The benefits of option use by mutual funds

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A B S T R A C T

Based on comprehensive regulatory data on equity mutual fund option use from the SEC's N-SAR filings, we are the first to present consistent evidence that equity funds' option use generates higher risk-adjusted performance. We further show that this is a direct effect of option use and not an indirect effect of other fund characteristics. Option use also directly results in lower systematic risk, as funds show significantly lower market betas during periods of options usage. Finally, mutual funds use options mainly for hedging as they primarily use protective puts and covered calls. These results are independent of known phenomena, such as the low beta anomaly, and robust to tests for endogeneity and a novel 5-factor model including an investable option strategy factor (IOS). Overall, our findings show that mutual fund option use is beneficial to investors and does not pose risk to the financial system as feared by the SEC. Our results are thus important for investors as well as regulators.

1. Introduction and literature overview

This is the first paper to present consistent evidence on whether the use of options by mutual funds is beneficial. A SEC concept paper in 2011, requesting comments on this matter, documents the vital importance of this question.[1] Moreover, the SEC's agenda for 2015 includes preparation of stricter regulation of mutual fund derivative use to limit potential risks posed to the financial system

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[1] U.S. Securities and Exchange Commision (2011), http://www.sec.gov/rules/concept/2011/ic-29776.pdf (accessed: 12/09/2015).

and the broader economy.[2,3] However, the three key findings of our analysis reveal (i) that option use creates higher risk-adjusted performance. (ii) Option users have significantly lower systematic risk during times of actual option use but not during times when they do not use options. (iii) Finally, mutual funds employ options for hedging rather than speculation purposes. Thus, mutual fund option use is beneficial to investors as it enhances performance. Moreover, contrary to the SEC's concerns, it reduces systematic risk. We base our results on a large and comprehensive set of regulatory information from the SEC's N-SAR filings on US domestic equity mutual funds from 1998 to 2013. The results withstand tests for endogeneity in the relationship between performance and option use, e.g., due to tournament behavior (e.g., Schwarz, 2011). Moreover, they are robust to a wide range of robustness checks, including a novel 5-factor investable option strategy (IOS) model that controls for the specific option exposures of mutual funds.

Previous research on mutual fund option use has not offered such clear and concise evidence. Lynch-Koski and Pontiff (1999), who are the first to examine mutual fund derivative use, find no significant differences in performance and risk characteristics of users and nonusers. However, their study is based on a telephone survey of a small sample of funds for the short period from 1992 to 1994.[4] Since then, however, capital markets have experienced dramatic growth and seen major booms and crises. Additionally, new regulations, such as the repeal of the short-short rule in 1997, which has facilitated the trading of derivatives, have been implemented. All of these developments necessitate a reassessment of the topic. Cao et al. (2011) find significantly higher raw returns of heavy derivative users during the Russian crisis of August 1998. However, they do not consider risk-adjusted returns and do not assess whether funds use derivatives for speculation or hedging purposes. Furthermore, the Russian crisis is limited to only one month.[5] In the international context, Johnson and Yu (2004) investigate derivative use by Canadian mutual funds finding no clear and economically relevant differences between users and nonusers. Chen (2011) and Aragon and Martin (2012) find superior performance of option using hedge funds, which are better at exploiting the potentially more efficient information pricing on options markets to generate higher performance at lower risk (e.g., Black, 1975; Cao et al., 2005; Pan and Poteshman, 2006). However, as hedge funds are not subject to SEC regulation and thus less restricted in their use of options, these findings cannot be transferred to mutual funds.

In the study most closely related to our own, Cici and Palacios (2015) find no significant differences between option users and nonusers, except in the case of mutual funds that excessively write puts. However, written puts are the least important option type in their dataset, as they account for only 10% of all identified option positions. For 90% of option positions, they find no significant effects. Moreover, their results potentially suffer from the limitations of using only information on funds' holdings of exchange-traded options from 2003 to 2010, which they obtain from Morningstar. Thus, they may underestimate option usage due to (i) window dressing in holding reports to make portfolios appear less risky (Musto, 1997, 1999; Morey and O'Neal, 2006; Agarwal et al., 2014), (ii) neglect of the important market of OTC-traded options,[6] and (iii) reliance on string searching algorithms to identify option positions from holdings' names. As a consequence, Cici and Palacios (2015) identify only 250 funds (10% of their sample funds) as option users, whereas the information contained in the SEC's mandatory N-SAR filings allows us to identify 612 (24% of our sample) mutual funds as users of options.[7]

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[2] Ackerman (2014), http://www.wsj.com/articles/sec-preps-mutual-fund-rules-1410137113 (accessed: 12/09/2015).

[3] Similar to our analysis of options, we also conducted analyses on mutual fund futures use. However, futures do not exhibit any significant influence on fund performance or risk. Therefore, we do not consider them in this paper.

[4] In the paper, Lynch-Koski and Pontiff (1999) admit that managers' answers to the survey proved unreliable.

[5] Cao et al. (2011) also use N-SAR filings but only for a small number of funds over a very short time period, June 1996 to January 1998, which does not even cover the Russian crisis in August 1998.

[6] In 2014, the dollar volume of options traded on the Chicago Board Options Exchange (CBOE) exceeded $579 billion, while more than $5445 billion in options were traded over-the-counter (OTC) (see Chicago Board Options Exchange, 2014, Annual Market Statistics and Bank for International Settlements, 2014).

