407.

Gromb, Denis, and Dimitri Vayanos, 2010, Limits of arbitrage: the state of the theory, *Annual Review of Financial Economics* 2, 251–275.

Hardouvelis, Gikas A, 1990, Margin requirements, volatility, and the transitory component of stock prices, *American Economic Review* 736–762.

Harvey, Campbell R., and Akhtar Siddique, 2000, Conditional skewness in asset pricing tests, *Journal of Finance* 55, 1263–1295.

He, Zhiguo, and Arvind Krishnamurthy, 2013, Intermediary asset pricing, *American Economic Review* 103, 732–70.

Hong, Harrison, Jeffrey D. Kubik, and Tal Fishman, 2012, Do arbitrageurs amplify economic shocks?, *Journal of Financial Economics* 103, 454–470.

Hsieh, David A., and Merton H. Miller, 1990, Margin regulation and stock market volatility, *Journal of Finance* 45, 3–29.

Jiang, Wenxi, 2014, Fixed operating costs, payoff convexities, and hedge fund leverage, *Working Paper* .

Khandani, Amir E., and Andrew W. Lo, 2011, What happened to the quants in august 2007? evidence from factors and transactions data, *Journal of Financial Markets* 14, 1–46.

Kindleberger, Charles P., 1978, *Manias, panics and crashes: a history of financial crises* (Palgrave Macmillan).

Kiyotaki, Nobuhiro, and John Moore, 1997, Credit cycles, *Journal of Political Economy* 105, 211–248.

Kyle, Albert S., and Wei Xiong, 2001, Contagion as a wealth effect, *Journal of Finance* 56, 1401–1440.

Lowenstein, Roger, 2000, *When genius failed: The rise and fall of Long-Term Capital Management* (Random House LLC).

Merrill, Craig B., Taylor D. Nadauld, René M. Stulz, and Shane Sherlund, 2012, Did capital requirements and fair value accounting spark fire sales in distressed mortgage-backed securities?, *NBER Working Paper* .

Mitchell, Mark, Lasse H. Pedersen, and Todd Pulvino, 2007, Slow moving capital, *American Economic Review* 97, 215–220.

Mitchell, Mark, and Todd Pulvino, 2012, Arbitrage crashes and the speed of capital, *Journal of Financial Economics* 104, 469–490.

Patton, Andrew J., Tarun Ramadorai, and Michael Streatfield, 2012, Change you can believe in? hedge fund data revisions, *CEPR Discussion Papers* .

Petersen, Mitchell A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *Review of Financial Studies* 22, 435–480.

Presidential Task Force on Market Mechanisms, and Nicholas F. Brady, 1988, *Report of the presidential task force on market mechanisms* (U.S. Government Printing Office).

Rappoport, Peter, and Eugene N. White, 1994, Was the crash of 1929 expected?, *American Economic Review* 271–281.

Roll, Richard, 1988, The international crash of october 1987, *Financial Analysts Journal* 19–35.

Rubin, Robert E., Alan Greenspan, Arthur Levitt, and Brooksley Born, 1999, Hedge funds, leverage, and the lessons of long-term capital management .

Schwert, G. William, 1989, Margin requirements and stock volatility, *Journal of Financial Services Research* 3, 153–164.

Shiller, Robert, 1988, Portfolio insurance and other investor fashions as factors in the 1987 stock market crash, in *NBER Macroeconomics Annual 1988, Volume 3*, 287–297 (MIT Press).

Shleifer, Andrei, and Robert W. Vishny, 1992, Liquidation values and debt capacity: A market equilibrium approach, *Journal of Finance* 47, 1343–1366.

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35–55.

Shleifer, Andrei, and Robert W. Vishny, 2010, Asset fire sales and credit easing, *American Economic Review* 46–50.

Shleifer, Andrei, and Robert W. Vishny, 2011, Fire sales in finance and macroeconomics, *Journal of Economic Perspectives* 29–48.

Singh, Manmohan, and James Aitken, 2010, The (sizable) role of rehypothecation in the shadow banking system, *IMF Working Paper* .

Stein, Jeremy C., 2009, Presidential address: Sophisticated investors and market efficiency, *Journal of Finance* 64, 1517–1548.

Stulz, René M., 2007, Hedge funds: Past, present, and future, *Journal of Economic Perspectives* 21, 175–194.

Voth, Hans-Joachim, 2003, With a bang, not a whimper: pricking germany's stock market bubble in 1927 and the slide into depression, *The Journal of Economic History* 63, 65–99.

White, Eugene N., 1990, The stock market boom and crash of 1929 revisited, *Journal of Economic Perspectives* 67–83.

Xiong, Wei, 2001, Convergence trading with wealth effects: an amplification mechanism in financial markets, *Journal of Financial Economics* 62, 247–292.

Table I Number of hedge funds and distribution of hedge fund leverage

Panel A reports the number of hedge funds in each year for Samples A, B, and C. Sample A consists of all hedge fund advisers in Form ADV filings. Sample B, a subset of Sample A, includes only equity hedge funds. "Equity hedge fund" refers to funds who have records in 13F filings and whose major investment strategy is equity long-short, event-driven, relative value, or multi-strategy. Sample C includes hedge funds in Sample B and funds on a supplementary list which contains equity hedge funds that went out of business before 2011. "Reporting" hedge funds refer to those who provide sufficient information in Form ADV to calculate their year-end leverage ratio. Panel B presents summary statistics of leverage of reporting hedge funds in Samples A and B, as well as sub-samples by investment strategies. Both Samples A and B are from 2011 to 2013, while Sample C is from 2001 to 2013.

