JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 46, No. 4, Aug. 2011, pp. 1073–1106

doi:10.1017/S0022109011000238

Derivatives Use and Risk Taking: Evidence from the Hedge Fund Industry

Yong Chen*

Abstract

This paper examines the use of derivatives and its relation with risk taking in the hedge fund industry. In a large sample of hedge funds, 71% of the funds trade derivatives. After controlling for fund strategies and characteristics, derivatives users on average exhibit lower fund risks (e.g., market risk, downside risk, and event risk), such risk reduction is especially pronounced for directional-style funds. Further, derivatives users engage less in risk shifting and are less likely to liquidate in a poor market state. However, the flow-performance relation suggests that investors do not differentiate derivatives users when making investing decisions.

I. Introduction

Hedge funds have experienced explosive growth both in assets under management (AUM) and in the number of funds in the past 2 decades. Because the majority of hedge funds, as part of their highly flexible investment strategies, trade derivative securities, the use of derivatives has become of great concern to fund investors and regulators (e.g., Geithner (2006)). On the one hand, given strikingly adverse consequences of derivatives trading often reported in popular press, fund

*Chen, yong.chen@vt.edu, Pamplin College of Business, Virginia Tech, 1016 Pamplin Hall, Blacksburg, VA 24061. This paper is based on chapter 1 of my doctoral dissertation at Boston College. I am grateful to my advisor Wayne Ferson and dissertation committee members David Chapman, Richard Evans, and Jeffrey Pontiff for invaluable guidance and encouragement. I thank an anonymous referee and Stephen Brown (the editor) for constructive feedback. This paper has benefited from helpful comments by George Aragon, Suleyman Basak, Nick Bollen, Mike Cliff, Mila Getmansky, Will Goetzmann (WFA discussant), Cliff Holderness, Edie Hotchkiss, Ed Kane, Runeet Kishore, Bing Liang, Alan Marcus, Narayan Naik, Tom Nohel, Jun Qian, Richard Roll, Vijay Singal, Phil Strahan, Melvin Teo, and seminar/conference participants at Baruch College, Boston College, Federal Reserve Bank of New York, London Business School (LBS) BNP Paribas Hedge Fund Centre, Loyola University Chicago, Nanyang Technological University, National University of Singapore, Singapore Management University, University of Hong Kong, University of Massachusetts at Amherst, Virginia Tech, Wayne State University, the 6th Annual LBS Transatlantic Doctoral Conference, the 2006 Financial Management Association Doctoral Consortium, the 2007 Swiss Finance Institute Conference on Portfolio Management and Derivatives, the 2008 Financial Intermediation Research Society Conference, the 2008 European Finance Association meetings, and the 2008 Western Finance Association meetings. All remaining errors are mine.

investors are worried about incurring substantial losses from trading derivative securities.[1] On the other hand, derivatives can be used to hedge portfolio risk and better exploit superior information. Despite the well-known pervasive use of derivatives by hedge funds, however, little is known about its effects on fund risks and performance. Some important questions therefore arise: How do derivatives users differ from nonusers with respect to fund risks and performance? Do hedge funds that use derivatives demonstrate a greater propensity for risk shifting? Are derivatives-using funds more likely to fail? Such questions, and their answers, are of great importance to investors, lenders, and regulators. This paper provides the first academic attempt to examine the use of derivatives in the hedge fund industry.

Due to their exemption from the Investment Company Act of 1940, hedge funds employ dynamic trading strategies that differ dramatically from the strategies used by mutual funds. Derivative contracts represent a substantial portion of hedge fund strategies, which may be related to managing risk and/or enhancing performance. Depending on the purpose (hedging or speculation), the use of derivatives may be associated with lower or higher fund risk. Brown, Goetzmann, and Park (2001) argue that hedge fund managers' career and reputation concerns can offset their risk-taking incentives. Thus, managers with career concerns or reputation costs would intend to reduce fund risk especially in down markets, which motivates using derivatives to manage fund risk. Recently, Ingersoll, Spiegel, Goetzmann, and Welch (2007) showed that derivative instruments can also be used to manipulate portfolio performance measures such as the Sharpe (1966) ratio. Finally, given the cross-sectional variation in various fund characteristics, the hedge fund industry provides an ideal laboratory for examining the relation between the use of derivatives and fund risk-taking behavior.

From a sample of over 5,000 hedge funds during the period of 1994–2006, 71% of the funds trade derivatives with considerable variation both within and across fund categories. The pervasive use of derivatives in hedge funds stands in sharp contrast to mutual funds, since Koski and Pontiff (1999) document that only 21% of mutual funds in their sample use derivative securities.[2] After controlling for fund investment strategies, derivatives are more likely to be used by funds that require higher minimum investment, charge higher fees, have a shorter capital lockup period, and employ an effective auditing service.

[1]Anecdotal evidence, such as the bankruptcy of Orange County, CA, in 1994, the collapse of Barings Bank in 1995, the failure of the hedge fund Amaranth in 2006, and the huge losses of Société Générale in 2008, suggests that the use of derivatives can sometimes be very costly to investors. Moreover, the popular press attributes the debacle of Long-Term Capital Management (LTCM) partially to excessive leverage from its derivative positions. Even Warren Buffett once commented that "derivatives are financial weapons of mass destruction, carrying dangers that, while now latent, are potentially lethal" (*Fortune*, March 3, 2003).

[2]Deli and Varma (2002), using information from investment companies' N-SAR forms, find that nearly ⅔ of mutual funds are allowed to invest in derivatives. This suggests that many mutual funds, even when permitted to, do not actually use derivatives. Almazan, Brown, Carlson, and Chapman (2004) confirm that only a small portion of the mutual funds that are permitted to trade derivatives actually use them.

This paper assesses the link between derivatives use and risk taking by examining 3 essential aspects of hedge fund risk profiles. First, I compare several risk measures between derivatives users and nonusers. Risk-management-motivated use of derivatives should be associated with lower risk. But if derivatives are mainly traded by funds with better information, they can enhance fund performance through leverage and transaction-cost savings. In the sample, derivatives use in hedge funds is *on average* associated with a lower level of fund risks (e.g., return volatility, market risk, downside risk, and extreme event risk). The negative relation between derivatives use and fund risks is both economically and statistically significant for most of the risk measures. For example, from a regression model that controls various fund characteristics and investment strategies, the derivatives-use dummy variable is associated with a reduction of market beta by –0.053, indicating that derivatives users on average have market risk about 27% lower than an average hedge fund whose market beta is 0.20. More strikingly, derivatives users on average bear downside and event risks over 80% lower than nonusers. Such evidence is robust to correcting data biases (e.g., survivorship bias and backfilling bias), to controlling fund characteristics, to using both net-of-fee and pre-fee fund returns, to examining a subperiod, and to applying 2-stage least squares (2SLS) regressions with fund managers' prior expertise in derivatives trading as an instrumental variable.

When looking into different fund styles, I find that the negative link between derivatives use and fund risks is especially pronounced for directional-style hedge funds as opposed to relative-value-style or event-driven-style funds. Also, the difference in fund risks between derivatives users and nonusers is more substantial for market-related systematic risk than for idiosyncratic risk.

Meanwhile, fund performance based on net-of-fee returns is not significantly different between derivatives users and nonusers. I also check the manipulation-proof performance measure (MPPM) proposed by Ingersoll et al. (2007), and I do not find an apparent pattern that hedge funds use derivatives to manipulate performance measures. However, there is some evidence that derivatives users realize higher pre-fee manipulation-proof performance, but the funds seem to keep superior profits through charging higher fees instead of distributing them to investors.

Second, this paper investigates whether derivatives users exhibit a different propensity to shift fund risks. Most hedge funds charge investors with performance-based fees (incentive fees), and thus fund managers receive convex payoffs relative to fund returns. Such convex compensation resembles a call option and may induce fund managers to shift fund risks upward when the option is out of the money. Because of leverage effect and low transaction costs, derivatives may provide a more powerful way to shift fund risks than rebalancing portfolios. On the other hand, if derivatives are used to manage and stabilize fund risk, possibly due to career concerns, derivatives users will be less involved in risk shifting. Consistent with Brown et al. (2001), this study documents the existence of the risk-shifting practice in hedge funds, that is, changes in fund risks are negatively related to past performance. However, derivatives users engage less in risk shifting than do funds that do not use derivatives. For instance, the derivatives-use dummy variable is associated with about a 50% lower level of shifting funds' total volatility risk. Moreover, despite clear evidence of risk shifting among nonusers, derivatives users do not show any pattern of shifting market risk relative to their high-water benchmarks.

Third, this paper addresses the question: Do derivatives users bear higher failure risk? Though trading derivatives almost certainly contributed to the failure of LTCM and Amaranth, it is unclear whether this is the common case in the hedge fund industry. In this paper the results from a hazard model show that, although using derivatives does not help prevent fund failure when fund performance is particularly low, it mitigates the unfavorable influence of severe market conditions on fund operation. This finding echoes the evidence that derivatives use in hedge funds is mainly associated with lower systematic risk and especially with lower downside/event risk, and possibly reflects fund managers' risk-management efforts due to career concerns and reputation costs.

This paper also tests whether investors treat derivatives-using funds differently by comparing the fund flow-performance relation between derivatives users and nonusers. In general, annual net fund flows are positively related to last year's fund performance, indicating that investors chase past fund performance. In accordance with Goetzmann, Ingersoll, and Ross (2003), the fund flow-performance relation tends to be concave. However, investors in derivatives-using funds do not appear to respond differently to fund performance. One explanation is that investors, who receive similar net-of-fee performance, are indifferent to whether or not the fund uses derivatives. Another possible explanation is that investors are not aware of the difference in risk taking between derivatives users and nonusers, or at least do not deem hedge funds' derivatives use to be particularly perilous to their investments.

This paper contributes to the literature in several aspects. First, it examines how derivatives, as an important component of hedge funds' dynamic trading strategies, are actually used by the funds through studying the effects of derivatives trading on various fund risk profiles as well as the risk-shifting practice. Overall, the findings do not suggest that derivatives use in hedge funds leads to higher fund risk. Second, the findings shed new light on how derivatives are used by professional fund managers. Koski and Pontiff (1999) find no difference in risk and returns between mutual funds that use derivatives and those that do not. Deli and Varma (2002) document that mutual funds invest in derivatives mainly to reduce transaction costs. Almazan et al. (2004) relate mutual fund constraints on derivatives use and short sales to fund monitoring systems. The present study complements the existing evidence on derivatives use in fund management by examining the association of derivatives use with hedge fund risk taking. Moreover, this paper presents the association of various fund characteristics, such as fund fees, redemption policy, and auditing service, with the decision to use derivatives, which may be related to fund managerial incentives. Therefore, the paper's findings should have important implications for hedge fund investors, lenders, and financial regulators.

The rest of this paper proceeds as follows. Section II describes the data. Sections III, IV, and V present empirical results about the relations between derivatives use and fund risk/performance profiles, the risk-shifting practice, and fund failure risk, respectively. Section VI tests the difference in the flow-performance relation between derivatives users and nonusers. Section VII concludes.

II. The Data

This section begins by describing the data on derivatives use in hedge funds, then moves on to summarize various fund characteristics, and finally shows the relation between fund characteristics and derivatives use.

A. Derivatives Use of Hedge Funds

The hedge fund data used in this paper are from the Lipper TASS database, one of the most comprehensive hedge fund databases. The TASS database has been employed in the hedge fund literature such as in Fung and Hsieh (1997), Liang (2000), Brown et al. (2001), Getmansky, Lo, and Makarov (2004), and Agarwal, Daniel, and Naik (2009). As of June 2006, TASS contained information about 6,241 individual hedge funds, of which 3,791 are live funds while 2,450 are defunct (graveyard) funds. Based on investment strategies, hedge funds are classified into 10 categories: convertible arbitrage, dedicated short bias, event driven, emerging markets, equity market neutral, fixed income arbitrage, funds of funds, global macro, long-short equity, and multistrategy.[3]

Table 1 presents summary statistics of hedge funds' derivatives use. For 5,551 individual funds, TASS provides information about whether each fund uses derivative instruments and, if any, what types of derivatives are used.[4] This table reports derivatives use for various fund categories as well as for the overall sample.[5] About 71% of the funds invest in at least one type of derivative in equity, fixed income, currency, and/or commodity securities. This finding stands in sharp contrast to the documented low level of derivatives use in mutual funds. Koski and Pontiff (1999) find that only 21% of mutual funds in their sample use derivatives. Almazan et al. (2004) report a similar finding from a broader sample of mutual funds. The pervasive use of derivatives by hedge funds is also consistent with

[3]This study does not include managed futures funds because, by nature, almost all such funds trade derivatives, and thus the data on derivatives use for this category lack variation across funds. An earlier version of this paper included managed futures and obtained the same inferences.

[4]The information on derivatives use is voluntarily reported by hedge funds to TASS with no obligation. To verify the reliability of the data, I conduct 2 manual checks of the TASS derivatives-use information with the 13F filings and the TASS "Notes" file. First, the TASS derivatives-use information is compared with the 13F filings data. I thank George Aragon and Spencer Martin for generously sharing some of their 13F filings data on derivatives use, detailed in Aragon and Martin (2009), for this analysis. Specifically, Aragon and Martin obtain a subsample of 535 hedge funds by merging their hedge fund sample based on the 13F filings with the TASS database. Then, the TASS derivatives-use information is compared with the 13F option-use information. The majority of funds labeled as option users in 13F also appear as derivatives users in TASS. Second, I randomly select about 1,000 hedge funds from the sample and compare their derivatives-use information with the supplemental "Notes.txt" file. The "Notes" file in TASS contains a qualitative description of each fund's investment strategies. The information on derivatives use from these 2 sources is highly consistent. That is, the funds that are described as trading derivatives in the "Notes" file also claim to use derivatives to the TASS database.