[7] We also match our N-SAR/CRSP sample to Morningstar portfolio holdings. On the matched sample, we use a string-searching algorithm, as described in Cici and Palacios (2015). In their sample period, from 2003 to 2010, the holdings identify 199 funds (10.0%) as option users, while N-SAR identifies 400 funds (20.1%). In our own (much longer) sample period, from 1998 to 2013, the holdings identify 279 funds (13.5%) as option users, while N-SAR identifies 505 funds (24.5%) for this matched

The contributions of this paper are as follows. (i) Regarding the literature on the benefits of mutual fund derivative use, we are, to the best of our knowledge, the first to find significant and consistent cross-sectional differences in risk-adjusted performance and systematic risk between option users and nonusers. Specifically, funds that use at least one option of some type during their existence outperform nonusers by an economically and statistically significant 44 basis points p.a. on a risk-adjusted basis, controlling for a wide range of other fund characteristics. In contrast to most previous studies, we analyze mutual fund option use over time, using panel regressions. We demonstrate that option users outperform by 67 basis points p.a. but only when they actually employ options. Comparing this, e.g., to the average annual expense ratio of around 130 basis points, option users are able to offset between 1/3 (cross-section) and 1/2 (panel) of investors' recurring costs, which is clearly of economic relevance. In times when they do not employ options, this outperformance vanishes. Further, option users have lower systematic market risk. This risk-reduction also vanishes during times when users do not use options. We show that our findings are a direct effect of option use and not based on alternative drivers of our findings like, e.g. the low beta anomaly (Frazzini and Pedersen, 2014) or the low volatility anomaly (e.g., Baker et al., 2011) by including systematic risk as a control variable in our analysis.

(ii) We also contribute to the literature on mutual funds' option investment strategies. Our panel regression methodology and balance sheet information on long and short options positions, contained in the N-SAR filings, allow us to infer the source of the options' impact on mutual funds. User funds' short option positions, which show a significant performance enhancement of 184 basis points p.a., are the main drivers of the performance-enhancing effect described above. This is consistent with income generating strategies via option premiums. At the same time, funds' short positions in options significantly reduce market beta by approximately 11 percentage points, from which we conclude that they mainly use covered calls. Moreover, option users' long positions in options, which significantly reduce market betas by approximately 13 percentage points, are the predominant drivers of the risk-reducing effect described above. Together with an insignificant effect on performance, this is consistent with a hedging strategy based on protective puts.

(iii) We contribute to the literature on mutual fund performance measurement in general by introducing a novel investable factor that controls for option exposures in mutual fund returns. Goetzmann et al. (2007), among others, show that classic linear performance measures may be biased or even manipulated through the use of options. Cremers et al. (2013) show that it is important for benchmark factors to be investable to generate realistic performance estimates. To control for both such caveats, our novel '5-factor investable option strategy (IOS)' model augments the index-based 4-factor model of Cremers et al. (2013) with the excess return of the CBOE S&P 500 BuyWrite Index. In contrast to related approaches from the hedge fund literature (e.g., Agarwal and Naik, 2004), the IOS factor represents returns of a passive option strategy, which is readily investable via index funds and ETFs.

The remainder of this paper is organized as follows. Section 2 introduces the regulatory environment for mutual fund options use, presents our dataset, and describes the performance models used. Section 3 presents our empirical results. Section 4 presents further tests and comments on robustness checks. Section 5 concludes.

2. Data and performance measurement

2.1. Regulatory framework and mandatory reporting

Any mutual fund registered in the US is regulated by the SEC. Mutual fund option use is codified in the Securities Act of 1933 and the Investment Company Act of 1940 (ICA). According to Sections 18(f), (g) and (h) of the ICA, mutual funds are generally prohibited from using any type of leverage or from buying and selling senior securities.[8] Long option positions are limited in their downside risk,

sample. Thus, Morningstar portfolio holdings severely underestimate mutual fund option use compared with the information contained in the SEC's mandatory N-SAR filings.

[8] The SEC conveniently provides a selected bibliography regarding this topic via their webpage under https://www.sec.gov/divisions/investment/seniorsecurities-bibliography.htm: (see U.S. Securities and Exchange Commission, 2015). For further reference on the regulation of mutual fund option use see Chen et al. (2013) and Cici and Palacios (2015).

and therefore, the SEC does not treat them as leverage. Uncovered written options on the other hand may bear unlimited downside risk and are thus understood as leverage. Mutual funds, nevertheless, have permission to sell options if they fulfill the SEC's asset coverage requirement, i.e., if a fund's total net assets (TNA) plus the options' market value divided by the options' market value is greater than 300%. Further they are allowed to short options by: (i) selling an option on an underlying asset the fund already owns, (ii) selling an option on an underlying asset, for which the fund already owns an offsetting option position, (iii) holding highly liquid assets, e.g., cash, treasuries, corporate bonds or liquid stocks, covering the option's market value in a segregated account. In either case, the SEC requires mutual funds to disclose their option use in mandatory semiannual N-SAR filings, which makes the latter an optimal data source for our study.

2.2. Sample construction

The mutual fund data used in our study come from different sources. Information regarding mutual fund option use is extracted from over 106,357 individual N-SAR filings obtained in unformatted text files from the SEC's EDGAR database.[9] Data on fund returns and characteristics are from the CRSP Mutual Fund Database. Both N-SAR and CRSP are survivorship bias free, as N-SAR filings are mandatory for mutual funds and reports are kept on the SEC's server even for dead funds. To attain the final dataset, we merge the N-SAR filings with the CRSP mutual fund database. Because no identifier matches funds uniquely, we employ algorithmic string matching techniques to match N-SAR and CRSP funds by their names. This requires extensive manual corrections of incorrect or inconsistent fund names in N-SAR. We rigorously remove potentially false matches with several screening techniques that are further described in Appendix.[10] Furthermore, only funds with valid answers regarding their option use are considered. Electronic N-SAR filings are available since 1996. However, as the repeal of the short-short-rule under the Taxpayer Relief Act of 1997 represents a structural break in the regulation of mutual fund derivative use, we limit our sample to the period from 1998 to 2013.[11]

Mutual fund data in N-SAR are at the fund level, whereas data obtained from CRSP are at the share class level. Therefore, we aggregate variables to the fund level by value-weighting according to share class TNA. We calculate fund level TNA as the sum of the share classes' TNA; fund age is the age of the longest existing share class; and the load variable contains load information on the largest share class. We exclude funds before they first surpass the threshold of $5 million (US) in TNA, as in Fama and French (2010), to mitigate incubation bias (Evans, 2010).[12] As we estimate performance measures via regression analysis, we also exclude funds with less than 24 monthly observations to obtain reliable results.[13] The final sample consists of 2576 actively managed domestic equity mutual funds with 231,641 monthly data points. To the best of our knowledge, this is the largest matched N-SAR/CRSP dataset, obtained using regulatory information, in the mutual fund derivative literature to date.