Panel A: Number of hedge fund advisers

	Sample A		Sample B		Sample C
	All	Reporting	All	Reporting	All
2001	-	-	-	-	152
2002	-	-	-	-	177
2003	-	-	-	-	196
2004	-	-	-	-	243
2005	-	-	-	-	288
2006	-	-	-	-	328
2007	-	-	-	-	382
2008	-	-	-	-	395
2009	-	-	-	-	374
2010	-	-	-	-	403
2011	796	208	396	144	445
2012	813	238	394	156	431
2013	790	250	370	148	439
# of unique hedge funds	983	357	448	209	621
Total fund-year obs	2399	696	1160	448	4253

Panel B: Summary statistics of hedge fund leverage

	Mean	StDev	P01	P25	P50	P75	P99	Skew.	Obs.
Sample A: all reporting HFs	1.96	1.40	0.98	1.29	1.54	1.92	8.81	3.85	696
Sample B: all reporting HFs	1.87	1.21	0.99	1.31	1.54	1.84	7.76	4.28	448
Subsamples by strategies:									
Equity long-short	1.62	0.47	0.99	1.35	1.53	1.75	3.48	2.13	240
Event-driven	1.39	0.28	0.98	1.20	1.32	1.56	2.46	1.28	58
Multi-strategy	2.33	1.88	1.00	1.31	1.66	2.32	10.68	2.90	126
Relative value	3.21	1.57	1.14	2.21	2.82	3.89	6.88	0.88	24

Table II Regression of hedge funds' leverage on portfolio characteristics

This table presents estimates of regressions of hedge funds' leverage on their 13F portfolio characteristics. LEVERAGE refers to the ratio of each hedge fund's year-end gross assets value to net assets value. LNLEV is the natural logarithm of LEVERAGE. Portfolio characteristics include portfolio turnover (PORTTURN), the number of stocks (NSTK), sum of squares of portfolio weights (SSPW), and active share (ACTSHARE). LNNSTK is the natural logarithm of one plus NSTK. All portfolio characteristic variables are constructed based on hedge funds' 4th-quarter 13F filings in each year. More details of variable definitions are in Appendix A. EVENT-DRIVEN, MULTI-STRATEGY, and RELATIVE VALUE are dummy variables indicating each hedge fund's major investment strategy. Panel A reports summary statistics, and Panel B presents regression results. Regressions are estimated on reporting hedge funds in Sample B from 2011 to 2013. Standard errors are clustered by hedge fund, and the corresponding *t*-statistics are reported in parentheses.

Panel A: Summary statistics of variables

	Mean	StDev	P01	P25	P50	P75	P99	Obs
LEVERAGE	1.87	1.21	1.00	1.31	1.54	1.84	7.76	421
LNLEV	0.52	0.40	0.00	0.27	0.43	0.61	2.05	421
PORTTURN	0.26	0.16	0.00	0.14	0.23	0.36	0.69	421
NSTK	144.9	387.5	4.0	21.0	35.0	66.0	2300.0	421
LNNSTK	3.83	1.24	1.61	3.09	3.58	4.20	7.74	421
SSPW	0.09	0.12	0.00	0.03	0.05	0.10	0.65	421
ACTSHARE	0.84	0.14	0.40	0.82	0.89	0.93	1.00	421

Panel B: Regressions of hedge fund leverage on portfolio characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CONSTANT	-0.16	0.56	1.67	0.68	0.87	0.45	0.33	0.73
	(-1.48)	(14.4)	(6.59)	(3.47)	(2.20)	(18.7)	(8.33)	(3.57)
LNNSTK	0.18			-0.23	-0.18			-0.28
	(5.90)			(-2.33)	(-1.30)			(-2.69)
LNNSTK^2				0.045	0.038			0.046
				(3.70)	(2.29)			(3.67)
SSPW		-0.42			0.083			
		(-2.22)			(0.34)			
ACTSHARE			-1.37		-0.31			
			(-4.83)		(-1.09)			
EVENT-DRIVEN						-0.14		-0.096
						(-3.23)		(-2.43)
MULTI-STRATEGY						0.21		0.069
						(2.51)		(1.35)
RELATIVE VALUE						0.60		0.47
						(4.00)		(2.81)
PORTTURN							0.75	0.28
							(4.40)	(2.40)
Obs.	421	421	421	421	421	421	421	421
Adj R^2	0.307	0.013	0.234	0.373	0.377	0.177	0.094	0.466

Table III Validation tests of the extrapolated hedge fund leverage

Panel A presents the results of a standard cross-validation test. Hedge funds in Sample B are randomly split into two half-samples, *training* sample and *test* sample. I run the regression in column (8) in Panel B of Table II on the *training* sample and use the regression coefficients to predict the leverage for hedge fund i in the *test* sample. The cross-validation tests compare predicted leverage (denoted as $\hat{L}$) with hedge funds' true leverage (denoted as L). $R^2(test) = Var(\hat{L_j})/Var(L_j)$, $j \in test$. $RMSE = \sqrt{\frac{1}{N_{test}} \sum_{j \in test} (\hat{L_j} - L_j)^2}$, where N_{test} is the number of hedge funds in the *test* sample. The OLS regression is specified as $L_j = a + b\hat{L_j} + e_j, j \in test$, and the regression coefficient b and the R^2 are reported. The procedure is repeated 400 times and summary statistics of each measure are presented. Panel B shows the result of time-series regressions of the mean or interquartile of actual hedge fund leverage reported in AGV (2011) on the mean or interquartile of XLEV, respectively, in both levels and first differences. XLEV, extrapolated hedge fund leverage, is generated using Eq.(3). The sample is from the 4th quarter of 2004 to the third quarter of 2009. Newey-West t-statistics with lags of order 4 are reported in parentheses.

Panel A: Cross validation

	Mean	StDev	Min	Max	# of sampling
Test Sample Fit					
R^2(test)	0.48	0.12	0.25	0.93	400
RMSE	0.30	0.02	0.26	0.35	400
OLS Regression					
b	0.98	0.16	0.59	1.42	400
R^2	0.44	0.06	0.24	0.58	400

Panel B: Regressions of actual hedge fund leverage in AGV (2011) on XLEV

	Mean in AGV		Interquartile in AGV	
	Level	1st Diff	Level	1st Diff
	(1)	(2)	(3)	(4)
Mean of XLEV	9.15	4.75		
	(5.89)	(2.49)		
Interquartile of XLEV			3.31	6.05
			(5.34)	(5.65)
Adj. R^2	0.70	0.29	0.38	0.38
# of quarters	20	19	20	19