[5]For funds of funds, their returns get involved with derivatives when they invest in individual hedge funds that hold derivative positions. Moreover, they sometimes trade derivatives directly to manage portfolio risk when the underlying funds cannot achieve the risk goal of the funds of funds.

TABLE 1

Distribution of Derivatives Use

Table 1 presents the distribution of derivatives use among the sample hedge funds by reporting the percentage of hedge funds that use derivatives across various fund categories. The sample is from the TASS hedge fund database as of June 2006. *N* is the number of funds, and FW, FU, OP, and SW denote forwards, futures, option, and swap contracts, respectively. "Total" reports the percentage of hedge funds that use at least one type of derivative in equity, fixed income, currency, and/or commodity securities.

		Equity			Fixed Income					Currency					Commodity				
Category	*N*	FU	OP	All	FW	FU	OP	SW	All	FW	FU	OP	SW	All	FW	FU	OP	All	Total
Convertible arbitrage	181	22.7	51.4	53.6	10.5	25.4	31.5	29.3	47.0	20.4	11.6	9.9	7.2	26.5	0.0	1.1	1.7	2.2	72.4
Dedicated short bias	36	22.2	50.0	55.6	0.0	0.0	0.0	5.6	5.6	5.6	0.0	0.0	0.0	5.6	0.0	2.8	2.8	2.8	61.1
Event driven	487	13.1	55.4	56.9	5.5	5.3	12.5	11.7	20.3	20.3	3.9	2.7	1.8	22.8	2.1	2.1	3.1	4.1	67.8
Emerging market	359	25.6	34.5	39.6	19.8	14.8	26.7	18.1	35.9	33.2	11.4	16.4	10.9	37.6	1.4	3.9	5.3	6.4	62.7
Equity market neutral	370	26.5	38.1	48.9	4.3	4.6	5.1	3.0	7.3	12.7	5.4	4.9	3.5	15.4	1.1	2.7	2.4	3.8	53.0
Fixed income arbitrage	290	5.5	8.3	9.0	47.2	59.7	54.5	61.4	79.3	25.2	17.9	19.0	12.1	30.3	0.0	2.1	0.3	2.1	83.8
Fund of funds	1,277	48.2	53.3	60.2	30.9	40.0	39.2	30.6	45.3	33.6	33.7	30.0	19.5	39.6	22.0	31.3	26.9	31.8	69.7
Global macro	326	47.2	34.1	50.9	31.0	53.7	41.4	29.5	61.0	70.3	50.6	54.6	21.5	85.3	12.9	42.3	23.9	43.9	92.6
Long/short equity	2,011	33.6	57.7	66.5	2.1	5.0	5.7	1.8	8.3	14.3	6.4	4.6	2.4	18.1	1.0	3.3	2.7	4.1	69.9
Multistrategy	214	40.7	63.1	68.2	17.8	34.1	32.7	24.3	45.3	25.2	25.2	23.8	12.2	37.4	4.2	14.0	12.6	16.4	80.8
Overall	5,551	33.4	49.7	57.0	15.3	21.2	21.8	17.0	29.1	24.8	16.8	15.6	9.0	30.1	6.7	12.2	9.9	13.2	70.6
Live funds	3,297	33.6	49.2	56.5	15.6	21.7	21.5	18.5	29.2	24.9	16.9	15.2	9.5	29.9	7.6	12.7	10.2	14.0	69.3
Defunct funds	2,254	33.0	50.3	57.7	14.8	20.4	22.3	14.8	28.9	24.6	16.6	16.2	8.3	30.3	5.4	11.6	9.6	12.1	72.5

Agarwal and Naik (2004), who find that hedge funds exhibit exposure to factors built on option returns on the Standard & Poor's (S&P) 500 index.[6]

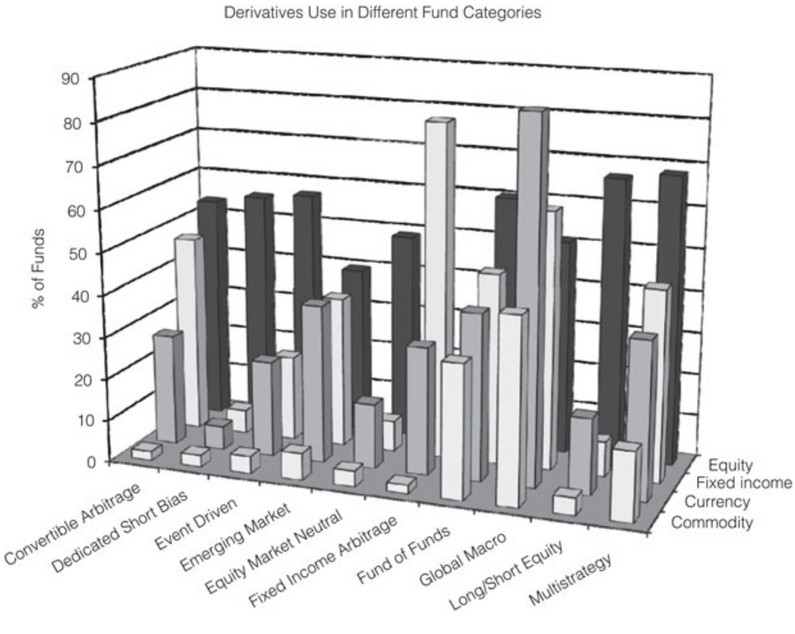
Considerable variation in derivatives use exists across fund categories. Global macro is the category with the highest proportion (93%) of derivatives users, whereas equity market neutral funds show the least use of derivatives, with 53% being derivatives users. Meanwhile, equity derivatives are most commonly used, with 57% of the sample funds trading at least one type of equity derivatives, while commodity derivatives are the least popular category, with only 13% of the sample funds trading in this category.

The overall pattern of participating in derivatives markets supports the transaction-cost saving hypothesis (Deli and Varma (2002)), in that the choice of derivative categories is consistent with the funds' main underlying assets traded and thus is associated with greater savings on transaction costs[7] (see also Figure 1). Equity-oriented funds are more involved in equity derivatives,

FIGURE 1

Derivatives Use across Hedge Fund Categories

Figure 1 shows the use of derivatives across hedge fund categories. The horizontal axis lists different hedge fund categories, and the vertical axis is the percentage of hedge funds that use derivatives.



[6]Of course, nonlinear payoffs may not necessarily result from holding derivatives. For example, trend following and market timing strategies can also generate option-like return patterns for hedge funds, according to Fung and Hsieh (2001) and Chen and Liang (2007).

[7]An alternative explanation for this derivative-category pattern is that hedge funds use derivatives in the markets where they have superior information, which implies that derivatives users should show better performance. Section III.B compares fund performance between derivatives users and nonusers.

bond-oriented funds in bond derivatives, and asset-allocation funds in multiple types of derivatives. For example, 79% of fixed income arbitrage funds trade interest rate or bond derivatives, but only 9% of them use equity derivatives.

Note that the data on derivatives use from TASS have potential limitations, since more detailed information about derivatives positions is not available. On the other hand, there are justifications for the suitability of the TASS data to study the question of interest—the relation between hedge fund derivatives use and risk taking. First, the TASS data set is relatively comprehensive, covering a large number of hedge funds and various types of derivatives. Aragon and Martin (2009) examine the information content of hedge funds' option holdings data obtained from the Securities and Exchange Commission (SEC) 13F filings, but their study is restricted to a sample of hedge funds that are 13F obligated and to equity options only (with no information on other types of derivatives). Second, as described by Jorion (2000), a hedge fund often simultaneously holds numerous derivatives positions that offset each other, and thus knowing the notional principal amount of derivative contracts is less informative. Third, simply observing derivatives positions for a sample period may not be enough to identify whether the fund is a derivatives user or not, because a derivatives user may decide not to hold any derivatives for some time when fund risk is already at a desired level. Finally, because most of the existing studies on how derivatives are used by mutual funds (e.g., Koski and Pontiff (1999), Deli and Varma (2002), and Almazan et al. (2004)) also employ indicator variables to measure derivatives use, the results from this paper can be easily compared with the prior findings about mutual funds.

B. Fund Characteristics

Table 2 summarizes various hedge fund characteristics. Following the convention of the hedge fund literature, this paper examines only funds that report monthly net-of-fee returns. This reduces the number of funds to 4,394. For a small fraction of the funds, the information on some fund characteristics (e.g., fund size) is missing.[8]

The average fund age as of June 2006 is 5.2 years, and the average (median) fund size is $145 million ($27 million) in AUM. The average fund requires at least $0.9 million for the initial investment. A median hedge fund charges an annual management fee of 1.5% of total assets plus an incentive fee of 20% of fund profits.

Some hedge funds apply restrictions on fund redemption through a lockup period and a redemption notice period. About 25% of the sample funds apply the lockup restriction that varies from 1 to 60 months, with an average of 3.7 months, while the average redemption notice period is 1.2 months.

Liang (2003) finds that, although most hedge funds in TASS claim to employ auditors, the data from funds that fail to provide an auditing statement to

[8]Specifically, 392 funds in the sample do not show information on fund size. These funds are scattered across fund categories, and their use of derivatives does not exhibit an atypical pattern. Thus, they are unlikely to systematically bias the analysis on derivatives use.

TABLE 2

Summary Statistics of Fund Characteristics

Table 2 summarizes fund characteristics for hedge funds that report monthly net-of-fee returns denominated in U.S. dollars. The information about fund age and assets under management (AUM) is as of June 2006. *N* is the number of funds.

Fund Characteristic	*N*	Mean	SD	Min	25%	Median	75%	Max
Fund age (year)	4,394	5.22	3.97	0.08	2.25	4.17	7.11	29.27
AUM ($mil)	4,002	145.47	415.71	0.02	6.89	27.00	104.42	8,110.30
Minimum investment ($mil)	4,378	0.89	5.56	0.00	0.10	0.50	1.00	250.00
Management fee (%)	4,392	1.38	0.52	0.00	1.00	1.50	1.50	6.00
Incentive fee (%)	4,392	17.07	6.61	0.00	17.50	20.00	20.00	50.00
Lockup period (months)	4,394	3.67	6.31	0.00	0.00	0.00	12.00	60.00
Notice period (months)	4,394	1.21	0.91	0.00	0.67	1.00	1.50	12.17
Auditing	4,394	0.64	0.48	0.00	0.00	1.00	1.00	1.00

the database exhibit greater inconsistencies across different databases. Following Liang (2003), this study defines effective auditing based on the existence of an auditing record in the database. Accordingly, 64% of the funds use effective auditing.

C. Relation between Fund Characteristics and Derivatives Use

Table 3 reports the results from a logit regression of derivatives use on fund characteristics with controls for investment strategies. First, fund age is positively related to derivatives use. This appears to support the conjecture that seasoned fund managers have higher reputation costs and thus have more incentives to manage risk (e.g., Brown et al. (2001)).[9]

Second, minimum investment requirement and fund fees are positively significantly related to derivatives use. For instance, the marginal probability for a 1-percentage-point increase in incentive fee is 0.6%; that means that a hedge fund charging the median incentive fee (20%) will show a 12% (0.6% $\times$ 20) higher probability of using derivatives compared to another fund that does not charge an incentive fee. This indicates that larger funds with higher entry requirement and more skilled fund managers who charge higher fees are more likely to trade complex derivative securities.

Third, compared to funds with no lockup provision, funds requiring a 3-year lockup period have an 11% (–0.3% $\times$ 36 months) lower chance of trading derivatives. Since unexpected fund inflows (outflows) could decrease (increase) the fund's market risk through changes in its cash positions (e.g., Ferson and Warther (1996)), fund managers can use derivatives (e.g., stock index futures) to adjust and maintain portfolio risk. Accordingly, funds with more stable capital face less need to manage the impact of fund flows on portfolio risk.

Finally, effective auditing is associated with 5% higher probability of using derivatives, indicating that investors in funds with a sound monitoring mechanism

[9]Another possible interpretation of the result is that hedge funds using derivatives (to manage risk) are less likely to fail. The ideal proxies for career concerns would be the manager's industry experience and past performance (before launching or joining the hedge fund), but unfortunately such information is not available.

TABLE 3

Logit Regression of Derivatives Use

Table 3 presents results from a logit regression where the dependent variable is the derivatives-use indicator and the independent variables include fund characteristics and the category dummy variables. The omitted category dummy variable is "multistrategy." ΔProb measures the marginal change in the probability of using derivatives when the independent variable changes by 1 unit.

Variable	ΔProb	*Z*-Score
Fund age	0.008	4.05
Min. investment	0.032	4.00
Management fee	0.027	1.90
Incentive fee	0.006	4.44
Lockup period	–0.003	–2.29
Notice period	–0.001	–0.74
Auditing	0.050	2.25
Convertible arbitrage	–0.103	–1.75
Dedicated short bias	–0.206	–2.04
Event driven	–0.116	–2.39
Emerging market	–0.135	–2.57
Equity market neutral	–0.265	–4.90
Fixed income arbitrage	0.056	1.26
Global macro	0.170	5.54
Long/short equity	–0.081	–2.03
Fund of funds	0.007	0.16
No. of funds	4,376	

are more comfortable allowing fund management to trade derivatives (e.g., Almazan et al. (2004)).