2.3. Option variable definition

N-SAR filings provide rich regulatory information on mutual funds' option use. Specifically, item 70 asks whether or not a mutual fund had the permission to use and actually used different derivatives during the respective semiannual reporting period. We base our option usage variables on a fund's answers contained in its N-SAR filing's items regarding single stock options (Item 70B), debt options (70C), stock index options (70D), options on futures (70G), and options on stock index futures (70H).[14] The main explanatory variable in our cross-sectional regressions, $User_i$, is a dummy variable

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9 http://www.sec.gov/edgar.shtml.

10 Table A.1 in the Appendix shows no significant deviations of our matched CRSP/NSAR sample from the complete CRSP-only sample of actively managed domestic equity funds with respect to major fund characteristics.

11 In unreported tests, the results hold if we begin our sample in 1996.

12 The results remain qualitatively the same for thresholds of $15 and $50 million in TNA.

13 The results are qualitatively unchanged, using 48 fund months as the minimum sample size per fund.

14 In additional checks, we show that our results are consistent when only equity options are considered.

Table 1
Option permission and usage.

	% permitted	% used	# months used	$\frac{\#\text{months used}}{\#\text{total months}}$
Panel A. Cross-sectional option usage				
All options	0.9406	0.2376	36.0	0.3959
Equity options	0.9321	0.1960	31.0	0.3316
Debt options	0.8218	0.0136	1.0	0.0109
Stock index options	0.9130	0.0641	6.7	0.0870
Futures options	0.8587	0.0206	1.8	0.0200
Stock index futures options	0.8599	0.0303	2.6	0.0313
	% permitted	% used	# months permitted	# months used
Panel B. Panel option usage				
All options	0.8882	0.0938	208,441	22,012
Equity options	0.8747	0.0807	205,275	18,944
Debt options	0.7091	0.0025	166,421	583
Stock index options	0.8435	0.0175	197,944	4104
Futures options	0.7839	0.0048	183,966	1117
Stock index futures options	0.7900	0.0067	185,391	1565

This table shows descriptive statistics on the permission and usage of options by mutual funds. The sample consists of actively managed U.S. domestic equity funds over the period 1998–2013. In Panel A, % permitted reports the percentage of all funds that are allowed to use options at least once during the sample period. % Used indicates the percentage of funds that actually use an option at least once. # months used is the average number of using months per user fund. The last column reports this number as a percentage of total months. Panel B contains descriptive statistics from the panel dataset. % permitted (% used) indicates the percentage of all monthly fund observations when funds are permitted (actually use) options. # months permitted (# months used) is the absolute number of fund months in our dataset with the permission to use options (actual option use).

that equals one if a fund uses any of these options at least once during our sample period and zero otherwise.[15] Panel A of Table 1 reports summary statistics on cross-sectional option permission and usage. 94% of funds are allowed to purchase and write options at least once over our sample period, but only a fraction of them actually make use of this permission.[16] 24% of all funds use some type of option at least once. This is consistent with Almazan et al. (2004), who show that mutual funds incorporate permissions in their fundamental investment policies to ensure the greatest possible scope for investment practices, regardless of their inclinations to actually use them. The underlying securities of the options are mainly stocks and stock indexes. This is not surprising because our sample consists solely of equity funds. Deli and Varma (2002) and Chen (2011) interpret the suitability of options to respective investment styles as evidence that funds seek to mitigate transaction costs by using derivatives. Panel A further reports that user funds actually employ options approximately 40% of the time.

The main explanatory variable in our panel regressions, $Using_{i,t}$, is a dummy variable that equals one for each month of a given reporting period in which a user fund employs at least one option type and zero otherwise.[17] Panel B of Table 1 presents statistics on option permissions and usage from our panel analysis. In 88.82% of all monthly fund observations, funds have permission to use at least one type of option. However, options are used in only 9.38% of all observations. To capture any differential effect of use and nonuse by user funds, we define the dummy variable $Nonusing_{i,t}$, which equals one

[15] In additional tests, we alternatively define $User_i$ as a fund that used some type of option at least 10%, 20% or 30% of the time. The results weaken with stricter requirements because more and more users migrate to the group of nonusers, thereby diluting the differences between the groups. In our panel analysis, we implicitly control for the frequency of option use by individual funds.

[16] If funds that have permission to use options differ significantly from funds that are not allowed to use options, our results may be spurious. However, our results hold if we consider only funds that have permission to use options during the respective reporting period.

[17] N-SAR filings report option usage on a semiannual basis. Hence, it is not clear if a fund uses options in all months or just selected months of the given reporting period. In additional tests, we therefore conduct our panel regressions for the semiannual reporting interval. The results are qualitatively the same as with the monthly interval and thus robust.

if a user fund does not use options in a specific month and zero otherwise.[18] We employ this variable in combination with $Using_{i,t}$. This enables us to distinguish between the direct effects of option use on performance and risk and any effect based on other differential characteristics between users and nonusers.

In addition, the N-SAR filings provide balance sheet data on option positions, i.e., the market value of purchased equity options (74G) and options on futures (74H) as well as on written equity options (74R3). This enables us to distinguish between long and short option positions and infer actual fund option strategies, i.e., whether funds use options for hedging or for speculation. To differentiate between the effects of long option positions and short option positions on performance and risk, we split the $Using_{i,t}$ dummy into two new dummy variables. $Long_{i,t}$ equals one in all periods in which a fund has a net long position in options and zero otherwise. Analogously, $Short_{i,t}$ equals one if a fund has a net short position in options and zero otherwise. We use these variables in combination with the $Nonusing_{i,t}$ dummy.