Table IV Summary statistics and correlation matrix

This table presents summary statistics and the correlation matrix of variables used in cross-sectional regressions. The sample is from January 2001 to December 2013 and only includes stocks with prices greater than $5. SKEW is the skewness of (daily) market-adjusted returns in each quarter. UDVOL is the log of the ratio of up-day to down-day standard deviation of (daily) market-adjusted returns in each quarter. SXLEV_EW is the average of extrapolated leverage of hedge funds holding the stock at the end of each quarter. DSXLEV_EW refers to Detrended SXLEV_EW, obtained by subtracting SXLEV_EW from its moving average in the prior eight quarters. SXLEV_VW is the value-weighted average of extrapolated leverage of hedge fund holders by each hedge fund's ownership of the stock at the end of each quarter. DSXLEV_VW refers to Detrended SXLEV_VW, obtained by subtracting SXLEV_VW from its moving average in the prior eight quarters. HFHOLD is the fraction of shares outstanding owned by hedge funds at the end of each quarter. IO is the total institutional ownership at the end of each quarter. SIGMA is the standard deviation of daily market-adjusted returns in each quarter. PRET is last quarter's market-adjusted return. LOGCAP is the log of market capitalization measured at the end of each quarter. BM is the ratio of most recent year-end book equity to market capitalization. MOM is the cumulative return in prior 12 months skipping the most recent month. TURN is the turnover rate measured in each quarter. LNCOV is the log of one plus the number of analysts covering the stock at the end of each quarter. LNLIQ is the log of one plus the ratio of total dollar trading volume to the sum of absolute value of daily raw returns in each quarter. Panel A presents summary statistics while Panel B shows the correlation matrix.

Panel A: Summary statistics

	Mean	StDev	P01	P25	P50	P75	P99	Obs
SKEW	0.13	1.37	-4.42	-0.36	0.11	0.63	4.52	168266
UDVOL	0.11	0.67	-1.77	-0.24	0.10	0.46	2.00	168266
SXLEV_EW	2.45	1.08	1.00	1.71	2.26	3.09	5.12	174363
SXLEV_VW	2.65	1.02	1.00	2.01	2.77	3.31	5.01	174363
DSXLEV_EW	0.08	0.79	-2.02	-0.29	0.00	0.41	2.52	164321
DSXLEV_VW	0.09	0.72	-2.15	-0.18	0.01	0.36	2.53	164321
HFHOLD	0.05	0.06	0.00	0.01	0.02	0.06	0.31	174363
SIGMA	0.02	0.02	0.01	0.01	0.02	0.03	0.08	168266
PRET	0.04	0.27	-0.47	-0.09	0.01	0.13	0.91	174235
LOGCAP	6.37	1.89	2.32	5.09	6.30	7.58	11.12	174363
BM	0.70	0.76	0.03	0.30	0.53	0.85	3.73	170331
MOM	0.19	0.57	-0.75	-0.11	0.11	0.37	2.25	173040
TURN	0.49	0.51	0.01	0.14	0.34	0.65	2.54	174363
IO	0.58	0.30	0.01	0.33	0.63	0.82	1.10	169056
LNLIQ	0.52	0.79	0.00	0.01	0.13	0.69	3.38	169946
LNCOV	1.55	1.02	0.00	0.69	1.61	2.40	3.40	171427

Panel B: Correlation matrix

	SKEW	UDVOL	SXLEV_EW	SXLEV_VW	HFHOLD	SIGMA	PRET	LOGCAP	BM	MOM	TURN	IO	LNLIQ	LNCOV
SKEW	1.00													
UDVOL	0.93	1.00												
SXLEV_EW	-0.02	-0.02	1.00											
SXLEV_VW	-0.02	-0.02	0.86	1.00										
HFHOLD	0.03	0.04	-0.12	0.01	1.00									
SIGMA	0.00	0.03	-0.11	-0.11	0.10	1.00								
PRET	-0.03	-0.04	0.00	-0.01	0.02	0.03	1.00							
LOGCAP	-0.02	-0.02	0.23	0.25	0.04	-0.39	0.00	1.00						
BM	0.02	0.02	-0.10	-0.14	-0.05	0.09	0.00	-0.27	1.00					
MOM	0.12	0.12	0.00	-0.02	0.05	0.04	0.47	0.02	-0.06	1.00				
TURN	-0.03	0.00	0.09	0.13	0.31	0.30	0.06	0.31	-0.18	0.10	1.00			
IO	-0.05	-0.04	0.23	0.35	0.35	-0.18	-0.03	0.55	-0.20	-0.04	0.47	1.00		
LNLIQ	-0.03	-0.03	0.09	0.05	0.02	-0.28	0.00	0.86	-0.20	0.01	0.34	0.38	1.00	
LNCOV	-0.06	-0.06	0.22	0.28	0.12	-0.22	-0.06	0.78	-0.30	-0.08	0.45	0.63	0.67	1.00

Table V Pooled regressions of return skewness on stock-level leverage

The sample is from January 2001 to December 2013 and only includes stocks with prices greater than \$5. The dependent variable is $SKEW_{t+1}$, the coefficient of daily return skewness for stock i (the subscript is omitted for simplicity) in quarter $t+1$. SKEW is computed based on market-adjusted returns, beta-adjusted returns, and simple excess returns in columns (1) and (4), (2) and (5), and (3) and (6), respectively. SXLEV is stock-level extrapolated leverage, and $DSXLEV_t$ is detrended SXLEV at the end of quarter t. In columns (1) to (3), $DSXLEV_t$ is calculated by subtracting equal-weighted $SXLEV_t$ from its moving average over the prior eight quarters, while in columns (4) to (6), $DSXLEV_t$ is calculated by subtracting value-weighted $SXLEV_t$ from its moving average over the prior eight quarters. $HFHOLD_t$ is the fraction of shares outstanding owned by hedge funds at the end of quarter t. $LOGCAP_t$ is the log of market capitalization measured at the end of quarter t. BM_t is the ratio of most recent year-end book equity to market capitalization. $SIGMA_t$ is the standard deviation of daily returns in quarter t. $DTURN_t$ is the detrended TURN, obtained by subtracting turnover from moving average over the prior eight quarters. RET_t ... RET_{t-3} are returns in quarters t through $t-3$. $SIGMA_t$ and RET_t are calculated using market-adjusted returns, beta-adjusted returns and excess returns in columns (1) and (4), (2) and (5), and (3) and (6), respectively. All regressions include dummies for each quarter (not shown). Standard errors are double clustered by stock and quarter; t-statistics are reported in parentheses.