III. Risks and Performance: Derivatives Users versus Nonusers

This section tests the relation between derivatives use and fund risks and performance. For the sake of brevity, hedge fund categories are grouped into 4 broad investment styles: the relative value style (including convertible arbitrage, equity market neutral, and fixed income arbitrage), the directional style (including dedicated short bias, emerging markets, global macro, and long-short equity), event driven, and fund of funds.[10] This grouping is similar to that used by Agarwal et al. (2009) and also corresponds to the investigation of marketwide risks, since the directional style has substantive market exposure, while the relative value style is less sensitive to market fluctuation.

This section uses post-January 1994 hedge fund return data in order to mitigate survivorship bias (Brown, Goetzmann, Ibbotson, and Ross (1992)), because the TASS database does not include defunct funds' return information before 1994. Return data before the fund was added to the database are deleted to alleviate backfilling bias (Ackermann, McEnally, and Ravenscraft (1999)) and incubation bias (Evans (2010)).[11] Further, the tests only consider funds with at least

[10]The category "long-short equity" is assigned to the directional style because the strategy definition used by TASS explicitly states that it is a directional strategy.

[11]Despite this adjustment, it is challenging to fully correct backfilling bias. Recently, Agarwal, Fos, and Jiang (2010) analyzed self-reporting bias in hedge funds using multiple hedge fund databases. While backfilling could bias the estimate of fund performance, it is not clear why backfilling should affect the inference about the relation between derivatives use and fund risk/performance.

24 monthly return observations to obtain meaningful estimates of fund risks and performance. As a result, the total number of funds reduces to 3,535.

A. Difference in Risks

It is well known that derivative instruments can be used to hedge or speculate. Depending on the purpose, the use of derivatives has distinct implications for portfolio risk exposure—hedging reduces risk, while speculation generally increases risk. This section analyzes whether the level of hedge fund risk is cross-sectionally related to derivatives use. Nine risk measures are considered: return volatility, market beta, idiosyncratic risk, downside risk, extreme event risk, return skewness, kurtosis, coskewness, and cokurtosis.

Total Risk. Return volatility is estimated by the standard deviation of the monthly net-of-fee returns for individual hedge funds. Total risk is comprised of both systematic risk and idiosyncratic risk.

Market Risk. Market risk measures the fund's exposure to the equity market. For each fund that shows 24 or more monthly returns, market risk is estimated by the time-series regression coefficient of fund returns on the market portfolio. Asness, Krail, and Liew (2001) and Getmansky et al. (2004) raise the concern that the traditional measure of market beta for a hedge fund can be biased if the fund holds a large portion of illiquid securities that have stale asset values or conducts return-smoothing practice. In the spirit of Scholes and Williams (1977), the regression includes the 1-month lagged market index, and consequently, the market beta reported later is the sum of regression coefficients on the contemporaneous and the lagged U.S. equity market index. Because hedge funds can invest in multiple asset classes, the regression also includes controls for other asset class indexes,

$$(1) \qquad r_t \quad = \quad \alpha + \beta_0 r_{m,t} + \beta_1 r_{m,t-1} + \sum_K \beta_k r_{k,t} + \varepsilon_t,$$

where r_t denotes the fund return in month t, in excess of the 1-month T-bill rate, and r_m is the excess return on the market portfolio, proxied by the Center for Research in Security Prices (CRSP) value-weighted U.S. equity market index. The other controls include the excess returns on the Morgan Stanley Capital International (MSCI) world equity index, the MSCI emerging market index, the Merrill Lynch U.S. government and corporate bond index, the Merrill Lynch non-U.S. government bond index, the Merrill Lynch high yield bond index, the Federal Reserve trade-weighted dollar index, and the Goldman Sachs commodity index. The index data are from CRSP, Datastream, and the Federal Reserve's Economic Data.

Idiosyncratic Risk. The standard deviation of the residuals from regression (1) is the measure of idiosyncratic risk.

Downside Risk. Following the early literature on lower partial moments (e.g., Bawa and Lindenberg (1977)), this paper measures downside risk as follows:

$$(2) \quad \text{DOWNSIDE\_RISK} \quad = \quad \beta^- - \beta \quad = \quad \frac{\text{cov}(r_p, r_m | \, r_m < 0)}{\text{var}(r_m | \, r_m < 0)} - \frac{\text{cov}(r_p, r_m)}{\text{var}(r_m)}.$$

Downside risk captures the difference between beta in ex post downside market conditions and the unconditional beta.

Extreme Event Risk. I propose a new risk measure, called "extreme event risk," that assesses the sensitivity of fund returns to extreme market states. In particular, the variable measures the difference between the fund's market beta in rare event periods (e.g., a market crash) and its average market beta at other times. The following regression generates an estimate of such risk for each fund:

$$(3) \qquad r_t = \alpha + \beta_0 r_{m,t} + \beta_1 r_{m,t-1} + \lambda r_{m,t} I(r_{m,t} < \text{CUTOFF}) + \sum_K \beta_k r_{k,t} + \varepsilon_t,$$

where $I(\cdot)$ is an indicator function, and the coefficient λ corresponds to the extreme event risk. The CUTOFF value is set as the 5th lowest market return over the fund's return history.[12] Extreme event risk is particularly relevant to the use of derivatives. If a hedge fund sells out-of-money options betting the market will not be very volatile, it will have consistent gains at normal times, but when a tail event occurs, the fund may incur heavy losses. By contrast, if another fund buys index options for risk-management purpose, it pays an "insurance" premium but will endure less loss in an unusually poor market state.

Skewness and Kurtosis. The 3rd and 4th moments of the distribution of fund returns are measured for each hedge fund over its operation period.

Coskewness and Cokurtosis. The 3rd and 4th comoments of the distribution of fund returns are measured as follows:

$$(4) \qquad \text{COSKEWNESS} = \frac{\mathrm{E}[(R_p - \overline{R_p})(R_m - \overline{R_m})^2]}{\mathrm{E}(R_m - \overline{R_m})^3},$$

$$(5) \qquad \text{COKURTOSIS} = \frac{\mathrm{E}[(R_p - \overline{R_p})(R_m - \overline{R_m})^3]}{\mathrm{E}(R_m - \overline{R_m})^4},$$

where R_p denotes the fund return and R_m is the return on the equity market index.

Table 4 reports the difference in various risk measures between derivatives users and nonusers.[13] Different from Koski and Pontiff (1999) who, in the setting of mutual funds, document no difference in fund risks between derivatives users and nonusers, the results indicate that, in general, derivatives-using hedge funds bear lower risks than nonusers. First, the total risk of derivatives users is somewhat lower than that of nonusers. The comparison about market risk and idiosyncratic risk reveals further details. Risk reduction in market risk (i.e., the sum of contemporaneous and lagged market beta) associated with derivatives use is substantial for the overall sample. The average market risk of derivatives users is 0.185, about 22% lower than 0.238 with nonusers; the difference is statistically significant. Meanwhile, idiosyncratic risk of derivatives users is only slightly smaller than that of nonusers, and the difference is not statistically significant.

[12]The empirical finding, reported below, about the extreme event risk is robust to alternative cutoffs (e.g., the 10th lowest market return).

[13]In robustness tests, I winsorize the measures of fund risks to alleviate the effect of outliers, and all the results hold in those tests.

TABLE 4

Fund Risks and Performance: Derivatives Users versus Nonusers

Table 4 tests for the differences in fund risks and performance between derivatives users and nonusers. Each hedge fund in the tests is required to report monthly net-of-fee returns denominated in U.S. dollars and to have at least 24 monthly returns. Alpha is estimated by the multifactor regression (1) of fund returns on equity (U.S., 1-month lagged U.S., Non-U.S., Emerging), bond (U.S., Non-U.S., High yield), currency, and commodity market indexes. Market risk is the sum of regression coefficients on the U.S. equity market index and its 1-month lagged term. Idiosyncratic risk is the standard deviation of the regression residuals. Downside risk is defined as $(\beta^{-} - \beta)$ in equation (2). Extreme event risk is estimated by the coefficient λ in regression (3). The manipulation-proof performance measure (MPPM) is defined as in equation (6). Average return and alpha are in annual percentage. "Relative Value" style subgroup includes the categories of convertible arbitrage, equity market neutral, and fixed income arbitrage; "Directional" subgroup includes dedicated short bias, emerging market, global macro, and long/short equity funds. Row 1 in each panel is the average level of various risk and performance measures for derivatives users, and row 2 is the average for nonusers. Here, diff measures the spread of the mean variables between derivatives users and nonusers, and *t*-diff is from a test of the null hypothesis that mean variables are the same for derivatives users and nonusers. The fund numbers in the subgroups do not add up to the overall sample because "multistrategy" funds are not assigned to any of the subgroups.

	N	Total Risk	Market Risk	Idiosyn. Risk	Downside Risk	Event Risk	Skew	Kurtosis	Coskew	Cokurtosis	Average Return	Sharpe Ratio	Alpha	MPPM
Panel A. Overall Sample														
Users	2,533	12.490	0.185	9.398	0.008	–0.040	–0.022	6.134	0.322	0.290	10.250	0.820	3.370	0.023
Nonusers	1,002	13.280	0.238	9.632	0.058	0.007	0.054	5.168	0.438	0.362	10.570	0.877	3.572	0.017
diff		–0.785	–0.053	–0.233	–0.050	–0.047	–0.076	0.965	–0.116	–0.072	–0.324	–0.057	–0.202	0.006
t-diff		–1.716	–2.276	–0.667	–3.251	–2.524	–2.032	4.773	–3.243	–3.618	–0.833	–1.619	–0.526	0.658
Panel B. Relative Value Subgroup														
Users	354	7.300	0.032	5.993	0.025	–0.018	–0.486	8.447	0.047	0.069	7.955	1.077	3.619	0.035
Nonusers	181	7.163	0.042	5.749	–0.003	–0.014	–0.161	5.028	–0.011	0.050	7.445	0.968	3.336	0.032
diff		0.137	–0.010	0.244	0.028	–0.003	–0.325	3.420	0.058	0.019	0.510	0.109	0.283	0.004
t-diff		0.261	–0.368	0.571	1.186	–0.117	–2.621	3.868	1.038	0.895	0.829	0.830	0.435	0.590
Panel C. Directional Subgroup														
Users	1,266	16.760	0.286	12.540	–0.006	–0.065	0.175	5.585	0.472	0.404	11.810	0.640	3.885	0.017
Nonusers	472	18.920	0.390	13.560	0.085	0.021	0.153	5.205	0.701	0.557	12.730	0.690	4.167	0.001
diff		–2.158	–0.104	–1.022	–0.091	–0.086	0.021	0.380	–0.229	–0.154	–0.917	–0.050	–0.282	0.016
t-diff		–2.876	–2.384	–1.788	–3.203	–2.669	0.421	1.723	–3.603	–4.311	–1.398	–1.239	–0.441	1.173
Panel D. Event Driven Subgroup														
Users	252	8.693	0.226	6.386	0.015	–0.022	–0.118	5.467	0.358	0.275	11.100	1.239	4.798	0.060
Nonusers	122	7.571	0.139	5.677	0.014	0.000	0.170	5.534	0.430	0.194	11.230	1.588	6.471	0.066
diff		1.122	0.086	0.709	0.001	–0.021	–0.288	–0.067	–0.072	0.081	–0.131	–0.349	–1.673	–0.007
t-diff		1.312	1.985	1.074	0.035	–0.498	–2.439	–0.192	–0.530	2.640	–0.156	–2.291	–1.775	–0.671
Panel E. Fund of Funds Subgroup														
Users	562	8.319	0.059	6.160	0.036	–0.008	–0.167	5.991	0.211	0.187	7.487	0.817	1.039	0.007
Nonusers	200	8.808	0.129	6.113	0.095	0.006	–0.151	4.686	0.305	0.290	7.262	0.875	–0.196	0.005
diff		–0.490	–0.070	0.048	–0.059	–0.014	–0.016	1.305	–0.094	–0.104	0.225	–0.058	1.235	0.002
t-diff		–0.681	–2.518	0.080	–2.251	–0.389	–0.209	3.583	–1.944	–3.976	0.390	–0.894	2.078	0.065

More importantly, derivatives users and nonusers exhibit a striking difference in downside risk and extreme event risk. For example, derivatives users have a negligible downside risk at the level of 0.008, which is about 86% lower than that of nonusers (0.058). The evidence on event risk is even more prominent. The average event risk is –0.04 for derivatives users, implying that, on average, such funds bear smaller market exposure when the market is in a rarely poor state. The opposite is true for nonusers, however; their loadings on the market index are even higher when the market is in a bad shape. This difference holds for all the hedge fund styles.[14] The reduction in downside and event risk should be important to investors, given widely held concerns about costly lower-tail outcomes in hedge funds.

The evidence about the higher return moments is somewhat mixed. In general, derivatives users show lower return skewness and larger kurtosis compared to nonusers. However, when examining the systematic higher moments (i.e., coskewness and cokurtosis), I find that derivatives use is associated with a significantly lower level of such risks. Thus, this could be parallel with the evidence that derivatives use is mainly negatively associated with marketwide risk rather than idiosyncratic risk.