2.4. Risk-adjusted performance measurement

To measure fund performance and risk, we use both fund gross and net returns. Fama and French (2010) and Pástor et al. (2015) argue that gross returns are more appropriate for the measurement of fund manager skill because they represent returns generated by investment decisions. To assess whether gross return results translate into actual benefits for investors, we also use net returns in this paper.

Our baseline performance model is Carhart's (1997) 4-factor model, as it is the widest spread model to date, and pricing factors are readily available on Kenneth French's homepage.[19] It is based on the following regression:

$$ER_{i,t} = \alpha_{i,4F} + \beta_{i,Mkt}ER_{Mkt,t} + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,Mom}UMD_t + \varepsilon_{i,t} \tag{1}$$

where $ER_{i,t}$ is the gross excess return of fund i in month t, $ER_{Mkt,t}$ is the market excess return, SMB_t is the size factor, HML_t is the value factor (Fama and French, 1993), and UMD_t is Fama and French's version of Carhart's momentum factor (Carhart, 1997). The main parameters of interest are funds' risk-adjusted performance, $\alpha_{i,4F}$, and their systematic market risk, $\beta_{i,Mkt}$.

Considering that mutual funds use options, the original Carhart 4-factor model might be subject to bias or even manipulation due to nonlinearity and asymmetry in option returns (e.g., Goetzmann et al., 2007). Moreover, Cremers et al. (2013) argue that passive benchmarks should represent feasible, low-cost investment opportunities. Therefore, we propose a novel '5-factor IOS-model, which is equivalent to the index-based Cremers et al. (2013) 4-factor model augmented by an investable option strategy (IOS) factor. As the IOS factor, we employ excess returns on the CBOE S&P 500 BuyWrite Index introduced by Whaley (2002).[20] This index replicates a feasible passive total return covered call strategy.[21] In particular, the strategy is long in the S&P 500 market portfolio and sells one-month near-the-money call options on the S&P 500 every month. Thus, it does not use model-inferred option prices but market prices of actually traded options, including potential mispricing due to market incompleteness (Guasoni et al., 2011) or buy pressure by portfolio insurers (Bollen and Whaley, 2004). The performance regression is as follows:

$$\begin{aligned} ER_{i,t} = {} & \alpha_{i,5F} + \beta_{i,S5}\left(S5_t - r_{f,t}\right) + \beta_{i,R2-S5}(R2_t - S5_t) + \beta_{i,R3V-R3G}(R3V_t - R3G_t) \\ & + \beta_{i,UMD}UMD_t + \beta_{i,IOS}IOS_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where $(S5_t - r_{f,t})$ is the excess return on the S&P 500 index; $(R2_t - S5_t)$ is the return on a zero-investment portfolio that is long in the Russell 2000 small-cap index and short in the S&P 500 index, representing the size factor; and $(R3V_t - R3G_t)$ is the return on a portfolio that is long in the Russell

[18] Here, we define a fund as a user fund from the first time it employs options.

[19] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We thank Kenneth French for providing the data.

[20] In additional tests, we alternatively use the CBOE S&P 500 PutWrite factor. The results are similar.

[21] http://www.cboe.com/micro/bxm.

3000 Value index and short in the Russell 3000 Growth index, representing the value factor. We follow Cremers et al. (2013) and use UMD_t from Fama and French as the momentum factor.[22]

To further control for higher moments in fund returns, especially those of option users, we additionally use Leland's alpha. Leland (1999) argues that long option positions generate positive skewness due to limited downside risk and lead to negatively biased alphas. Conversely, short option positions generate negative skewness due to limited upside potential and therefore lead to positively biased alphas. Thus, we control for higher moments in fund returns by using the following model, where $E(r_i)$ is the expected gross return of fund i, and $E(r_{Mkt})$ is the expected market return:

$$\begin{aligned} &\alpha_{i,L} = E(r_i) - B_{i,L}[E(r_{Mkt}) - r_f] - r_f, \\ &\text{where } B_{i,L} = \frac{cov\left[r_i, -(1+r_{Mkt})^{-b}\right]}{cov\left[r_{Mkt}, -(1+r_{Mkt})^{-b}\right]} \\ &\text{with } b = \frac{ln[E(1+r_{Mkt})] - ln(1+r_{Mkt})}{var[ln(1+r_{Mkt})]} \end{aligned} \tag{3}$$

Finally, symmetric CAPM-based performance models may also be inadequate because options generate asymmetric payoff profiles. Bawa and Lindenberg (1977) argue that downside risk is more relevant. Thus, we use the Bawa/Lindenberg-alpha as in Anthonisz (2012), which uses semi-variance instead of symmetric variance, to measure fund performance:

$$\begin{aligned} &\alpha_{i,BL} = E(r_i) - B_{i,BL}[E(r_{Mkt}) - r_f] - r_f, \\ &\text{where:} B_{i,BL} = \frac{cov[r_i, r_{Mkt} \mid r_{Mkt} < 0]}{var[r_{Mkt} \mid r_{Mkt} < 0]} \end{aligned} \tag{4}$$

The models of Leland (1999) and Bawa and Lindenberg (1977) consider only the market factor. To control for size, value and momentum, we orthogonalize fund and market returns against the remaining Carhart factors, using a transition similar to that of Rohleder et al. (2011).[23]

Consistent with standard procedure in the empirical financial literature, as we use the performance and market beta estimations from Eqs. (1)–(4) as dependent and independent variables in all cross-sectional and panel regressions of our empirical analysis, we account for extreme measurement errors in variables by winsorizing alphas and market betas at the 1% and 99% percentiles (e.g., Fama and French, 2008; Coles et al., 2008; Pontiff and Woodgate, 2008).[24]

3. Empirical analysis of option usage, performance and risk

3.1. Descriptive statistics

Table 2 reports cross-sectional summary statistics on mutual fund characteristics separately for option users and nonusers. Option users are larger on average, although the median option user is smaller than the median nonuser. This implies that there are many small funds using options and only a small number of large funds using option. Option users, on average, are older than nonusers, but the median option user is younger, so that many users are rather young. Both the average and median user fund have higher turnover than the average and median nonuser fund. Option users charge higher expense ratios, and the fraction of load funds is higher, consistent with Lynch-Koski and Pontiff (1999). Higher fees may be charged to compensate for higher costs associated with more sophisticated information and risk management systems as well as more experienced fund managers. There is no significant difference in manager tenure between option users and nonusers. Users hold more cash on average, which could be associated with the requirement of holding liquid assets in a segregated account. Additionally, user funds experience smaller net flows on average. We use all of

[22] In additional tests, we use the IOS factor to augment Eq. (1). The results are similar.