	Equal-Weighted SXLEV			Value-Weighted SXLEV		
	Market-adj. returns	Beta-adj. returns	Excess returns	Market-adj. returns	Beta-adj. returns	Excess returns
Dep. Var.: $SKEW_{t+1}$	(1)	(2)	(3)	(4)	(5)	(6)
$SKEW_t$	0.0039	0.0049	0.014	0.0040	0.0050	0.014
	(1.05)	(1.29)	(3.62)	(1.06)	(1.30)	(3.64)
$DSXLEV_t$	-0.018	-0.018	-0.015	-0.015	-0.015	-0.011
	(-2.90)	(-2.85)	(-2.42)	(-2.97)	(-2.94)	(-2.43)
$HFHOLD_t$	0.22	0.21	0.15	0.21	0.20	0.14
	(2.22)	(2.01)	(1.65)	(2.15)	(1.94)	(1.59)
$LOGCAP_t$	-0.026	-0.035	-0.036	-0.026	-0.035	-0.036
	(-5.56)	(-6.31)	(-8.99)	(-5.50)	(-6.25)	(-8.92)
BM_t	0.023	0.025	0.019	0.024	0.025	0.019
	(4.02)	(4.02)	(3.23)	(4.05)	(4.04)	(3.24)
$SIGMA_t$	0.040	-1.62	-1.20	0.034	-1.62	-1.21
	(0.084)	(-2.57)	(-2.49)	(0.070)	(-2.59)	(-2.51)
$DTURN_t$	-0.056	-0.037	-0.030	-0.056	-0.036	-0.030
	(-3.75)	(-2.51)	(-2.43)	(-3.73)	(-2.48)	(-2.41)
RET_t	-0.13	-0.11	-0.12	-0.13	-0.11	-0.12
	(-4.49)	(-3.78)	(-4.78)	(-4.50)	(-3.79)	(-4.78)
RET_{t-1}	-0.047	-0.041	-0.030	-0.047	-0.041	-0.030
	(-2.55)	(-2.28)	(-1.89)	(-2.54)	(-2.27)	(-1.88)
RET_{t-2}	-0.041	-0.035	-0.038	-0.040	-0.035	-0.038
	(-2.09)	(-1.89)	(-2.33)	(-2.08)	(-1.89)	(-2.33)
RET_{t-3}	-0.0032	-0.00049	-0.0052	-0.0030	-0.00028	-0.0051
	(-0.20)	(-0.036)	(-0.35)	(-0.19)	(-0.021)	(-0.35)
Quarter dummy	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	153,358	153,347	153,358	153,358	153,347	153,358
Adj. R^2	0.012	0.011	0.011	0.012	0.011	0.011

Table VI Pooled regressions of return skewness on stock-level leverage: robustness

The sample is from January 2001 to December 2013 and only includes stocks with prices greater than $5. In columns (1) to (3), and (5), the dependent variable is SKEW_{t+1}, skewness of daily market-adjusted returns during quarter $t+1$. In column (4), the dependent variable is UDVOL_{t+1}, the log of the ratio of up-day to down-day standard deviation of (daily) market-adjusted returns in quarter $t+1$. SKEW_t, ..., SKEW_{t-3} are skewness of daily market-adjusted returns in quarters t through $t-3$. SIGMA_t, ..., SIGMA_{t-3} are standard deviation of daily market-adjusted returns in quarters t through $t-3$. DSXLEV_EW_t is calculated by subtracting SXLEV_EW (i.e., equal-weighted stock-level extrapolated leverage) at quarter t from its moving average over the prior eight quarters. HFHOLD_t is the fraction of shares outstanding owned by hedge funds at the end of quarter t. LOGCAP_t is the log of market capitalization measured at the end of quarter t. BM_t is the ratio of most recent year-end book equity to market capitalization. DTURN_t is the detrended TURN, obtained by subtracting turnover from moving average over the prior eight quarters. RET_t ... RET_{t-3} are market-adjusted returns in quarters t through $t-3$. IO_t is the total institutional ownership at the end of quarter t. LNCOV_t is the log of one plus the number of analysts covering the stock at the end of quarter t. LNLIQ_t is the log of one plus the ratio of total dollar trading volume to the sum of absolute value of daily raw returns in quarter t. DSPLEV_EW_t is the equal-weighted stock-level placebo mutual fund leverage detrended by its moving average in the prior eight quarters at quarter t. Placebo mutual fund leverage is calculated using Eq.(3) with each mutual fund's LNNSTK and PORTURN based on its quarterly holding reports. All regressions include dummies for each quarter (not shown). Standard errors are double clustered by stock and quarter; corresponding t-statistics are reported in parentheses.

	More controls	Interact DSXLEV with HFHOLD	More lags of past SIGMA and SKEW	Using UDVOL	Placebo leverage
	(1)	(2)	(3)	(4)	(5)
SKEW_t	0.0027	0.0038	0.0041	0.017	0.0034
(UDVOL_t in col. (4))	(0.71)	(1.02)	(1.11)	(4.50)	(0.85)
SKEW_{t-1}			0.017		
			(4.31)		
SKEW_{t-2}			0.010		
			(3.00)		
SKEW_{t-3}			0.0058		
			(1.38)		
DSXLEV_EW_t	-0.018	-0.0048	-0.017	-0.0080	0.083
(DSPLEV_EW_t in col. (5))	(-2.97)	(-0.75)	(-2.75)	(-2.49)	(3.19)
HFHOLD_t	0.43	0.24	0.25	0.21	-0.18
(MFHOLD_t in col. (5))	(4.10)	(2.38)	(2.63)	(3.72)	(-3.97)
DSXLEV_EW_t*HFHOLD_t		-0.57			
		(-3.63)			
LOGCAP_t	-0.0041	-0.027	-0.028	-0.0091	-0.018
	(-0.49)	(-5.69)	(-6.17)	(-3.40)	(-4.13)
BM_t	0.017	0.023	0.023	0.0073	0.026
	(2.93)	(4.01)	(4.11)	(2.35)	(4.14)
SIGMA_t	0.36	0.054	1.25	1.32	-0.00
	(0.78)	(0.11)	(2.26)	(4.10)	(-0.00)
SIGMA_{t-1}			-0.89		
			(-1.54)		
SIGMA_{t-2}			-0.21		
			(-0.47)		
SIGMA_{t-3}			-0.89		
			(-1.92)		
DTURN_t	-0.059	-0.059	-0.068	-0.027	-0.043
	(-3.64)	(-3.91)	(-4.49)	(-3.16)	(-2.72)
RET_t	-0.14	-0.13	-0.12	-0.12	-0.14
	(-4.62)	(-4.50)	(-4.27)	(-5.97)	(-4.23)
RET_{t-1}	-0.057	-0.046	-0.066	-0.029	-0.050
	(-3.01)	(-2.51)	(-2.62)	(-2.17)	(-2.48)
RET_{t-2}	-0.049	-0.040	-0.048	-0.021	-0.044
	(-2.43)	(-2.06)	(-2.37)	(-1.90)	(-2.08)
RET_{t-3}	-0.0097	-0.0020	-0.0038	0.0048	-0.000
	(-0.59)	(-0.13)	(-0.22)	(0.52)	(-0.001)
IO_t	-0.088				
	(-3.34)				
LNLIQ_t	0.0035				
	(0.22)				
LNCOV_t	-0.037				
	(-5.10)				
Quarter dummy	Yes	Yes	Yes	Yes	Yes
Obs.	153,358	153,358	153,349	153,358	143,484
Adj. R^2	0.012	0.012	0.012	0.021	0.012