Table 4 also examines the link between derivatives use and fund risks for different hedge fund styles. In general, the negative association between the use of derivatives and fund risks is most pronounced with directional-style funds and funds-of-funds. For these subgroups, derivatives use is significantly negatively related to most of the risk measures, especially the systematic risk measures such as market risk, downside risk, event risk, and higher comoments. For example, the average market risk (0.286) of derivatives-using directional funds is 27% lower than that (0.39) of nonusers, and the difference in the average event risk is even more remarkable. This seems intuitive, since directional hedge funds in general have higher market risk compared to funds of other styles and thus have more incentive to use derivatives to manage their market exposure. On the other hand, the effect of risk reduction through derivatives use is less noticeable with the relative-value and event-driven styles. These 2 subgroups mainly consist of arbitrage-oriented funds that intend to exploit firm-level inefficiencies. Given the fact that such funds (e.g., a market-neutral fund) bear little market risk, it is not very surprising that their use of derivatives is not associated with a lower level of fund risk. Instead, they may use derivatives to help exploit price inefficiencies.

[14]Considering the fact that extreme events are defined differently for different funds, I conduct a robustness test by running the following pooled regression:

$$\begin{aligned} r_{p,t} \quad = \quad & \alpha + \beta r_{m,t} + \beta_1 r_{m,t-1} + \lambda r_{m,t} I(r_{m,t} < \text{CUTOFF}) \\ & + \delta r_{m,t} I(r_{m,t} < \text{CUTOFF}) D_p + \sum_K \beta_k r_{k,t} + \varepsilon_{p,t}, \end{aligned}$$

where D is the derivatives-use dummy variable, and the CUTOFF value is set as the 5% lowest market return over the whole sample period. The regression coefficient δ is negative and statistically significant, suggesting that derivatives users are associated with significantly lower event risk. Further, in another robust test I replace the above indicator function with *I(Asian Crisis or LTCM Event)*, to find that, on average, derivatives users exhibit lower market exposure during the periods of the Asian crisis (July–September 1997) and the LTCM event (August–December 1998). Details of these robust tests are available from the author.

For example, derivatives users in the relative-value subgroup show smaller return skewness and fatter tails, which might indicate speculation-based trading of derivatives.

Overall, these results do not suggest that the use of derivatives in hedge funds leads to higher fund risk, since derivatives users tend to have lower fund risk than nonusers. There is heterogeneity across fund styles. Therefore, although it cannot be ruled out that some hedge funds speculate with trading derivatives, the fact that most hedge funds trade derivatives should not in itself raise severe concerns about excessive risk taking.

B. Difference in Performance

Next, this paper examines the difference in fund performance between derivatives users and nonusers by comparing 4 alternative performance measures: average fund return, the Sharpe ratio, risk-adjusted performance (alpha) from regression (1), and the MPPM proposed by Ingersoll et al. (2007). The average levels of mean return, the Sharpe ratio, and alpha are 10.3%, 0.84, and 3.43% per year, respectively. These figures are consistent with the prior studies on hedge fund performance (e.g., Brown, Goetzmann, and Ibbotson (1999), Liang (1999)).

Ingersoll et al. (2007) show that the following measure is an MPPM,

$$\text{(6)} \qquad \text{MPPM} = \frac{1}{(1-\rho)\Delta t} \ln \left(\frac{1}{T} \sum_{t=1}^{T} [(1+r_t)/(1+r_{f,t})]^{1-\rho} \right),$$

where r_t is fund return at month t, and r_f is the 1-month T-bill rate. Following Ingersoll et al., the risk aversion parameter ρ is set to 3 and $\Delta t = 1/12$. As explained by Ingersoll et al., this measure can be considered as the annualized continuously compounded excess return "certainty equivalent" of the portfolio.

Table 4, in the two right-most columns, reports the difference in the performance measures between derivatives users and nonusers. In general, the difference is small in magnitude and statistically insignificant for the overall sample. This indicates that at the aggregate level hedge funds that use derivatives do not enhance investors' welfare. This impression holds for all the fund styles, except that derivatives-using event-driven funds realize a smaller average Sharpe ratio than nonusers, and fund alpha of derivatives users among funds-of-funds is on average higher than that of nonusers.

Ingersoll et al. (2007) show that derivatives can be used to manipulate traditional performance measures such as the Sharpe ratio. Hence, if derivatives were used to artificially inflate the Sharpe ratio, one would expect that derivatives users tend to show a higher Sharpe ratio than nonusers, and at the same time their MPPM is no higher (or even lower) than nonusers. Since this is not the case in the empirical findings, it suggests that derivatives are not mainly used by hedge funds to manipulate performance measures.[15]

[15]Note that derivatives are not necessary for manipulating performance measures. Hedge funds may employ other dynamic trading strategies to inflate their Sharpe ratios (see Ingersoll et al. (2007) for details). I thank Stephen Brown (the editor) for suggesting this point.

There can be another interpretation of the findings. The fact that derivatives users bear lower downside/event risk and have similar performance to nonusers may imply that derivatives users achieve "insurance" protection without suffering performance (i.e., paying an insurance premium), which can be consistent with successful market timing (Jagannathan and Korajczyk (1986)). A more detailed examination of the relation between derivatives use and market timing is beyond the scope of this paper.[16] Nevertheless, no matter how the results on performance difference are interpreted, the use of derivatives is associated with lower fund risk.

C. Evidence Based on Sort Portfolios

To further assess the economic relevance of derivatives use, I construct 2 portfolios based on the use of derivatives. Specifically, the derivatives-user portfolio is an equal-weighted portfolio of all individual funds that use derivatives, while the nonuser portfolio is an equal-weighted portfolio of the funds that do not use derivatives. I then calculate the spread in risk and performance measures between the 2 portfolios.

Consistent with the preceding results, derivatives use is associated with economically substantive reduction in fund risk. A strategy of buying derivatives-using funds will bear a market risk of 0.22, which is –0.082 (27%) lower than the market risk from buying derivatives nonusers only. The downside risk of the derivatives-user portfolio is virtually 0, compared to 0.09 from buying nonusers only. The derivatives-user portfolio shows an event risk of –0.024, dramatically lower than that of the nonuser portfolio (0.049). The results on downside risk and event risk hold for all the subgroups, though the magnitude of risk reduction varies across different styles. Meanwhile, the 2 portfolios share similar performance measures. To conserve space, the details of the results are not tabulated but are available from the author.

D. Regression Analysis

The results shown to this point have not controlled for the impact of various fund characteristics. Next, I conduct a cross-sectional regression analysis of fund risks and performance on the derivatives-use dummy variable together with controls for fund characteristics as well as investment categories.[17] Since hedge funds started operation at different times, the regressions include each fund's inception year as an independent variable to control time effect.

Table 5 presents the results. Consistent with the preceding findings, derivatives use is both economically and statistically significantly associated with lower fund risks, even after controlling for fund characteristics and categories. For example, the regression coefficient of market risk on the derivatives-use indicator

[16]See Chen and Liang (2007) for some relevant discussion.

[17]In this regression, fund age and size variables are not included to avoid look-ahead bias. However, from unreported tests, the inferences are the same if these 2 variables appear in the regression.

TABLE 5

Regressions of Fund Risks and Performance on Derivatives Use

Table 5 presents the results from the cross-sectional regressions of fund risk and performance measures on derivatives use. The dependent variable in each regression (each column of the table) is a measure of fund risk or performance calculated from net-of-fee fund returns. Derivatives use is a dummy variable that equals 1 when the fund uses derivatives, and 0 otherwise. The independent variables include fund characteristics, category dummy variables, and a time-effect control; and *t*-statistics, reported in parentheses, are calculated from White (1980) standard errors. The total number of funds in each regression is 3,519. The sample period is from January 1994 to June 2006.

Variable	Total Risk	Market Risk	Idiosyn. Risk	Downside Risk	Event Risk	Skew	Kurtosis	Coskew	Cokurtosis	Average Return	Sharpe Ratio	Alpha	MPPM
Derivatives use	–1.206	–0.053	–0.714	–0.043	–0.046	–0.060	0.474	–0.104	–0.065	–0.314	–0.026	–0.025	0.010
	(–2.90)	(–2.37)	(–2.22)	(–2.31)	(–2.31)	(–1.49)	(2.45)	(–3.09)	(–3.72)	(–0.84)	(–0.83)	(–0.07)	(1.02)
Min. investment	–0.025	–0.238	–0.022	0.001	0.001	–0.002	–0.001	0.001	–0.001	0.001	0.004	–0.002	0.001
	(–1.42)	(–0.75)	(–1.51)	(0.97)	(0.58)	(–1.67)	(–0.16)	(0.29)	(–0.56)	(1.11)	(2.22)	(–0.34)	(1.61)
Management fee	0.505	–0.043	0.723	0.013	0.005	0.106	–0.212	–0.010	–0.028	0.315	0.001	–0.111	–0.004
	(1.44)	(–2.42)	(2.39)	(0.78)	(0.32)	(2.56)	(–0.89)	(–0.39)	(–1.84)	(0.99)	(0.01)	(–0.37)	(–0.66)
Incentive fee	0.063	–0.002	0.094	–0.006	–0.001	0.010	0.018	–0.010	–0.008	0.075	0.002	0.111	–0.001
	(1.91)	(–1.08)	(3.40)	(–3.19)	(–0.54)	(2.75)	(1.07)	(–4.72)	(–5.90)	(2.69)	(0.86)	(4.16)	(–0.63)
Lockup period	0.062	0.005	0.057	–0.001	–0.001	0.008	–0.001	0.002	0.002	0.134	0.008	0.161	0.002
	(2.23)	(3.12)	(2.56)	(–0.80)	(–0.62)	(2.42)	(–0.07)	(0.76)	(1.80)	(4.71)	(3.09)	(6.40)	(4.75)
Notice period	–0.021	–0.001	–0.013	0.001	0.001	0.002	0.013	0.001	–0.001	0.053	0.008	0.050	0.001
	(–2.92)	(–0.02)	(–2.45)	(0.46)	(2.89)	(1.67)	(2.31)	(0.79)	(–0.17)	(6.50)	(13.91)	(7.19)	(5.43)
Auditing	–1.993	–0.069	–1.072	–0.084	–0.047	0.037	0.216	–0.077	–0.087	1.582	0.152	2.066	0.057
	(–4.65)	(–2.78)	(–3.29)	(–3.52)	(–2.10)	(0.81)	(1.05)	(–2.04)	(–4.62)	(3.52)	(4.43)	(4.32)	(3.67)
Intercept	14.951	0.318	9.693	0.218	0.030	–0.502	7.922	0.522	0.614	7.179	0.538	0.654	–0.034
	(10.55)	(4.99)	(8.57)	(3.33)	(0.51)	(–2.92)	(9.07)	(5.36)	(10.86)	(4.99)	(4.65)	(0.49)	(–1.67)
Category dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Start year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.246	0.135	0.231	0.054	0.012	0.082	0.095	0.095	0.232	0.111	0.229	0.083	0.139

equals –0.053, suggesting that derivatives use is associated with a reduction of market risk by about 27% compared to the average market risk of 0.20.[18]

Table 5 also includes the cross-sectional regressions of fund performance measures on derivatives use. Similar to the earlier evidence, fund after-fee performance is not significantly associated with the use of derivatives. Nevertheless, performance is related to some other fund characteristics. Incentive fee is positively associated with fund alpha, indicating that skilled fund managers tend to charge higher performance-based fees to extract more rents from investors. Ackermann et al. (1999) and Agarwal et al. (2009) document a similar relationship. Consistent with Aragon (2007), funds with longer lockup and redemption notice periods show higher alpha, which reflects a premium for restrictions on share redemption. In addition, funds with effective auditing exhibit better performance, which is consistent with Brown, Fraser, and Liang (2008) that due diligence can be a source of hedge fund alpha.

E. Regression Analysis Based on Pre-Fee Returns

The analysis thus far has used net-of-fee returns to calculate the risk and performance measures. Therefore, the fact that there is no significant difference in fund performance could be consistent with the conjecture that derivatives-using hedge funds actually realize higher performance but keep the extra profits to themselves through higher fees. Indeed, recall that Table 3 reveals that derivatives users tend to charge higher fees. This motivates the following test using pre-fee returns.

Table 6 repeats the cross-sectional regressions using pre-fee returns. Following Teo (2009), I back out pre-fee fund returns by taking the T-bill rate as the hurdle rate and applying a high-water mark when adding back incentive fees, then adjusting for management fees, and assuming that fund returns accrue to a 1st-year investor.[19] The inferences in regard to fund risks are in accordance with the preceding results from net returns. On average, derivatives users bear lower risk: The regression coefficients on the derivatives-use dummy variable are significantly negative for most of the risk measures, including total risk, market risk, idiosyncratic risk, downside risk, event risk, coskewness, and cokurtosis.

Based on gross return, there is some evidence that derivatives use is associated with a higher MPPM, and the magnitude (0.007) is also economically significant relative to the average MPPM, indicating the existence of information-based trading of derivatives. Compared to the evidence from net-of-fee returns, this evidence suggests that some derivatives users can realize better performance, but the fund managers seem to extract superior profits through fees. However, the differences in other performance measures such as mean returns are not substantive.