[23] In additional analyses, we use the classic CAPM model without orthogonalization. The results are unchanged.

[24] In additional cross-sectional and panel regressions using the raw measures, the results for the coefficient estimates are unchanged.

Table 2
Summary statistics.

	Mean			Median		
	User	Non-user	User–nonuser	User	Non-user	User–nonuser
TNA ($mil)	1172	866	306**	145	301	−156***
Age (years)	12.21	9.73	2.48***	6.87	8.77	−1.90***
Turnover ratio (% TNA, p.a.)	1.3680	0.8886	0.4794***	0.8389	0.6566	0.1823***
Expense ratio (% TNA, p.a.)	0.0139	0.0117	0.0022***	0.0133	0.0117	0.0016***
Load dummy	0.7745	0.6349	0.1396***	1.0000	1.0000	0.0000
Manager tenure (years)	5.72	5.81	−0.09	4.56	4.53	0.03
Cash (% TNA)	0.0588	0.0394	0.0194***	0.0332	0.0252	0.0080***
Net flow (% TNA)	0.0143	0.0188	−0.0045*	0.0036	0.0060	−0.0024**
Gross return (% p.m.)	0.0048	0.0052	−0.0006	0.0052	0.0058	−0.0006**
Net return (% p.m.)	0.0053	0.0057	−0.0004	0.0057	0.0062	−0.0005**
Volatility (% p.m.)	0.0528	0.0523	0.0005	0.0509	0.0502	−0.0007
Skewness	−0.4464	−0.4817	0.0357*	−0.4682	−0.4940	0.0258*
Kurtosis	4.2507	4.1682	0.0825	4.0316	4.0103	0.0213
% Nonsurvivor	0.3431	0.3564	0.0133	0.0000	0.0000	0.0000
Carhart alpha (% p.a.)	0.0067	0.0009	0.0058***	0.0069	0.0012	0.0057***
IOS alpha (% p.a.)	0.0119	0.0058	0.0061***	0.0105	0.0054	0.0051***
Leland alpha (% p.a.)	0.0066	0.0008	0.0058***	0.0068	0.0011	0.0057***
Bawa/Lindenberg alpha (% p.a.)	0.0059	0.0000	0.0059***	0.0059	0.0012	0.0047***
Carhart alpha (% p.a.)	−0.0070	−0.0108	0.0038***	−0.0063	−0.0092	0.0029***
IOS alpha (% p.a.)	−0.0019	−0.0060	0.0041***	−0.0022	−0.0048	0.0026*
Leland alpha (% p.a.)	−0.0071	−0.0109	0.0038***	−0.0063	−0.0093	0.0030***
Bawa/Lindenberg alpha (% p.a.)	−0.0050	−0.0068	0.0018	−0.0059	−0.0080	0.0021
Carhart market beta	0.9584	0.9907	−0.0323***	0.9937	0.9967	−0.0030
IOS market beta	0.9316	0.9763	−0.0447***	0.9698	0.9771	−0.0073
Leland market beta	0.9593	0.9915	−0.0322***	0.9936	0.9978	−0.0042
Bawa/Lindenberg market beta	0.9942	1.0216	−0.0274**	1.0096	1.0208	−0.0112

This table reports descriptive statistics for 612 user and 1964 nonuser funds. The sample consists of actively managed U.S. domestic equity funds over the period 1998–2013. User funds use an option at least once and nonusers completely avoid using options. Differences in means are tested using two-sided, unpaired mean comparison tests. Differences in medians are tested using Wilcoxon rank-sum tests. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

the fund characteristics as control variables in the analyses below (e.g., Almazan et al., 2004; Ferreira et al., 2012).

Gross excess returns are basically the same for user and nonuser funds. Total risk, as measured by the standard deviation of returns, does not differ between users and nonusers. Regarding the return distribution's higher moments, there are no significant differences between users and nonusers except for slightly less negative skewness of users. This could be due to more long option positions, such as protective puts (e.g., Leland, 1999) used for hedging purposes.

The statistics on risk-adjusted performance provide the first evidence in favor of a positive performance effect of options, as user funds have significantly higher alphas than nonusers on average as well as in the median, according to all four performance models (e.g., 67 vs. 9 basis points p.a. gross of fees in the case of the Carhart model). Market betas associated with the four performance models offer the first evidence in favor of a risk reducing effect of options. They are significantly lower on average for option users than for nonusers (95.84% vs. 99.07% in the case of the Carhart model). However, there is no significant beta difference in the median between users and nonusers.