Table VII Time-series regressions of market return skewness on hedge fund leverage

The sample is from 2001 to 2013 in columns (1) and (2), and from 1996 to 2013 in columns (3) and (4). The dependent variable is MKTSKEW_{t+1}, skewness of (daily) market returns in excess of risk-free rate in quarter $t+1$, where the market is defined as the value-weighted portfolio of all NYSE/AMEX/NASDAQ stocks. Agg.DSXLEV_EW_t is the value-weighted average of all stocks' $\text{DSXLEV\_EW}_{i,t}$, as defined in Table IV. HFHOLD_t is the change of the value-weighted average of all stocks' hedge fund ownership during quarter t. MKTSIGMA_t is the standard deviation of (daily) excess market returns in quarter t. MKTRET_t, ..., MKTRET_{t-3} are excess market returns in quarters t through $t-3$. BM_t and DTURN_t are the value-weighted average of all stocks' book-to-market ratio and detrended turnover, respectively, at the end of quarter t. Newey-West t-statistics with lags of order 4 are reported in parentheses.

	2001-2013		1996-2013	
Dep. Var.: MKTSKEW_{t+1}	(1)	(2)	(3)	(4)
MKTSKEW_t	0.24	0.14	0.19	0.089
	(2.53)	(1.08)	(2.25)	(0.95)
Agg.DSXLEV_EW_t	-0.79	-0.99	-0.99	-0.85
	(-1.66)	(-1.45)	(-2.98)	(-2.19)
HFHOLD_t		-16.7		-23.9
		(-0.40)		(-0.85)
BM_t		-2.84		-0.53
		(-3.75)		(-1.61)
MKTSIGMA_t		24.0		-7.06
		(1.33)		(-0.54)
DTURN_t		-1.42		-0.83
		(-1.96)		(-1.40)
MKTRET_t		-0.72		-1.51
		(-1.05)		(-2.86)
MKTRET_{t-1}		0.49		-1.18
		(0.63)		(-1.61)
MKTRET_{t-2}		0.58		-0.033
		(0.85)		(-0.075)
MKTRET_{t-3}		0.63		-0.094
		(1.05)		(-0.20)
Adj. R^2	0.05	0.14	0.14	0.14
Obs.	52	52	72	72

Table VIII Regressions of sensitivity of returns to unexpected earnings on leverage

The sample is from January 2001 to December 2012 and only includes stocks with prices greater than \$5 and which have analyst forecast records in IBES. The dependent variable in columns (1) to (4) is CAR$[-1,+1]_{t+1}$, cumulative abnormal return (%) over trading days -1 to +1 relative to earnings release in quarter $t+1$ for stock i (the subscript is omitted), and in columns (5) to (8) is CAR$[+2,+126]_{t+1}$, cumulative abnormal return (%) from trading days +2 to +126 relative to earnings release in quarter $t+1$. UELO$_{t+1}$ is a dummy variable which equals one if the stock's unexpected earnings for quarter $t+1$ is in the bottom tertile of the sample distribution in the quarter. SXLEV_EW$_t$ (equal-weighted stock-level extrapolated leverage) and SXLEV_VW$_t$ (value-weighted stock-level extrapolated leverage) are independent variables in the regressions in Panels A and B, respectively. All regressions control for HFHOLD$_t$ (hedge fund ownership), IO$_t$ (institutional ownership), LOGCAP$_t$ (size), BM$_t$ (book-to-market ratio), MOM$_t$ (momentum), SIGMA$_t$ (standard deviation of returns), TURN$_t$ (turnover), LNLIQ$_t$ (liquidity ratio) and LNCOV$_t$ (analyst coverage). All variables are defined as in Table IV. In columns (3), (4), (7), and (8), interactions of UELO$_{t+1}$ and all the controls are included (not shown). Quarter dummies are added into columns (1) to (3) and (5) to (7), while columns (4) and (8) have quarter times industry fixed effects (not shown). Standard errors are clustered by stock; t-statistics are reported in parentheses.

Panel A: Equal-weighted stock-level leverage

	CAR$[-1, +1]_{t+1}$				CAR$[+2, +126]_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UELO$_{t+1}$	-2.96	-1.14			-1.31	-4.05		
	(-46.7)	(-5.31)			(-6.73)	(-5.03)		
SXLEV_EW$_t$	-0.037	0.16	0.18	0.19	-0.059	-0.36	-0.31	-0.25
	(-0.98)	(3.95)	(4.37)	(4.55)	(-0.39)	(-2.22)	(-1.87)	(-1.62)
UELO$_{t+1}$ $*$ SXLEV_EW$_t$		-0.63	-0.63	-0.64		0.95	0.90	0.72
		(-8.61)	(-8.35)	(-8.63)		(3.61)	(3.29)	(2.76)
HFHOLD$_t$	1.72	1.69	2.03	2.20	6.48	6.54	5.56	3.47
	(3.32)	(3.25)	(3.25)	(3.62)	(2.97)	(2.99)	(2.25)	(1.44)
UELO$_{t+1}$ $*$ HFHOLD$_t$			-0.75	-0.75			3.13	3.29
			(-0.73)	(-0.74)			(0.82)	(0.90)
Quarter dummy	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Quarter*Industry dummy	No	No	No	Yes	No	No	No	Yes
Interactions of controls with UELO	No	No	Yes	Yes	No	No	Yes	Yes
Obs.	105,164	105,164	101,661	101,661	105,176	105,176	101,673	101,673
Adj. R^2	0.033	0.034	0.038	0.035	0.012	0.012	0.013	0.005