[18]In a robustness check, I repeat the regressions excluding nonequity-oriented fund categories (i.e., fixed income arbitrage, global macro, and fund of funds), since the funds' systematic risk, such as market risk and downside risk, is measured with respect to the equity market. Still, such regressions show a significantly negative association of derivatives use with funds' systematic risk.

[19]This approach to backing out pre-fee returns is only an approximation. Alternatively, a more realistic and complex methodology has been suggested by Agarwal et al. (2009).

TABLE 6

Regressions of Fund Risks and Performance on Derivatives Use (based on pre-fee returns)

Table 6 presents the results from the cross-sectional regressions of fund risk and performance measures on derivatives use. The dependent variable in each regression (each column of the table) is a measure of fund risk or performance calculated from pre-fee fund returns. Derivatives use is a dummy variable that equals 1 when the fund uses derivatives, and 0 otherwise. The independent variables include fund characteristics, category dummy variables, and a time-effect control; and *t*-statistics, reported in parentheses, are calculated from White (1980) standard errors. The total number of funds in each regression is 3,519. The sample period is from January 1994 to June 2006.

Variable	Total Risk	Market Risk	Idiosyn. Risk	Downside Risk	Event Risk	Skew	Kurtosis	Coskew	Cokurtosis	Average Return	Sharpe Ratio	Alpha	MPPM
Derivatives use	–1.328	–0.056	–0.805	–0.044	–0.048	–0.049	0.424	–0.107	–0.067	–0.648	–0.026	–0.315	0.007
	(–2.82)	(–2.23)	(–2.19)	(–2.15)	(–2.22)	(–1.23)	(2.19)	(–2.93)	(–3.54)	(–1.39)	(–0.77)	(–0.71)	(1.66)
Min. investment	–0.025	–0.189	–0.022	0.001	0.001	–0.002	–0.001	0.001	–0.001	0.005	0.004	–0.001	0.001
	(–1.28)	(–0.55)	(–1.33)	(0.91)	(0.52)	(–1.50)	(–0.18)	(0.20)	(–0.69)	(0.60)	(1.93)	(–0.23)	(1.80)
Management fee	0.557	–0.051	0.794	0.015	0.007	0.096	–0.150	–0.015	–0.032	1.353	0.081	0.917	0.010
	(1.41)	(–2.60)	(2.31)	(0.78)	(0.37)	(2.33)	(–0.65)	(–0.49)	(–1.84)	(3.47)	(2.89)	(2.55)	(2.80)
Incentive fee	0.163	–0.001	0.176	–0.008	–0.002	0.026	0.012	–0.010	–0.007	0.333	0.011	0.345	0.002
	(4.52)	(–0.24)	(5.88)	(–3.77)	(–1.28)	(7.64)	(0.78)	(–4.35)	(–5.08)	(9.61)	(4.09)	(11.38)	(7.31)
Lockup period	0.069	0.006	0.065	–0.001	–0.001	0.008	0.002	0.002	0.002	0.151	0.006	0.179	0.001
	(2.19)	(3.21)	(2.54)	(–0.86)	(–0.62)	(2.41)	(0.13)	(0.76)	(1.89)	(4.16)	(2.25)	(5.87)	(4.80)
Notice period	–0.021	–0.001	–0.013	0.001	0.001	0.001	0.012	0.001	–0.001	0.056	0.009	0.052	0.001
	(–2.57)	(–0.03)	(–2.10)	(0.43)	(2.88)	(1.61)	(2.23)	(0.84)	(–0.01)	(5.56)	(13.66)	(6.52)	(7.68)
Auditing	–2.199	–0.075	–1.210	–0.087	–0.041	0.044	0.201	–0.077	–0.094	1.089	0.155	1.679	0.025
	(–4.56)	(–2.67)	(–3.28)	(–3.34)	(–1.68)	(0.96)	(0.98)	(–1.85)	(–4.62)	(2.02)	(4.31)	(3.07)	(5.36)
Intercept	14.962	0.326	9.628	0.214	0.024	–0.492	7.663	0.508	0.629	7.423	0.632	0.978	–0.031
	(9.50)	(4.67)	(7.61)	(3.07)	(0.39)	(–2.91)	(9.01)	(4.73)	(10.24)	(4.29)	(5.26)	(0.64)	(–2.05)
Category dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Start year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.250	0.132	0.237	0.055	0.013	0.095	0.083	0.094	0.232	0.161	0.251	0.130	0.146

Interestingly, when examining the pre-fee returns, I find that the levels of both management fee and incentive fee are significantly positively related to all 4 performance measures. This suggests that more skilled managers collect more fees as their rents after realizing higher profits since the after-fee performance is much less related to fund fees, especially to management fee.

F. Employing Derivatives-Use Variable Observed in 2001

Data on derivatives use and other fund characteristics in TASS are the latest "snapshot" information, and time-series observations of derivatives use are not available from the 2006 sample alone. Ideally, the derivatives-use variable (independent variable) should be observed before fund risks and performance are measured if one wants to infer *effects* of derivatives use. Hence, an endogeneity problem may arise if derivatives use varies over time related to fund risks and performance. To mitigate this concern, I repeat the regressions analysis using as the independent variables the data on derivatives use and fund characteristics from an earlier 2002 version of TASS data where the derivatives-use information was recorded at the end of 2001. Then, I calculate the dependent variables (i.e., the risk and performance measures) using fund returns between January 2002 and June 2006. These tests drop all funds that exited the database before 2002, and 1,634 funds remain in the sample.[20]

These additional tests deliver qualitatively similar inferences. Derivatives use is associated with lower risks, while the difference in fund performance is not apparent. In this subperiod, the relation between derivatives use and downside/event risk is not as prominent as in the tests using the full sample period. Perhaps this is because during 2002–2006, there were not as many dramatic market downturns and events as occurred in the late 1990s and early 2000. To conserve space, the details are not reported but are available from the author.

G. 2SLS Regressions

To further address the endogeneity concern, I conduct 2SLS regressions that jointly estimate the determinants of derivatives use and fund risks and performance. Such 2SLS regressions require at least one instrumental variable that is exogenous and highly correlated with the derivatives-use variable. The TASS "Notes" file contains "Biographies" of funds' managers for most hedge funds covered by the database. Such biographical information often describes fund managers' work experience before they launch or join the hedge funds. For example, the biographies for a hedge fund include the following description: "Dr. Huang was Head of Fixed Income Derivative Research at Goldman Sachs & Co. in New York from mid-1993 to the end of 1994." After manually searching derivatives-related key words through these "Biographies," I am able to identify

[20]To examine the variation in derivatives use over time, I have checked a few more versions of the database acquired in 2003, 2004, and 2005. Between 2002 and 2006, less than 1% of hedge funds switched from a derivatives user to a nonuser or from a nonuser to a user from one year to another. Ackermann et al. (1999), Liang (2000), and Aragon (2007) document that other fund characteristics (e.g., incentive fees and lockup provisions) also rarely change.

968 funds whose managers have prior expertise in derivatives trading. I then generate an indicator variable called "prior expertise" that equals 1 if TASS "Notes" reveal that the fund manager(s) have prior working experience in trading derivatives, and 0 otherwise.[21] Therefore, I use fund managers' prior expertise in derivatives trading as the instrument, and this variable is exogenous in the context of fund risk taking.

Table 7 reports the 2SLS results. The 1st-stage regression result, shown in Panel A, clearly verifies the validity of the instrument. As expected, a fund is more likely to use derivatives if the managers have prior exposure to derivatives trading before launching or joining the hedge fund. The regression coefficient on the instrument is 0.196 (t-statistic = 9.83). Panel A also reports the F-test for significance of the instrument. The F-statistic (96.60) is much larger than the critical value (16.38) of the Stock-Yogo (2005) weak instrument test, which means that the weak-instrument problem is not a concern in the data. Panel B repeats the 2nd-stage results that overall confirm the negative relation between derivatives use and most of the risk measures. For several cases, the effect of derivatives use on risk taking, estimated from 2SLS, has an even larger magnitude than that reported in Table 5, after controlling for endogeneity. Meanwhile, derivatives users do not show significantly better performance than nonusers, except for the MPPM.

TABLE 7

Regressions of Fund Risks and Performance on Derivatives Use (2SLS regressions)

Table 7 presents the results from 2-stage least squares (2SLS) regressions of fund risk and performance measures on derivatives use. In Panel A, the instrumental variable is a dummy variable of the fund managers' prior expertise in derivatives trading, which equals 1 if the TASS "Notes" file reveals that the fund manager(s) have prior working experience in derivatives trading, and 0 otherwise. Panel A reports the 1st-stage regression result and the F-test for the validity of the instrument. In Panel B, the dependent variable in each regression (each column of the table) is a measure of fund risk or performance calculated from net-of-fee fund returns. Derivatives use is a dummy variable that equals 1 when the fund uses derivatives, and 0 otherwise. The independent variables include fund characteristics, category dummy variables, and a time-effect control; and t-statistics, reported in parentheses, are calculated from White (1980) standard errors. Panel B reports the results from the 2nd-stage regressions. The total number of funds in each regression is 3,519. The sample period is from January 1994 to June 2006.

Panel A. The 1st-Stage Regression

Variable	Coefficient	t-Statistic
Prior expertise	0.196	9.83
Min. investment	0.002	3.02
Management fee	0.026	1.98
Incentive fee	0.006	4.03
Lockup period	–0.002	–1.06
Notice period	0.001	1.31
Auditing	0.047	2.62
Intercept	0.597	11.27
Category dummies	Yes	
Start year dummies	Yes	
Adjusted R^2	0.070	
F-statistic	96.600	

(continued on next page)

[21]Note that a fund manager does not necessarily lack past experience in derivatives trading, even though TASS "Notes" do not mention that the manager has it. Hence, the prior expertise variable can be noisy, which may reduce the test power and make the results conservative.

TABLE 7 (continued)

Regressions of Fund Risks and Performance on Derivatives Use (2SLS regressions)

Panel B. The 2nd-Stage Regressions

Variable	Total Risk	Market Risk	Idiosyn. Risk	Downside Risk	Event Risk	Skew	Kurtosis	Coskew	Cokurtosis	Average Return	Sharpe Ratio	Alpha	MPPM
Derivatives use	–3.569	–0.194	–1.361	–0.149	–0.150	–0.262	0.352	0.059	–0.398	1.641	–0.258	1.211	0.010
	(–2.96)	(–2.35)	(–1.88)	(–1.90)	(–1.72)	(–0.74)	(0.18)	(0.09)	(–3.95)	(0.71)	(–0.63)	(0.95)	(2.53)
Min. investment	–0.013	0.001	–0.016	0.001	0.001	–0.001	–0.001	0.001	0.001	0.001	0.003	–0.006	0.000
	(–0.80)	(0.86)	(–1.15)	(1.38)	(1.10)	(–1.10)	(–0.11)	(0.82)	(1.78)	(0.15)	(2.14)	(–0.94)	(0.66)
Management fee	0.676	–0.035	0.807	0.017	0.009	0.113	–0.208	0.123	–0.018	0.253	0.013	–0.109	–0.007
	(1.81)	(–1.87)	(2.55)	(0.92)	(0.49)	(2.67)	(–0.87)	(1.57)	(–1.04)	(0.77)	(0.25)	(–0.34)	(–1.01)
Incentive fee	0.093	–0.001	0.108	–0.005	–0.000	0.011	0.018	–0.013	–0.006	0.065	0.003	0.096	–0.001
	(2.63)	(–0.29)	(3.70)	(–2.81)	(–0.21)	(2.72)	(0.94)	(–2.30)	(–4.21)	(2.11)	(0.79)	(3.28)	(–1.13)
Lockup period	0.050	0.005	0.051	–0.002	–0.001	0.007	–0.001	–0.010	0.001	0.138	0.005	0.165	0.002
	(1.69)	(2.71)	(2.22)	(–0.93)	(–0.79)	(2.22)	(–0.09)	(–1.03)	(1.03)	(4.76)	(1.54)	(6.42)	(4.75)
Notice period	–0.017	0.001	–0.012	0.001	0.001	0.002	0.013	0.002	0.001	0.051	0.010	0.049	0.001
	(–2.32)	(0.34)	(–2.07)	(0.57)	(2.97)	(1.76)	(2.26)	(1.10)	(0.36)	(6.26)	(7.09)	(6.90)	(4.77)
Auditing	–1.749	–0.058	–0.952	–0.079	–0.042	0.046	0.222	0.211	–0.072	1.493	0.217	2.083	0.053
	(–3.97)	(–2.26)	(–2.88)	(–3.33)	(–1.87)	(0.94)	(0.97)	(1.22)	(–3.57)	(3.36)	(3.92)	(4.24)	(3.68)
Intercept	18.292	0.468	11.342	0.278	0.094	–0.377	7.997	–0.111	0.822	5.961	0.597	–0.950	–0.088
	(9.47)	(4.61)	(7.57)	(2.58)	(1.01)	(–1.34)	(5.10)	(–0.23)	(9.22)	(2.76)	(2.38)	(–0.47)	(–2.60)
Category dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Start year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.201	0.105	0.212	0.046	0.030	0.077	0.095	0.015	0.146	0.104	0.124	0.074	0.019

H. Effects of Different Types of Derivatives Use

Thus far, a hedge fund is treated as a derivatives user as long as it invests in at least one type of derivative. Table 8 examines the effects of different types of derivatives where fund risk/performance measures are regressed on 4 types of derivatives (i.e., equity, fixed income, currency, and commodity) with controls for fund characteristics and strategies. The use of derivatives in equity, fixed income, and currency securities is associated with lower total risk. The use of equity derivatives is related to a significantly lower level of market risk and downside/event risk as well as higher MPPM.[22] For example, the coefficient of estimated market beta on the use of equity derivatives is -0.07 (t-statistic $= -3.13$), which is considerable given the average beta of 0.20 for the overall sample. Further, the use of currency derivatives is also associated with lower market risk and event risk, indicating the hedge funds may manage market-related risk through trading derivatives in foreign exchange markets. Interestingly, the use of commodity derivatives is linked to higher total risk and idiosyncratic risk. In general, hedge funds have little incentive to hedge the underlying risk in commodity markets, since they generally do not hold physical commodities. Therefore, their trading of commodity derivatives may reflect speculation in addition to diversification needs.