3.2. Cross-sectional analysis of option use and performance

The effect of option use on performance is not clear a priori. Arguments for a negative performance effect include higher administration costs, as option use might require more sophisticated information and risk management systems (Lynch-Koski and Pontiff, 1999). Furthermore, options are complex instruments that require more experienced fund managers with higher compensation demands (Chevalier and Ellison, 1999). Bollen and Whaley (2004) argue that, due to increased buy pressure by portfolio insurers, options used for hedging are too expensive, which could reduce returns. On the other hand, a positive performance effect of option use may arise because of lower transaction costs (Merton, 1995) or the facilitation of altering portfolio risk and return profiles (Merton et al., 1978, 1982). Mutual funds may profit from the more efficient information pricing on option markets, as shown by Black (1975), Cao et al. (2005) and Pan and Poteshman (2006). Guasoni et al. (2011) provide theoretical evidence that fund managers can generate abnormal returns by using option strategies because traded option prices might deviate from fair model-implied prices due to market incompleteness.[25] This is especially true with respect to single stock options. Furthermore, selling options generates steady option premium income. To formally test the effect of option on risk-adjusted performance, we run the following cross-sectional regression:

$$Performance_i = \varphi_0 + \varphi_1 User_i + \sum_{j=2}^{J} \varphi_j Controls_j + \eta_i \tag{5}$$

where the dependent variable *Performance*$_i$ is defined as fund *i*'s risk-adjusted performance, measured with Carhart (1997) alpha as defined in Eq. (1) in Section 2.4, our own IOS alpha (Eq. (2)), Bawa and Lindenberg (1977) alpha (Eq. (3)), and the Leland (1999) alpha (Eq. (4)), respectively. The measures are calculated using monthly gross and net returns, respectively, over the entire sample period for each fund and are winsorized at the 1% and 99% percentiles to control for outliers. The independent variable of interest, *User*$_i$, is defined as in Section 2.3. It takes a value of one if a fund uses options of some type at least once and zero otherwise. Standard errors are heteroscedasticity consistent based on White (1980) estimator. In this setup, the coefficient on the *User*$_i$ dummy is directly interpretable as the additional risk-adjusted performance p.a. associated with option use.

Table 3 reports the results. The *User*$_i$ dummy has a significantly positive influence on Carhart (1997) alpha. If a fund uses options at least once during its existence, it offers superior risk-adjusted performance on average compared with a nonuser fund. The outperformance is statistically significant 44 basis points p.a. Comparing this, e.g., to the average annual expense ratio of around 130 basis points (Table 2), option users are able to offset around one third of investors' recurring costs, which is clearly of economic relevance. The other measures, which explicitly control for option-specifics in fund returns, display similar results, with yearly risk-adjusted outperformance of option user funds ranging from 39 to 44 basis points p.a. for both net and gross returns.

The coefficients of the control variables indicate that larger funds with more experienced fund managers generate significantly higher performance. Higher turnover, on the other hand, reduces performance, which is in line with higher transaction costs associated with more intensive trading (e.g., Carhart, 1997) or with overconfidence (e.g., Puetz and Ruenzi, 2011). Management fees positively (negatively) affect gross (net) fund performance. The coefficients for loads and for net fund flows have positive signs, although only the latter is statistically significant. Older funds have a slightly lower risk-adjusted performance albeit insignificantly so, consistent with Pástor et al. (2015). Funds that hold more cash exhibit (insignificantly) higher performance, in line with Simutin's (2014) findings.

3.3. Cross-sectional analysis of option use and market risk

Apart from these effects of option use on performance, the collapses of Barings Bank and Long Term Capital Management show that investing in options may lead to large losses due to the high risk induced by the leverage inherent in options. On the other hand, mutual funds may also employ options for hedging purposes to reduce fund risk. To test the effect of option use on fund risk, we run a second cross-sectional regression, where the dependent variable, *Risk*$_i$, is defined as the market beta of fund *i* from a regression of monthly gross and net returns over the entire sample period for each fund in any of the four performance models defined by Eqs. (1)–(4) in Section 2.4. As with

[25] Option pricing models, such as Black and Scholes (1973) model, assume continuous stochastic processes for the underlying asset as well as continuous rebalancing of a duplication portfolio in order to price options. This is not always feasible in practice.

Table 3
Cross-sectional regressions of performance on option usage.

	Gross				Net			
	Carhart	IOS	Leland	Bawa/ Lindenberg	Carhart	IOS	Leland	Bawa/ Lindenberg
User	0.0044***	0.0040***	0.0044***	0.0039**	0.0044***	0.0040***	0.0044***	0.0039**
	(0.0014)	(0.0014)	(0.0014)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0015)
Manager tenure (years)	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log TNA ($mil)	0.0029***	0.0034***	0.0029***	0.0032***	0.0030***	0.0035***	0.0030***	0.0033***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Turnover ratio (% TNA, p.a.)	−0.0034***	−0.0032***	−0.0034***	−0.0033***	−0.0033***	−0.0031***	−0.0033***	−0.0031***
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0007)
Expense ratio (% TNA, p.a.)	0.6351***	0.9059***	0.6413***	0.7619***	−0.3082*	−0.0476	−0.3022*	−0.1796
	(0.1819)	(0.1783)	(0.1823)	(0.2086)	(0.1673)	(0.1646)	(0.1675)	(0.1898)
Load dummy	0.0013	0.0012	0.0013	0.0008	0.0011	0.0011	0.0012	0.0006
	(0.0014)	(0.0013)	(0.0014)	(0.0015)	(0.0013)	(0.0013)	(0.0013)	(0.0015)
Age (years)	−0.0001	−0.0002**	−0.0001	−0.0001	−0.0001	−0.0002**	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Cash (% TNA)	0.0159	0.0154	0.0161	0.0279**	0.0156	0.0148	0.0157	0.0272**
	(0.0110)	(0.0114)	(0.0110)	(0.0138)	(0.0110)	(0.0114)	(0.0110)	(0.0135)
Net flow (% TNA)	0.0631***	0.0586***	0.0625***	0.0551***	0.0627***	0.0581***	0.0620***	0.0537***
	(0.0206)	(0.0202)	(0.0205)	(0.0211)	(0.0205)	(0.0200)	(0.0203)	(0.0207)
Intercept	−0.0223***	−0.0219***	−0.0227***	−0.0261***	−0.0232***	−0.0229***	−0.0236***	−0.0271***
	(0.0031)	(0.0030)	(0.0031)	(0.0036)	(0.0030)	(0.0029)	(0.0030)	(0.0035)
Adjusted R^2	0.08	0.08	0.08	0.07	0.09	0.09	0.09	0.08
N	2576	2576	2576	2441	2576	2576	2576	2441