Panel B: Value-weighted stock-level leverage

	CAR$[-1, +1]_{t+1}$				CAR$[+2, +126]_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UELO$_{t+1}$	-2.96	-2.33			-1.31	-2.43		
	(-46.7)	(-13.7)			(-6.75)	(-4.02)		
SXLEV_VW$_t$	-0.013	0.062	0.091	0.099	-0.16	-0.29	-0.28	-0.22
	(-0.46)	(1.94)	(2.85)	(3.15)	(-1.40)	(-2.35)	(-2.20)	(-1.82)
UELO$_{t+1}$ $*$ SXLEV_VW$_t$		-0.24	-0.31	-0.32		0.43	0.43	0.34
		(-3.96)	(-4.99)	(-5.14)		(2.04)	(1.97)	(1.61)
HFHOLD$_t$	1.75	1.70	2.18	2.37	5.83	5.92	4.70	2.83
	(3.25)	(3.16)	(3.39)	(3.80)	(2.59)	(2.63)	(1.86)	(1.14)
UELO$_{t+1}$ $*$ HFHOLD$_t$			-1.09	-1.09			3.59	3.63
			(-1.02)	(-1.04)			(0.92)	(0.97)
Quarter dummy	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Quarter*Industry dummy	No	No	No	Yes	No	No	No	Yes
Interactions of controls with UELO	No	No	Yes	Yes	No	No	Yes	Yes
Obs.	105,164	105,164	101,661	101,661	105,176	105,176	101,673	101,673
Adj. R^2	0.033	0.033	0.038	0.035	0.012	0.012	0.013	0.005

Table IX Time-series regressions of hedge fund leverage on investment bank CDS

The sample is from September 2001 to December 2013. The dependent variable is ΔHFXLEV_t, the change of average hedge fund extrapolated leverage over quarter t. ΔIBCDS_t is the log change of investment bank CDS index over quarter t. MKTSIGMA_t is the standard deviation of (daily) excess market returns in quarter t. MKTRET_t is the market excess returns in quarter t. RF_t is the risk-free rate over quarter t. Newey-West t-statistics with lags of order 4 are reported in parentheses.

	ΔHFXLEV_t	
	(1)	(2)
ΔIBCDS_t	-0.014	-0.0100
	(-3.22)	(-1.89)
MKTRET_t		0.066
		(1.24)
RF_t		0.24
		(0.42)
MKTSIGMA_t		0.44
		(0.89)
Adj. R^2	0.116	0.149
# of qrts	49	49

Table X Regressions of sensitivity of stocks returns to IBCDS shocks on leverage

The sample is from September 2001 to December 2013 and only includes stocks with prices greater than \$5. The dependent variable in columns (1) to (3) is $\text{CAR}[0]_{i,t+1}$, the cumulative abnormal return (%) during the week $t+1$ for stock i, and in columns (4) to (6) is $\text{CAR}[1,4]_{i,t+1}$, the cumulative abnormal return (%) from week +1 to +4 relative to week $t+1$. IBCDS_HI_{t+1} equals one if the investment bank CDS index increases by more than 20% during week $t+1$ and zero otherwise. SXLEV_EW_t (equal-weighted stock-level extrapolated leverage) and SXLEV_VW_t (value-weighted stock-level extrapolated leverage) are independent variables in the regressions in Panels A and B, respectively. All regressions control for HFHOLD_t (hedge fund ownership), IO_t (institutional ownership), LOGCAP_t (size), BM_t (book-to-market ratio), MOM_t (momentum), SIGMA_t (standard deviation of returns), TURN_t (turnover), LNLIQ_t (liquidity ratio) and LNCOV_t (analyst coverage). All variables are defined as in Table IV. Columns (3) and (6) include interactions of IBCDS_HI_{t+1} and all the controls (not shown). Standard errors are clustered by week; t-statistics are reported in parentheses.

Panel A: Equal-weighted stock-level leverage

	$\text{CAR}[0]_{i,t+1}$			$\text{CAR}[+1, +4]_{i,t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
IBCDS_HI_{t+1}	0.023	0.90	3.31	0.034	-0.59	-2.20
	(1.85)	(3.12)	(3.35)	(1.46)	(-1.19)	(-1.50)
$\text{SXLEV\_EW}_{i,t}$	-0.0099	0.0048	-0.0050	-0.019	-0.030	-0.029
	(-1.16)	(0.52)	(-0.59)	(-1.21)	(-1.71)	(-1.84)
$\text{IBCDS\_HI}_{t+1} * \text{SXLEV\_EW}_{i,t}$		-0.31	-0.15		0.22	0.20
		(-2.98)	(-2.42)		(1.28)	(2.07)
$\text{HFHOLD}_{i,t}$	0.27	0.26	0.28	0.93	0.94	1.27
	(1.67)	(1.62)	(1.76)	(2.87)	(2.89)	(4.08)
$\text{IBCDS\_HI}_{t+1} * \text{HFHOLD}_{i,t}$			-0.22			-5.79
			(-0.23)			(-2.97)
Interactions of controls with IBCDS_HI	No	No	Yes	No	No	Yes
Obs	1,953,458	1,953,458	1,953,458	1,953,458	1,953,458	1,953,458
Adj. R^2	0.000	0.001	0.001	0.000	0.000	0.000