IV. Derivatives Use and Risk Shifting

The results so far have shown the relation between derivatives use and static measures of fund risks and performance. This section investigates how derivatives use relates to fund risk taking from a dynamic perspective by analyzing risk shifting in response to performance.

Brown et al. (2001) provide the first evidence on risk shifting in hedge funds, but they do not study the impact of derivatives use on risk shifting. Derivatives use can be significantly related to risk shifting. On the one hand, the use of derivatives might increase risk-shifting incentives, because derivatives trading can be a powerful way to alter fund risks due to its low transaction costs and high leverage effect. On the other hand, as emphasized by Brown et al. (2001), career concerns may offset the manager's incentives to shift portfolio risk. Thus, if derivatives use reflects the manager's motivation to maintain a stable level of fund risk, fund risk will change less frequently.

A. The Risk-Shifting Regression

Risk shifting in fund management refers to the practice that funds performing poorly in the 1st half of a given year tend to increase portfolio risk in hopes of catching up in the 2nd half, while funds performing well try to lock in their

[22] Aragon and Martin (2009), based on hedge fund 13F option holdings data, find similar evidence that option users on average have lower return volatility than nonusers, but the difference in fund returns and alpha is insignificant. While they document that option users tend to have a higher Sharpe ratio, I find that funds using equity derivatives have higher MPPM.

TABLE 8

Regressions of Fund Risks and Performance on Derivatives Use: Effects of Different Types of Derivatives

Table 8 presents the results from the cross-sectional regressions of fund risk and performance measures on different types of derivatives use. The dependent variable in each regression (each column of the table) is a measure of fund risk or performance calculated from net-of-fee fund returns. The independent variables include the dummy variables for 4 different types of derivatives use (i.e., equity, fixed income, currency, and commodity), as well as fund characteristics, category dummy variables, and a time-effect control; and *t*-statistics, reported in parentheses, are calculated from White (1980) standard errors. The total number of funds in each regression is 3,519. The sample period is from January 1994 to June 2006.

Variable	Total Risk	Market Risk	Idiosyn. Risk	Downside Risk	Event Risk	Skew	Kurtosis	Coskew	Cokurtosis	Average Return	Sharpe Ratio	Alpha	MPPM
Equity deriv	–1.013	–0.068	–0.430	–0.048	–0.062	0.083	–0.035	–0.135	–0.092	–0.319	–0.050	0.235	0.008
	(–2.58)	(–3.13)	(–1.65)	(–2.54)	(–3.40)	(1.44)	(–1.21)	(–3.95)	(–5.24)	(–0.79)	(–1.53)	(0.53)	(2.02)
Fixed income deriv	–1.572	–0.015	–1.428	0.021	0.032	–0.346	1.341	–0.014	–0.021	–0.652	0.007	–0.468	–0.017
	(–3.84)	(–0.64)	(–4.44)	(0.90)	(1.49)	(–4.91)	(3.40)	(–0.38)	(–1.07)	(–1.51)	(0.18)	(–1.05)	(–0.79)
Currency deriv	–1.987	–0.153	–1.268	–0.012	–0.053	0.020	0.070	–0.031	0.014	0.111	0.035	–0.224	0.033
	(–5.16)	(–6.66)	(–3.84)	(–0.52)	(–2.66)	(0.48)	(0.34)	(–0.94)	(0.77)	(0.31)	(0.92)	(–0.60)	(2.43)
Commodity deriv	2.505	–0006	2.158	–0.049	0.028	0.252	–1.600	0.080	–0.020	1.620	0.036	0.289	0.016
	(4.11)	(–0.16)	(4.39)	(–1.18)	(0.80)	(3.67)	(–4.63)	(1.41)	(–0.71)	(2.37)	(0.80)	(0.39)	(0.80)
Min. investment	–0.027	–0.001	–0.023	0.001	0.001	–0.002	–0.001	0.001	–0.001	0.005	0.004	–0.001	0.001
	(–1.65)	(–1.40)	(–1.70)	(0.96)	(0.85)	(–1.93)	(–0.09)	(0.11)	(–1.20)	(1.03)	(2.26)	(–0.13)	(1.72)
Management fee	0.554	–0.034	0.753	0.015	0.006	0.104	–0.167	–0.008	–0.023	0.280	–0.004	–0.039	–0.006
	(1.58)	(–1.89)	(2.48)	(0.86)	(0.32)	(2.53)	(–0.71)	(–0.28)	(–1.47)	(0.86)	(–0.14)	(–0.13)	(–0.91)
Incentive fee	0.062	–0.002	0.093	–0.006	–0.001	0.009	0.021	–0.010	–0.008	0.072	0.002	0.109	–0.001
	(1.89)	(–0.96)	(3.42)	(–3.15)	(–0.50)	(2.67)	(1.28)	(–4.79)	(–5.95)	(2.57)	(0.79)	(4.07)	(–0.71)
Lockup period	0.055	0.004	0.053	–0.001	–0.001	0.008	–0.004	0.001	0.002	0.134	0.008	0.161	0.002
	(1.97)	(2.71)	(2.35)	(–0.86)	(–0.78)	(2.49)	(–0.24)	(0.57)	(1.46)	(4.70)	(3.17)	(6.38)	(4.82)
Notice period	–0.021	–0.001	–0.014	0.001	0.001	0.002	0.012	0.001	–0.001	0.053	0.008	0.051	0.001
	(–3.07)	(–0.34)	(–2.53)	(0.45)	(2.97)	(1.71)	(2.24)	(0.69)	(–0.48)	(6.51)	(13.95)	(7.28)	(5.58)
Auditing	–1.955	–0.065	–1.038	–0.083	–0.046	0.040	0.225	–0.077	–0.086	1.568	0.150	2.199	0.056
	(–4.61)	(–2.63)	(–3.22)	(–3.49)	(–2.08)	(0.88)	(1.09)	(–2.02)	(–4.57)	(3.50)	(4.37)	(4.48)	(3.66)
Intercept	14.763	0.310	9.668	0.212	0.034	–0.505	8.057	0.497	0.591	7.016	0.528	0.587	–0.034
	(10.54)	(4.91)	(8.66)	(3.29)	(0.59)	(–2.98)	(9.39)	(5.10)	(10.52)	(4.92)	(4.58)	(0.43)	(–1.70)
Category dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Start year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.254	0.145	0.239	0.056	0.016	0.092	0.101	0.096	0.237	0.114	0.230	0.084	0.141

returns by lowering risk—like a "tournament" (e.g., Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997)). The tournament explanation is not universally accepted though. Koski and Pontiff (1999) suggest that the slow reaction of fund managers to new fund flows may also result in a negative relationship between past performance and fund risk changes.[23] Busse (2001) attributes the earlier evidence of tournament in mutual funds to statistical biases arising from changes in return autocorrelation within the year.

In this paper, I propose the following pooled cross-sectional regression model, explicitly controlling for fund flows and changes in return autocorrelation, to examine risk shifting in hedge funds and the effect of derivatives use on such practice:

$$\Delta\text{RISK}_{p,y} = \alpha + \beta_1\text{PERF}_{p,y} + \beta_2 D_p + \beta_3\text{PERF}_{p,y}D_p + \beta_4\text{FLOW}_{p,y} + \beta_5\Delta\rho_{p,y} + \text{CONTROLS} + \varepsilon_{p,y}, \quad (7)$$

where ΔRISK is the change of fund risk (measured by return volatility, market risk,[24] and idiosyncratic risk) between the 2nd half and the 1st half of a given year;[25] PERF is fund return in the half of the year y in excess of a benchmark; and D is the derivatives-use dummy variable. The fund's net flow in the 2nd half of the year is calculated as

$$\text{FLOW}_{p,t} = \frac{\text{AUM}_{p,t} - \text{AUM}_{p,t-1} \times (1 + R_{p,t})}{\text{AUM}_{p,t-1}}, \quad (8)$$

where AUM stands for assets under management, and R denotes the fund return. Here, $\Delta\rho$ is the change in the 1st-order autocorrelation of returns between the 2nd and the 1st halves of the year. The regression also includes additional controls, including the lagged level of fund risk in the 1st half of the year (LAGRISK), various fund characteristics and their interactions with derivatives use, the dummy variables for funds' investment strategies, and the year dummy variables. The year dummy variables control for the possibility that funds adjust risk to some macrolevel factors (see Ferson and Schadt (1996)). Following Petersen (2009), I cluster standard errors by fund to adjust for correlation across observations belonging to the same fund.

Two benchmarks are considered when calculating the variable PERF in regression (7). The 1st benchmark is the median return for funds within the same investment category during the 1st half of the year. This benchmark corresponds to the tournament behavior in that the manager alters riskiness in response to the fund's relative performance to peer funds. The 2nd benchmark, corresponding to the high-water mark provision, equals the return that the fund needs to recover

[23] Ferson and Warther (1996) find that mutual funds experiencing unexpected fund inflows will take time to allocate the cash into securities, and in the meantime the fund risk is relatively low because of cash holdings.

[24] Here, market risk is estimated from a regression that, different from regression (1), does not control for other market indexes, because of the small number of observations in a 6-month horizon.

[25] In a robustness check, I remove return data for Decembers to control possible window dressing problems (Lakonishok, Shleifer, Thaler, and Vishny (1991)), and the results remain qualitatively unchanged.

the (possible) previous year's losses. Specifically, the value of this benchmark is as follows:

$$\text{(9)} \qquad \text{HIGH-WATER\_BENCHMARK}_y \quad = \quad \max\left(\frac{1}{1+R_{y-1}} - 1,\ 0\right),$$

where R_{y-1} is the fund return in the prior year (y – 1).[26]

B. Evidence on Risk Shifting

Table 9 presents the results from regression (7) based on the relative performance benchmark.[27] Consistent with the results in Brown et al. (2001), this table shows clear evidence of risk shifting that hedge funds realizing poor relative performance in the 1st half of a year exhibit greater risk increase in the 2nd half of the year.

However, derivatives users engage less in risk shifting. For example, the coefficient on the interaction term of performance and the derivatives-use dummy variable is 0.016 for the test of shifting total risk, offsetting about half of the risk-shifting coefficient –0.031. Further, I test whether volatility change comes from change in market risk or change in idiosyncratic risk. It appears that hedge funds mainly shift idiosyncratic risk in response to their performance relative to peer funds. This seems intuitive, since when a fund falls behind its peer funds, it may want to stand out by differentiating itself from other funds, and so idiosyncratic risk increases. This is also consistent with the findings in the mutual fund literature (e.g., Chevalier and Ellison (1997), Li and Tiwari (2006)) that mutual funds engage in the tournament practice mainly through changing nonsystematic risk.

The results are robust to the controls for fund flows and change in return autocorrelation. Consistent with the arguments of Koski and Pontiff (1999) and Busse (2001), fund inflows are negatively associated with future return volatility, while the increase of return autocorrelation raises volatility. The other controls in the regression include the interaction terms between the performance variable and fund characteristics. The regression coefficients on these interaction terms indicate that older and smaller hedge funds tend to distort fund risks more actively. In a mutual fund setting, Brown et al. (1996) and Chevalier and Ellison (1997) find that smaller funds manipulate risk more than larger funds.

Table 10 reports the evidence on risk shifting corresponding to funds' absolute performance relative to their own high-water benchmark as described in

[26]To see how the benchmark works, consider a fund that realized a return of -0.5 in the last year. Thus, its assets dropped by 50% (for simplicity, ignoring any new money flow). In order to collect an incentive fee that year, the fund must realize a return surpassing the threshold $[1/(1-0.5)] - 1 = 1$ (i.e., a return of 100%). Of course, this calculation is only an approximation. Brown et al. (2001) and Goetzmann et al. (2003) recognize the difficulty of accurately measuring the high-water benchmark. For example, funds with a high-water mark sometimes apply a hurdle rate. Furthermore, the fact that investors entering the fund in different periods will have heterogeneous high-water marks makes calculating the benchmark more complex. Alternative ways of calculating the high-water benchmark were attempted, such as adding a 1-month T-bill rate as the hurdle rate and using returns for the past 2 years. The empirical results are qualitatively similar.

[27]The number of funds in this test is smaller than the full sample, because a number of funds do not report information on all the fund characteristics used in the regressions.