This table reports cross-sectional regressions of performance on the option usage. The sample consists of actively managed U.S. domestic equity funds over the period 1998-2013. Fund performance is measured using the Carhart (1997) 4-factor model, the Cremers et al. (2013) model plus an investable option strategy (IOS) factor based on the CBOE BuyWrite index, the Leland (1999) model and the Bawa and Lindenberg (1977) model. All performance measures are calculated for each fund individually using monthly gross and net return data and are winsorized at the 1% and 99% percentiles. The dummy variable User is one if a fund uses any kind of option at least once during its existence and zero otherwise. All variables are averages over time for each individual fund. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively. Heteroscedasticity consistent standard errors are given in parentheses (White, 1980).

our performance measures, market betas are winsorized at the 1% and 99% percentiles to control for outliers. Standard errors are heteroscedasticity consistent based on White (1980) estimator.

$$Risk_i = \varphi_0 + \varphi_1 User_i + \sum_{j=2}^{J} \varphi_j Controls_j + \eta_i \tag{6}$$

In this setup, the coefficient on the $User_i$ dummy is directly interpretable as the additional market beta exposure associated with option use. Table 4 shows significant and negative effects of option use on systematic risk. Hence, option users have lower market betas compared with nonusers. This risk-reducing effect ranges from 2.05 in the Bawa/Lindenberg model to nearly 5.1 percentage points in our IOS model, all statistically significant and economically relevant. The control variables indicate that more experienced fund managers have lower market risk, in line with Chevalier and Ellison (1999). Funds with higher expense ratios have significantly higher market risk. Loads and net flow correlate negatively with market risk. The loadings of cash positions are negative, as cash creates no market risk exposure.

Overall, the results of our cross-sectional regressions show that option users have economically meaningful higher risk-adjusted performance, which is beneficial to investor. Moreover, option user funds have significantly lower systematic risk than nonuser funds which contrasts with the SEC's con-

Table 4
Cross-sectional regressions of market beta on option usage.

	Gross				Net			
	Carhart	IOS	Leland	Bawa/ Lindenberg	Carhart	IOS	Leland	Bawa/ Lindenberg
User	−0.0301***	−0.0509***	−0.0296***	−0.0205*	−0.0302***	−0.0510***	−0.0297***	−0.0206*
	(0.0092)	(0.0099)	(0.0092)	(0.0119)	(0.0092)	(0.0099)	(0.0091)	(0.0119)
Manager tenure (years)	−0.0043***	−0.0040***	−0.0043***	−0.0047***	−0.0043***	−0.0040***	−0.0043***	−0.0047***
	(0.0008)	(0.0008)	(0.0008)	(0.0010)	(0.0008)	(0.0008)	(0.0008)	(0.0010)
Log TNA ($mil)	0.0067***	0.0064**	0.0067***	0.0042	0.0068***	0.0065**	0.0067***	0.0042
	(0.0025)	(0.0027)	(0.0025)	(0.0033)	(0.0025)	(0.0027)	(0.0025)	(0.0033)
Turnover ratio (% TNA, p.a.)	0.0013	0.0075	0.0011	0.0010	0.0013	0.0075	0.0011	0.0011
	(0.0052)	(0.0058)	(0.0051)	(0.0069)	(0.0052)	(0.0058)	(0.0051)	(0.0069)
Expense ratio (% TNA, p.a.)	6.9325***	7.0392***	6.8587***	6.3939***	6.9356***	7.0609***	6.8562***	6.3433***
	(1.0699)	(1.1768)	(1.0628)	(1.3684)	(1.0705)	(1.1781)	(1.0628)	(1.3688)
Load dummy	−0.0187**	−0.0263***	−0.0191**	−0.0091	−0.0187**	−0.0263***	−0.0190**	−0.0091
	(0.0087)	(0.0091)	(0.0086)	(0.0113)	(0.0087)	(0.0091)	(0.0086)	(0.0113)
Age (years)	0.0011***	0.0011***	0.0010***	0.0000	0.0011***	0.0010***	0.0010***	0.0000
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Cash (% TNA)	−0.7125***	−0.7221***	−0.7168***	−0.7706***	−0.7126***	−0.7220***	−0.7169***	−0.7709***
	(0.1116)	(0.1160)	(0.1115)	(0.1274)	(0.1116)	(0.1160)	(0.1115)	(0.1274)
Net flow (% TNA)	−0.1273	−0.1982*	−0.1251	−0.0531	−0.1264	−0.1968*	−0.1241	−0.0509
	(0.0985)	(0.1100)	(0.0977)	(0.1031)	(0.0984)	(0.1097)	(0.0976)	(0.1028)
Intercept	0.9365***	0.9158***	0.9391***	0.9922***	0.9365***	0.9155***	0.9391***	0.9927***
	(0.0189)	(0.0201)	(0.0188)	(0.0240)	(0.0189)	(0.0201)	(0.0188)	(0.0240)
Adjusted R^2	0.15	0.14	0.15	0.10	0.15	0.14	0.15	0.10
N	2576	2576	2576	2441	2576	2576	2576	2441

This table reports cross-sectional regressions of market beta on the option usage. The sample consists of actively managed U.S. domestic equity funds over the period 1998–2013. Market beta is measured using the Carhart (1997) 4-factor model, the Cremers et al. (2013) model plus an investable option strategy (IOS) factor based on the CBOE BuyWrite index, the Leland (1999) model and the Bawa and Lindenberg (1977) model. All market betas are calculated for each fund individually using monthly gross and net return data and are winsorized at the 1% and 99% percentiles. The dummy variable User is one if a fund uses any kind of option at least once during its existence and zero otherwise. All variables are averages over time for each individual fund. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively. Heteroscedasticity consistent standard errors are given in parentheses (White, 1980).

cerns that mutual fund option use could pose risk to the financial system or the broader economy. Below, we analyze the sources of these effects in more detail.