Panel B: Value-weighted stock-level leverage

	$\text{CAR}[0]_{i,t+1}$			$\text{CAR}[+1, +4]_{i,t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
IBCDS_HI_{t+1}	0.023	0.45	3.23	0.035	-0.55	-2.12
	(1.82)	(2.39)	(3.34)	(1.47)	(-2.13)	(-1.49)
$\text{SXLEV\_VW}_{i,t}$	-0.0059	0.0025	-0.0033	-0.018	-0.030	-0.025
	(-0.87)	(0.35)	(-0.49)	(-1.37)	(-2.10)	(-1.87)
$\text{IBCDS\_HI}_{t+1} * \text{SXLEV\_VW}_{i,t}$		-0.16	-0.086		0.22	0.13
		(-2.20)	(-1.99)		(2.31)	(2.15)
$\text{HFHOLD}_{i,t}$	0.26	0.25	0.27	0.89	0.89	1.22
	(1.62)	(1.61)	(1.74)	(2.78)	(2.80)	(3.94)
$\text{IBCDS\_HI}_{t+1} * \text{HFHOLD}_{i,t}$			-0.33			-5.59
			(-0.34)			(-2.87)
Interactions of controls with IBCDS_HI	No	No	Yes	No	No	Yes
Obs.	1,953,458	1,953,458	1,953,458	1,953,458	1,953,458	1,953,458
Adj. R^2	0.000	0.001	0.001	0.000	0.000	0.000

Figure 1. Total assets and leverage of hedge funds

The figure plots the log change of annual total assets (y-axis) to the log change of annual leverage (x-axis) with a linear fitted line, for all reporting hedge funds in Sample A from 2011 to 2013.

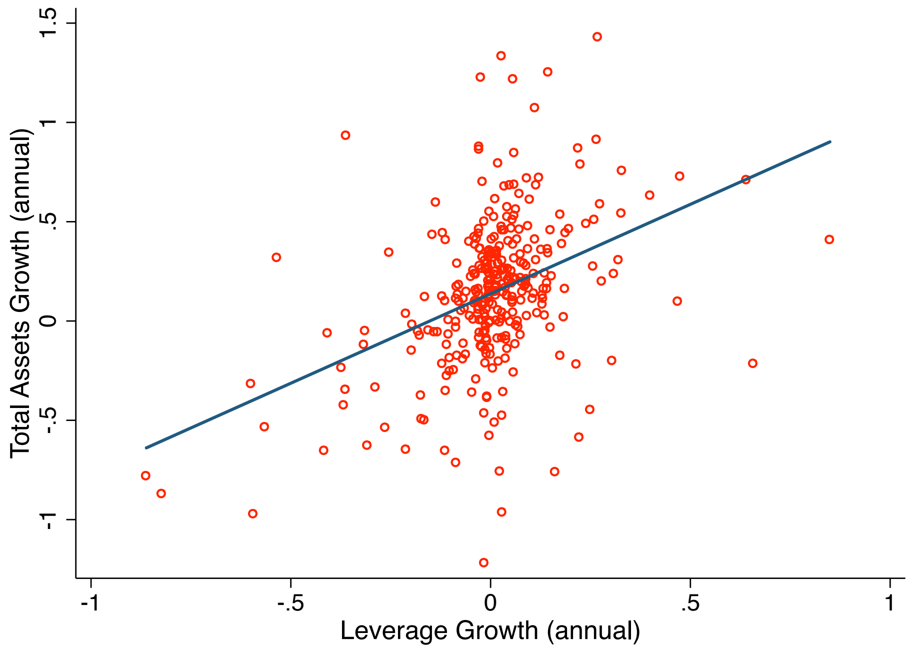
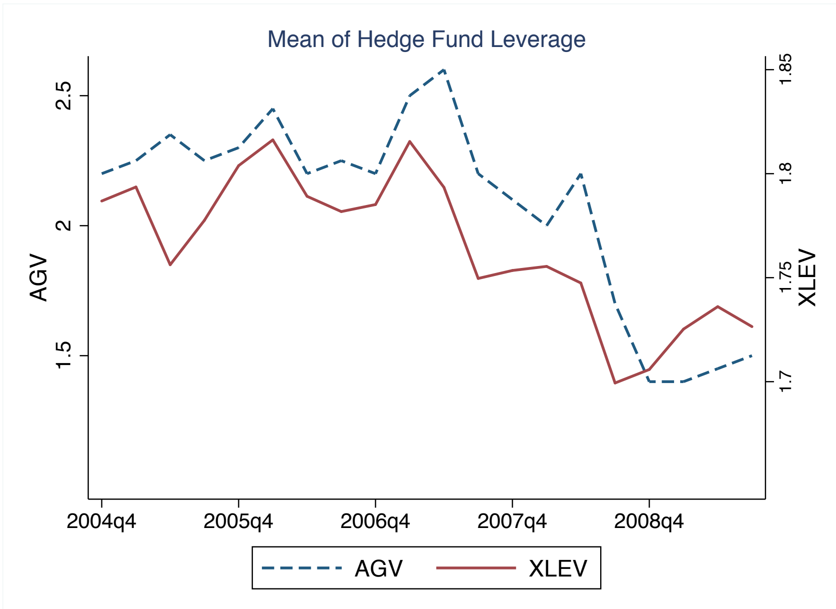


Figure 2. Time series of actual and extrapolated hedge fund leverage

The top figure plots the time trend of average hedge fund leverage reported in AGV (2011) (labeled as AGV for the left y-axis) and the average of extrapolated leverage (labeled as XLEV for the right y-axis) from 2004Q4 to 2009Q3. The bottom figure plots the time trend of interquartile of both variables.