TABLE 9

Derivatives Use and Risk Shifting: Relative Performance Benchmarks

Table 9 reports the results of hedge funds' risk shifting to relative-performance benchmarks over the period of 1994–2006 from the following pooled regression:

$$(7) \qquad \Delta\text{RISK}_{p,y} = \alpha + \beta_1\text{PERF}_{p,y} + \beta_2 D_p + \beta_3\text{PERF}_{p,y}D_p + \beta_4\text{FLOW}_{p,y} + \beta_5\Delta\rho_{p,y} + \text{CONTROLS} + \varepsilon_{p,y},$$

where p represents the fund p, and y represents the year y; ΔRISK is the change of fund risk (measured by return volatility, market risk, or idiosyncratic risk) in the 2nd half of the year y from that in the 1st half; PERF is the fund p's return minus the median return of funds within the same category in the 1st half of the year; D is the derivatives-use dummy variable; FLOW is the net fund flow in the 2nd halves of the year; $\Delta\rho$ is the change of 1st-order autocorrelation of returns between the 1st and the 2nd halves of the year; LAGRISK is the risk level in the 1st half of the year; and t-statistics are in parentheses, based on standard errors clustered by fund to adjust for correlation across observations belonging to the same fund.

	Δ Total Risk		Δ Market Risk		Δ Idiosyn. Risk	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
PERF	–0.031	–0.171	–0.008	1.030	–0.022	–0.156
	(–3.73)	(–3.52)	(–0.06)	(1.35)	(–2.82)	(–3.49)
Derivatives use	–0.002	–0.002	–0.044	–0.038	–0.002	–0.002
	(–3.36)	(–3.19)	(–2.93)	(–2.42)	(–3.29)	(–3.15)
PERF × Derivatives use	0.016	0.019	0.261	0.342	0.014	0.016
	(1.67)	(2.11)	(1.53)	(2.02)	(1.65)	(1.97)
FLOW	–0.0002	–0.0001	–0.003	–0.003	–0.0001	–0.0001
	(–12.02)	(–13.94)	(–19.09)	(–19.01)	(–9.47)	(–10.61)
$\Delta\rho$	0.004	0.004	0.032	0.030	0.002	0.002
	(7.50)	(7.53)	(2.80)	(2.59)	(5.28)	(5.30)
LAGRISK	–0.389	–0.406	–0.778	–0.783	–0.525	–0.542
	(–17.31)	(–17.51)	(–29.47)	(–28.77)	(–24.16)	(–25.10)
ln(Fund age)		0.001		0.023		0.001
		(4.50)		(3.18)		(3.94)
ln(AUM)		–0.001		–0.008		–0.001
		(–7.04)		(–1.81)		(–7.43)
Min. investment		–0.0002		–0.0004		–0.0002
		(–1.09)		(–0.12)		(–1.25)
Management fee		0.001		–0.033		0.001
		(0.95)		(–2.66)		(2.39)
Incentive fee		0.0001		–0.003		0.0001
		(0.31)		(–2.42)		(1.98)
Lockup period		0.001		0.002		0.0001
		(2.31)		(1.49)		(1.99)
Notice period		0.001		0.0001		–0.0001
		(0.06)		(0.38)		(–0.99)
Auditing		–0.0001		–0.030		–0.0003
		(–0.08)		(–1.69)		(–0.39)
PERF × ln(Fund age)		–0.012		–0.259		–0.008
		(–2.45)		(–2.85)		(–2.07)
PERF × ln(AUM)		0.009		–0.039		0.008
		(3.62)		(–0.88)		(3.33)
PERF × Incentive fee		–0.0001		–0.013		0.0001
		(–0.78)		(–1.85)		(0.24)
PERF × Lockup period		0.001		–0.012		0.001
		(0.91)		(–0.77)		(1.31)
PERF × Notice period		–0.004		–0.069		–0.001
		(–0.90)		(–0.67)		(–0.24)
PERF × Auditing		0.003		0.247		0.003
		(0.30)		(1.16)		(0.28)
Category dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fund-semester obs.	13,536	13,000	13,536	13,000	13,536	13,000
No. of funds	3,381	3,300	3,381	3,300	3,381	3,300
Adjusted R^2	0.317	0.322	0.588	0.594	0.414	0.421

TABLE 10
Derivatives Use and Risk Shifting: High-Water Benchmarks

Table 10 reports results of hedge funds' risk shifting to high-water benchmarks over the period 1994–2006 from the following pooled time-series and cross-sectional regression:

$$\Delta\text{RISK}_{p,y} = \alpha + \beta_1\text{PERF}_{p,y} + \beta_2 D_p + \beta_3\text{PERF}_{p,y}D_p + \beta_4\text{FLOW}_{p,y} + \beta_5\Delta\rho_{p,y} + \text{CONTROLS} + \varepsilon_{p,y}, \quad (7)$$

where p represents the fund p, and y represents the year y; ΔRISK is the change of fund risk (measured by return volatility, market risk, or idiosyncratic risk) in the 2nd half of the year y from that in the 1st half; PERF is the fund p's return minus the high-water benchmark that the fund needs to surpass in order to recover losses from the previous year; D is the derivatives-use dummy variable; FLOW is the net fund flow in the 2nd half of the year; $\Delta\rho$ is the change of 1st-order autocorrelation of returns between the 1st and the 2nd halves of the year; LAGRISK is the risk level in the 1st half of the year; and t-statistics are in parentheses, with standard errors clustered by fund to adjust for correlation across observations belonging to the same fund.

	Δ Total Risk		Δ Market Risk		Δ Idiosyn. Risk	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
PERF	–0.042	–0.183	–0.470	0.038	–0.031	–0.157
	(–5.94)	(–3.50)	(–4.64)	(0.06)	(–4.26)	(–3.12)
Derivatives use	–0.003	–0.003	–0.064	–0.057	–0.002	–0.002
	(–3.84)	(–3.70)	(–3.62)	(–3.14)	(–3.29)	(–3.21)
PERF × Derivatives use	0.020	0.021	0.514	0.505	0.015	0.016
	(2.45)	(2.49)	(3.91)	(3.76)	(1.87)	(1.99)
FLOW	–0.0005	–0.0003	–0.0034	–0.003	–0.0005	–0.0003
	(–1.40)	(–1.01)	(–0.78)	(–0.78)	(–1.44)	(–1.03)
$\Delta\rho$	0.004	0.004	0.027	0.031	0.002	0.002
	(6.09)	(6.35)	(2.07)	(2.37)	(4.14)	(4.31)
LAGRISK	–0.393	–0.415	–0.774	–0.774	–0.524	–0.550
	(–18.14)	(–19.31)	(–26.17)	(–25.50)	(–23.86)	(–26.23)
ln(Fund age)		0.001		0.020		0.001
		(3.51)		(1.87)		(3.56)
ln(AUM)		–0.001		–0.001		–0.001
		(–5.78)		(–0.25)		(–6.39)
Min. investment		–0.0003		–0.0007		–0.0002
		(–1.56)		(–0.19)		(–1.46)
Management fee		0.001		–0.028		0.001
		(1.43)		(–2.12)		(2.74)
Incentive fee		0.0001		–0.003		0.0001
		(0.04)		(–2.22)		(1.61)
Lockup period		0.001		0.002		0.0001
		(1.83)		(1.17)		(1.36)
Notice period		0.001		0.0002		–0.0001
		(0.06)		(0.65)		(–0.88)
Auditing		0.0001		–0.026		–0.001
		(0.48)		(–1.26)		(–0.70)
PERF × ln(Fund age)		–0.008		–0.271		–0.007
		(–1.60)		(–2.37)		(–1.47)
PERF × ln(AUM)		0.009		–0.007		0.008
		(3.22)		(–0.18)		(3.00)
PERF × Incentive fee		0.0001		–0.001		–0.0004
		(0.01)		(–0.06)		(–0.71)
PERF × Lockup period		–0.0001		–0.014		0.0002
		(–0.24)		(–1.21)		(0.28)
PERF × Notice period		–0.001		–0.042		0.003
		(–0.38)		(–0.50)		(0.81)
PERF × Auditing		0.003		0.101		0.002
		(0.27)		(0.53)		(0.21)
Category dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fund-semester obs.	10,930	10,855	10,930	10,855	10,930	10,855
No. of funds	2,806	2,792	2,806	2,792	2,806	2,792
Adjusted R^2	0.314	0.325	0.581	0.578	0.406	0.422

equation (9). The test includes only hedge funds that use a high-water mark, and thus 2,806 funds remain in the sample. Hedge funds tend to increase portfolio risk when their interim returns are below the high-water benchmark, suggesting the funds alter their risk level when their option-like fee contracts become out of the money.[28] Moreover, funds distort both market risk and idiosyncratic risk, which is intuitive in that a fund behind its absolute benchmark may intend to boost its performance by taking whatever type of risk. Similar to the results shown in Table 9, derivatives users are associated with significantly less risk shifting. For instance, the risk-shifting coefficient for derivatives nonusers is -0.47 (t-statistic $= -4.64$) for the market risk, while risk shifting for derivatives users is negligible given the coefficient on the interaction term PERF $\times$ DERIVATIVE (0.514 with t-statistic $= 3.91$).

In summary, the evidence in this section suggests that although hedge funds in general shift portfolio risk in response to recent (both relative and absolute) performance, the use of derivatives is associated with less risk shifting. At first glance this evidence seems puzzling, since derivatives can be a convenient tool to shift fund risk. However, due to career concerns, hedge funds may use derivatives to manage and stabilize fund risk.

V. Derivatives Use and Fund Failure Risk

Another important question regarding derivatives use is whether it increases hedge funds' failure risk. Brown et al. (1999) document that hedge funds feature a high attrition rate. If derivatives are primarily used to speculate on security prices or take on risk, derivatives use would be expected to be linked with high failure likelihood. Indeed, it has been argued that the excessive use of derivatives played a central role in the collapse of LTCM and Amaranth. On the other hand, if derivatives users can better manage portfolio risk, they will be less likely to fail. This section tests whether derivatives use is related to fund liquidation.

The funds labeled as graveyard funds in the TASS database are not necessarily "dead." TASS provides the reasons why funds dropped from the database, including "fund liquidation," "no longer report," "unable to contact," "closing to new investment," "merged into another fund," and "unknown reason." Thus, treating all defunct funds as dead funds would bias the survival analysis. This section considers only liquidated funds as failed funds and excludes funds that dropped for other reasons. In order to have the full history of liquidated funds, the analysis includes only the funds whose operation started in or after January 1994, since return data of defunct funds first became available then.

[28] Brown et al. (2001) document the evidence of risk shifting to the high-water benchmark to a lesser extent than reported in this study. For example, the t-value in their study is -1.72 over the sample period of 1989–1998 (panel B of Table II in their paper). This difference may be due to a few reasons. First, the sample period (1994–2006) in this paper features keener competition within the hedge fund industry, which may accelerate funds' gaming incentives. Second, their hedge fund sample includes data before 1994, when defunct funds have not been included in TASS. Brown et al. (1996) argue that omitting failure funds could bias against finding evidence of risk shifting, since poorly performing funds cease operations at a high rate. Finally, they adopt the methodology proposed by Brown et al. (1996) that is subject to the concerns related to fund flows and change in return autocorrelation.

Table 11 presents the results from the Cox proportional hazard model using data at a semiannual frequency. The model reports a hazard ratio for each independent variable. A hazard ratio greater (smaller) than 1 indicates the independent variable is positively (negatively) associated with failure risk. Consistent with Baquero, ter Horst, and Verbeek (2005), fund past returns as well as a higher return standard deviation in the prior year are negatively related to fund failure. Following Brown et al. (2001), this paper employs a dummy variable "underwater," that equals 1 if the fund experiences negative cumulative returns over the previous 2 years, and 0 otherwise. The hazard ratio for the variable underwater is 2.607 (with a *Z*-score of 5.01), indicating that when it becomes too difficult to recover past losses the fund simply executes the option of fund liquidation. This is consistent with the observation in Brown et al. (2001). A novel finding here is that higher liquidation chances occur in downmarket periods when the cumulative excess return of the stock market is negative in the recent 6 months. In addition, larger funds, funds with longer redemption periods, and funds with effective auditing have lower failure risk.

TABLE 11

Derivatives Use and Fund Failure Risk

Table 11 presents the effect of derivatives use on fund failure risk, based on the Cox proportional hazard model. Derivatives use a dummy variable. Fund failure is measured by fund liquidation at a semiannual frequency. Here, RET_*n* denotes fund return in the *n*th semester since the fund's inception, SD_1YEAR refers to the prior year's return standard deviation, UNDERWATER is a dummy variable indicating whether the fund's cumulative return over the past 2 years is negative, and DOWNMARKET is a dummy variable indicating whether the cumulative market excess return over the prior 6 months is negative. A hazard ratio greater (smaller) than 1 indicates that the explanatory variable is positively (negatively) related to fund failure risk.

	(1)		(2)	
Variable	Hazard Ratio	*Z*-Score	Hazard Ratio	*Z*-Score
RET_1	0.977	–5.48	0.976	–5.65
RET_2	0.980	–4.39	0.982	–4.07
RET_3	1.001	0.34	1.001	0.16
RET_4	0.997	–0.97	0.998	–0.64
SD_1YEAR	0.973	–4.80	0.974	–4.63
Derivatives use			1.071	0.49
UNDERWATER	2.114	5.77	2.607	5.01
UNDERWATER × Derivatives use			0.761	–1.29
DOWNMARKET	1.611	2.25	2.736	2.76
DOWNMARKET × Derivatives use			0.611	–2.07
ln(AUM)	0.666	–14.27	0.667	–14.09
Min. investment	1.050	0.88	1.049	0.86
Management fee	1.042	0.43	1.076	0.74
Incentive fee	1.009	0.96	1.010	1.13
Lockup period	0.995	–0.55	0.996	–0.51
Notice period	0.572	–7.91	0.570	–7.94
Auditing	0.388	–8.82	0.390	–8.75
Category dummies	Yes		Yes	
Year dummies	Yes		Yes	
Fund-semester obs.	16,567		16,567	
No. of funds	2,165		2,165	

The relation between derivatives use and liquidation risk is interesting. First, the use of derivatives itself does not materially affect fund liquidation. Second, the coefficient on the interaction term of underwater and derivatives use suggests that underwater derivatives users are less likely to fail than underwater nonusers, but the result is statistically insignificant. Finally, the use of derivatives is associated with significantly lower liquidation likelihood during down markets, and the coefficient on the interaction term between the downmarket state and derivatives use is 0.611 (Z-score = –2.07). This suggests that using derivatives does not help prevent fund failure when fund performance is particularly low (e.g., underwater), but it can somewhat mitigate the unfavorable influence of severe market conditions on fund operation. This finding echoes the preceding evidence that hedge fund derivatives use is mainly associated with lower systematic risk and especially with lower downside/event risk.

VI. Derivatives Use and Investor Flows

This section asks the question whether hedge fund investors treat derivatives users differently than nonusers, by examining and comparing the patterns of how investor flows respond to fund performance. Specifically, I employ the following regression analysis of investor flows at an annual frequency:

$$\text{(10)} \qquad \text{FLOW}_{p,t} = \alpha + \beta_1 \text{PERF}_{p,t-1} + \beta_2 \text{PERF}^2_{p,t-1} + \beta_3 D_p + \beta_4 \text{PERF}_{p,t-1} D_p + \text{CONTROLS} + \varepsilon_{p,y},$$

where $\text{FLOW}_{p,t}$ is the net fund flows of fund p in the year t, PERF_{t-1} is the prior year's fund return in excess of the median return of all funds within the same investment category, and D is the derivatives-use dummy variable.

Table 12 presents of the flow-performance regression results. Annual fund flows are positively related to the prior year's fund performance. Consistent with the finding of Goetzmann et al. (2003), the flow-performance relation seems

TABLE 12

Derivatives Use and the Fund Flow-Performance Relation

Table 12 reports the effect of derivatives use on the fund flow-performance relation at annual frequency from the following pooled regression:

$$\text{(10)} \qquad \text{FLOW}_{p,t} = \alpha + \beta_1 \text{PERF}_{p,t-1} + \beta_2 \text{PERF}^2_{p,t-1} + \beta_3 D_p + \beta_4 \text{PERF}_{p,t-1} D_p + \text{CONTROLS} + \varepsilon_{p,y},$$

where $\text{FLOW}_{p,t}$ is the net fund flows, as defined in equation (8), of fund p in year t, PERF_{t-1} is the prior year's fund return in excess of the median return of all funds within the same investment category, D is the derivatives-use dummy variable, and t-statistics are calculated from the standard errors clustered at the fund level.

	(1)		(2)	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic
PERF_{t-1}	1.088	8.36	1.002	4.49
PERF^2_{t-1}	–0.196	–1.63	–0.194	–1.65
Derivatives use			0.037	0.80
PERF_{t-1} × Derivatives use			0.124	0.36
ln(Fund age)	–0.420	–7.75	–0.421	–7.77
ln(AUM)	0.175	2.74	0.172	2.69
Min. investment	0.053	0.99	0.052	0.97
Management fee	0.034	0.84	0.032	0.82
Incentive fee	–0.008	–1.07	–0.008	–1.09
Lockup period	–0.004	–0.79	–0.004	–0.80
Notice period	0.001	1.17	0.001	1.16
Auditing	–0.037	–0.49	–0.040	–0.53
Category dummies	Yes		Yes	
Year dummies	Yes		Yes	
Fund-year obs.	9,090		9,090	
No. of funds	2,446		2,446	
Adjusted R^2	0.028		0.029	

to be somewhat concave since the regression coefficient on the square term of performance is negative.[29] Meanwhile, there is no apparent difference in the flow-performance relation between derivatives users and nonusers, indicating that investors in derivatives-using hedge funds do not appear to respond differently to fund performance. One explanation is that investors, who receive a similar level of after-fee performance, are indifferent to whether or not the fund uses derivatives. Another possible explanation is that investors are not aware of the difference in risk taking between derivatives users and nonusers, or at least do not deem hedge funds' derivatives use to be particularly perilous to their investments.

VII. Conclusion

This paper examines the link between derivatives use and risk taking in the hedge fund industry. In a large sample as of June 2006, 71% of the funds trade derivative securities. The proportion of hedge funds using derivatives is over 3 times as large as among mutual funds. Different from the popular press's portrait of derivatives as perilous investments, derivatives-using hedge funds on average display lower risk under several measures such as return volatility, market risk, downside risk, and extreme event risk, while there is some trace of speculation-motivated use of derivatives. Meanwhile, the after-fee risk-adjusted performance, including the MPPM proposed by Ingersoll et al. (2007), is similar between derivatives users and nonusers. These empirical findings are robust to correcting fund data biases, to controlling various fund characteristics, to using both after-fee and pre-fee fund returns, to examining a subsample period, and to applying 2SLS regressions with fund managers' prior expertise in derivatives trading as an instrumental variable.

Further, derivatives users engage less in risk shifting compared to funds that do not use derivatives. Derivatives use is also associated with lower fund failure risk, especially during severe market states. In addition, I test whether investors distinguish derivatives users and nonusers and find that derivatives use has little influence on the fund flow-performance relation.

Taken together, the evidence does not suggest that hedge fund derivatives use leads to more risk taking. The findings of this paper are remarkably different from previously documented for mutual funds (Koski and Pontiff (1999)) and should have important implications for hedge fund investors, lenders, and regulators. Finally, it would be interesting for future research to examine other aspects of hedge funds' flexible trading strategies, such as short selling and leverage.

References

Ackermann, C.; R. McEnally; and D. Ravenscraft. "The Performance of Hedge Funds: Risk, Return and Incentives." *Journal of Finance*, 54 (1999), 833–874.

Agarwal, V.; N. D. Daniel; and N. Y. Naik. "Role of Managerial Incentives and Discretion in Hedge Fund Performance." *Journal of Finance*, 64 (2009), 2221–2256.

[29]In the mutual fund literature, the flow-performance relation is found to be convex (e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998)). See Ding, Getmansky, Liang, and Wermers (2010) for a more detailed analysis of the flow-performance relation in hedge funds.

Agarwal, V.; V. Fos; and W. Jiang. "Inferring Reporting Biases in Hedge Fund Databases from Hedge Fund Equity Holding." Working Paper, Columbia University and Georgia State University (2010).

Agarwal, V., and N. Y. Naik. "Risks and Portfolio Decisions Involving Hedge Funds." *Review of Financial Studies*, 17 (2004), 63–98.

Almazan, A.; K. C. Brown; M. Carlson; and D. A. Chapman. "Why Constrain Your Mutual Fund Manager?" *Journal of Financial Economics*, 73 (2004), 289–321.

Aragon, G. O. "Share Restrictions and Asset Pricing: Evidence from the Hedge Fund Industry." *Journal of Financial Economics*, 83 (2007), 33–58.

Aragon, G., and J. S. Martin. "A Unique View of Hedge Fund Derivatives Usage: Safeguard or Speculation?" Working Paper, Arizona State University (2009).

Asness, C.; R. Krail; and J. Liew. "Do Hedge Funds Hedge?" *Journal of Portfolio Management*, 28 (2001), 6–19.

Baquero, G.; J. ter Horst; and M. Verbeek. "Survival, Look-Ahead Bias, and Persistence in Hedge Fund Performance." *Journal of Financial and Quantitative Analysis*, 40 (2005), 493–517.

Bawa, V. S., and E. B. Lindenberg. "Capital Market Equilibrium in a Mean-Lower Partial Moment Framework." *Journal of Financial Economics*, 5 (1977), 189–200.

Brown, K. C.; W. V. Harlow; and L. T. Starks. "Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry." *Journal of Finance*, 51 (1996), 85–110.

Brown, S.; T. Fraser; and B. Liang. "Hedge Fund Due Diligence: A Source of Alpha in a Hedge Fund Portfolio Strategy." *Journal of Investment Management,* 6 (2008), 23–33.

Brown, S. J.; W. N. Goetzmann; and R. G. Ibbotson. "Offshore Hedge Funds: Survival and Performance, 1989–95." *Journal of Business,* 72 (1999), 91–117.

Brown, S. J.; W. N. Goetzmann; R. G. Ibbotson; and S. A. Ross. "Survivorship Bias in Performance Studies." *Review of Financial Studies*, 5 (1992), 553–580.

Brown, S. J.; W. N. Goetzmann; and J. Park. "Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry." *Journal of Finance*, 56 (2001), 1869–1886.

Busse, J. A. "Another Look at Mutual Fund Tournaments." *Journal of Financial and Quantitative Analysis*, 36 (2001), 53–73.

Chen, Y., and B. Liang. "Do Market Timing Hedge Funds Time the Market?" *Journal of Financial and Quantitative Analysis*, 42 (2007), 827–856.

Chevalier, J., and G. Ellison. "Risk Taking by Mutual Funds as a Response to Incentives." *Journal of Political Economy*, 105 (1997), 1167–1200.

Deli, D. N., and R. Varma. "Contracting in the Investment Management Industry: Evidence from Mutual Funds." *Journal of Financial Economics*, 63 (2002), 79–98.

Ding, B.; M. Getmansky; B. Liang; and R. Wermers. "Share Restrictions and Investor Flows in the Hedge Fund Industry." Working Paper, University of Massachusetts at Amherst and University of Maryland (2010).

Evans, R. B. "Mutual Fund Incubation." *Journal of Finance*, 65 (2010), 1581–1611.

Ferson, W. E., and R. W. Schadt. "Measuring Fund Strategy and Performance in Changing Economic Conditions." *Journal of Finance,* 51 (1996), 425–461.

Ferson, W. E., and V. A. Warther. "Evaluating Fund Performance in a Dynamic Market." *Financial Analysts Journal*, 52 (1996), 20–28.

Fung, W., and D. A. Hsieh. "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds." *Review of Financial Studies*, 10 (1997), 275–302.

Fung, W., and D. A. Hsieh. "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers." *Review of Financial Studies*, 14 (2001), 313–341.

Geithner, T. F. "Hedge Funds and Derivatives and Their Implications for the Financial System." Federal Reserve Bank of New York (2006).

Getmansky, M.; A. W. Lo; and I. Makarov. "An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns." *Journal of Financial Economics*, 74 (2004), 529–609.

Goetzmann, W. N.; J. E. Ingersoll Jr.; and S. A. Ross. "High-Water Marks and Hedge Fund Management Contracts." *Journal of Finance*, 58 (2003), 1685–1717.

Ingersoll, J.; M. Spiegel; W. Goetzmann; and I. Welch. "Portfolio Performance Manipulation and Manipulation-Proof Performance Measures." *Review of Financial Studies*, 20 (2007), 1503–1546.

Jagannathan, R., and R. A. Korajczyk. "Assessing the Market Timing Performance of Managed Portfolios." *Journal of Business*, 59 (1986), 217–235.

Jorion, P. "Risk Management Lessons from Long-Term Capital Management." *European Financial Management*, 6 (2000), 277–300.

Koski, J. L., and J. Pontiff. "How Are Derivatives Used? Evidence from the Mutual Fund Industry." *Journal of Finance*, 54 (1999), 791–816.

Lakonishok, J.; A. Shleifer; R. Thaler; and R. Vishny. "Window Dressing by Pension Fund Managers." *American Economic Review*, 81 (1991), 227–231.

Li, W., and A. Tiwari. "On the Consequences of Mutual Fund Tournaments." Working Paper, University of Iowa (2006).

Liang, B. "On the Performance of Hedge Funds." *Financial Analysts Journal*, 55 (1999), 72–85.

Liang, B. "Hedge Funds: The Living and the Dead." *Journal of Financial and Quantitative Analysis*, 35 (2000), 309–326.

Liang, B. "The Accuracy of Hedge Fund Returns." *Journal of Portfolio Management*, 29 (2003), 111–122.

Petersen, M. A. "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches." *Review of Financial Studies*, 22 (2009), 435–480.

Scholes, M., and J. Williams. "Estimating Betas from Nonsynchronous Data." *Journal of Financial Economics*, 5 (1977), 309–327.

Sharpe, W. F. "Mutual Fund Performance." *Journal of Business*, 39 (1966), 119–138.

Sirri, E. R., and P. Tufano. "Costly Search and Mutual Fund Flows." *Journal of Finance*, 53 (1998), 1589–1622.

Stock, J. H., and M. Yogo. "Testing for Weak Instruments in Linear IV Regression." In *Identification and Inference for Econometric Models*, D. W. K. Andrews and J. H. Stock, eds. New York, NY: Cambridge University Press (2005).

Teo, M. "The Geography of Hedge Funds." *Review of Financial Studies*, 22 (2009), 3531–3561.

White, H. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica*, 48 (1980), 817–838.