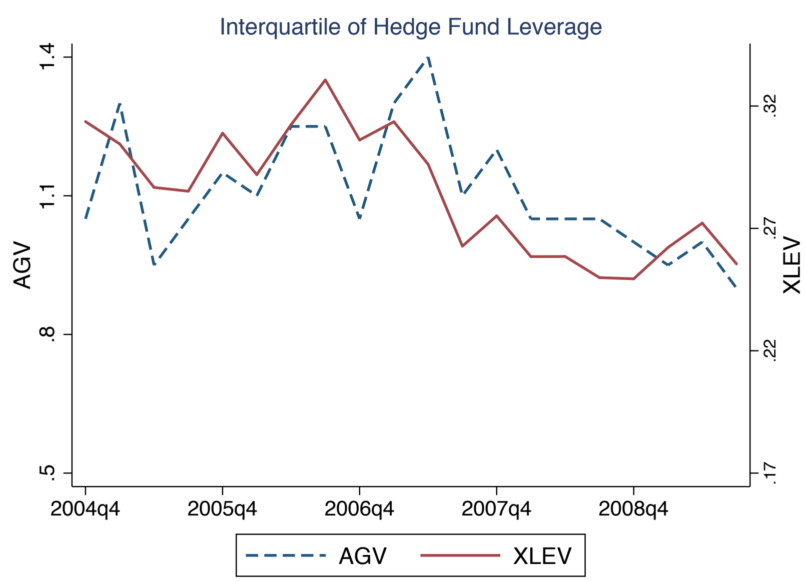


Figure 3. Sensitivity of returns to unexpected earnings: high *vs* low SXLEV

This figure plots cumulative abnormal returns (CAR, in percent) for stocks with extremely negative unexpected earnings (i.e., UELO=1) from event day -5 to 30. UELO is a dummy variable which equals one if a stock's unexpected earnings for the quarter is in the bottom tertile of the sample distribution in that quarter. LO SXLEV (HI SXLEV) refers to stocks with SXLEV_EW lower (higher) than the median of the sample distribution at the beginning of the quarter of the event. SXLEV_EW is the equal-weighted average of extrapolated leverage of hedge funds holding the stock. The sample is from January 2001 to December 2012.

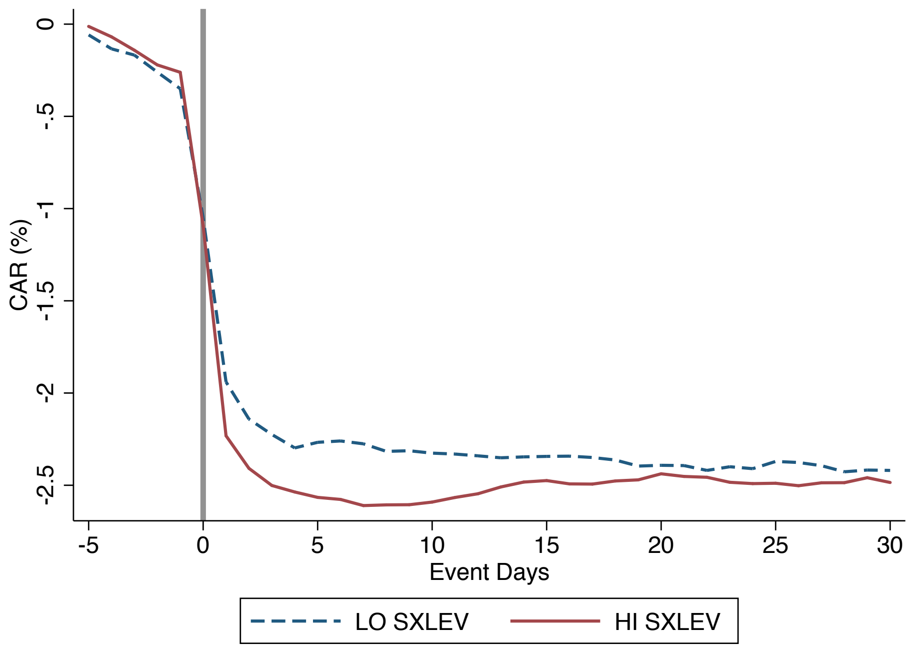


Figure 4. Time series of the investment bank CDS index

The figure plots the (weekly) time series of the investment bank CDS index (denoted as IBCDS) from September 2001 to December 2013. The red bar corresponds to the weeks in which IBCDS increases by more than 20% (i.e., IBCDS_HI=1).

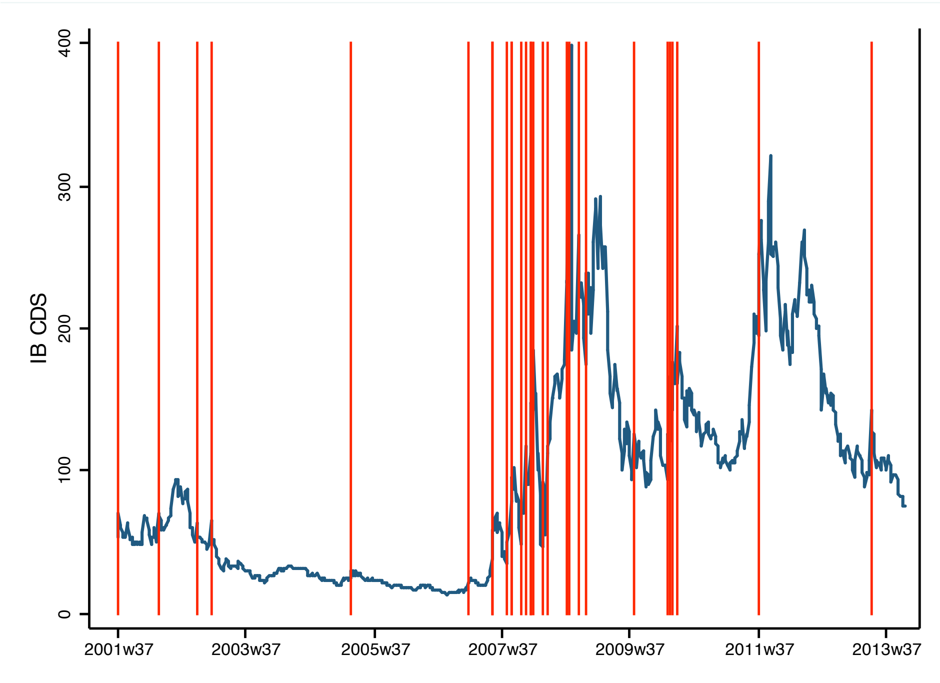


Figure 5. Sensitivity of returns to IBCDS shocks: high *vs* low SXLEV

This figure plots Abnormal CARs (in percent) of stocks from event week -5 to +5. Event weeks are defined as those in which the investment bank CDS index increases by more than 20% (i.e., IBCDS_HI=1). Abnormal CAR equals the CAR during the event week minus the average CAR during non-event weeks. LO SXLEV (HI SXLEV) refers to stocks with SXLEV_EW lower (higher) than the median of the sample distribution at the beginning of the week. SXLEV_EW is the equal-weighted average of extrapolated leverage of hedge funds holding the stock. The sample is from September 2001 to December 2013.