3.4. Panel analysis of option usage on performance and market risk

Our cross-sectional regressions show that option users have higher performance. This effect might arise directly from option characteristics or indirectly from other characteristics of option users. In the latter case, the performance-enhancing effect should also be observable during times when user funds do not employ options. To test this, we run the following panel regression, which explains performance with time-variable option use variables and control variables, including style- and time-fixed effects. Standard errors are 2-dimensionally clustered by fund and month to be consistent with regard to heteroscedasticity, time-series correlation and cross-sectional correlation.

$$Performance_{i,t} = \varphi_0 + \varphi_1 Using_{i,t} + \varphi_2 Nonusing_{i,t} + \sum_{j=3}^{J} \varphi_j Controls_{j,t} + \eta_{i,t} \tag{7}$$

Here, $Performance_{i,t}$ is the risk-adjusted performance of fund i in month t, measured using daily net and gross returns for the given month, respectively, via any of the four performance models defined

Table 5
Panel regressions of performance and market beta on option usage.

	Gross				Net			
	Carhart	IOS	Leland	Bawa/ Lindenberg	Carhart	IOS	Leland	Bawa/ Lindenberg
Panel A: Performance								
Using	0.0067**	0.0091***	0.0081***	0.0070**	0.0067**	0.0076***	0.0081***	0.0070**
	(0.0028)	(0.0030)	(0.0027)	(0.0028)	(0.0028)	(0.0029)	(0.0027)	(0.0028)
Nonusing	0.0005	0.0004	0.0002	−0.0008	0.0005	0.0002	0.0002	−0.0008
	(0.0017)	(0.0017)	(0.0016)	(0.0019)	(0.0017)	(0.0017)	(0.0016)	(0.0019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.07	0.04	0.10	0.08	0.07	0.10	0.10	0.08
N	231,641	231,641	231,634	231,641	231,641	231,641	231,634	231,641
Panel B: Market beta								
Using	−0.0776***	−0.0831***	−0.0711***	−0.0683***	−0.0776***	−0.0831***	−0.0711***	−0.0683***
	(0.0122)	(0.0142)	(0.0127)	(0.0147)	(0.0122)	(0.0142)	(0.0127)	(0.0147)
Nonusing	0.0051	0.0065	0.0041	0.0043	0.0051	0.0065	0.0041	0.0043
	(0.0063)	(0.0069)	(0.0072)	(0.0076)	(0.0063)	(0.0069)	(0.0072)	(0.0076)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.11	0.10	0.12	0.07	0.11	0.10	0.12	0.07
N	231,641	231,641	231,634	231,641	231,641	231,641	231,634	231,641

This table reports panel regressions of fund performance and market beta on option usage. The sample consists of actively managed U.S. domestic equity funds over the period 1998-2013. Fund performance and market beta are measured using the Carhart (1997) 4-factor model, the Cremers et al. (2013) model plus an investable option strategy (IOS) factor based on the CBOE BuyWrite index, the Leland (1999) model and the Bawa and Lindenberg (1977) model. All performance measures and market betas are calculated for each fund and month individually using daily gross and net return data and are winsorized at the 1% and 99% percentiles. Panel A displays the results for performance and Panel B for market beta. The option variable Using is one if a user fund invests in options in the respective month and zero otherwise. Nonusing is one if a user fund does not use options in the respective month and in all other cases zero. Control variables are as in Tables 3 and 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are 2-dimensionally clustered by fund and month to be consistent with regard to heterosedasticity, time-series correlation and cross-sectional correlation.

by Eqs. (1)–(4) in Section 2.4.[26, 27] The variables of interest, $Using_{i,t}$ and $Nonusing_{i,t}$, are defined as in Section 2.3 and indicate whether a fund uses options in a specific month and whether a user fund does not use options in a specific month, respectively.

In Panel A of Table 5, the coefficient on $Using_{i,t}$ shows that option employment generates an outperformance of 67 basis points p.a. on average compared to nonusers measured by Carhart's (1997) alpha.[28] Comparing this to the average expense ratio of around 130 basis points p.a., option use directly offsets one half of investor recurring costs, which is certainly of economic importance. This result holds for all four of our performance measures, ranging from 70 to 91 basis points of yearly outperformance, regardless of whether gross or net fund returns are employed in performance regressions. This is further evidence in favor of a performance enhancing effect of option use.[29] Moreover, the coefficient for $Nonusing_{i,t}$ is insignificant for all four performance models with values ranging between −0.0008 and 0.0005 implying economic irrelevance. Thus, we conclude that the superior performance

[26] In unreported analyses, we alternatively use Dimson (1979) approach to control for any bias caused by non-synchronous trading in daily returns. The results are qualitatively the same.

[27] In additional analyses, we also calculate monthly alphas using monthly returns via rolling window regressions for 12- and 36-months windows, both overlapping and non-overlapping. The results are qualitatively the same.

[28] For brevity, we do not report control variable coefficients in the following tables. They are, however, qualitatively similar to the coefficients reported in Tables 3 and 4.

[29] In additional analyses, we use $Using_{i,t}$ exclusively. The performance-enhancing effect of option use is the same.

of user funds stems directly from the employment of options. Hence, mutual fund option use is directly beneficial to investors.[30]

Similarly to our cross-sectional analysis, Panel B tests whether $Using_{i,t}$ and $Nonusing_{i,t}$ have differing effects on systematic risk. If risk-reduction shown in our cross-sectional analysis is also observable during times of nonuse, option users would be less risky per se. However, if actual option use drives our results directly, then the risk reduction effect should only be observable during times of actual option employment. To test this, we run the following panel regression analog to Regression (7). Standard errors are 2-dimensionally clustered by fund and month to be consistent with regard to heteroscedasticity, time-series correlation and cross-sectional correlation.

$$Risk_{i,t} = \varphi_0 + \varphi_1 Using_{i,t} + \varphi_2 Nonusing_{i,t} + \sum_{j=3}^{J} \varphi_j Controls_{j,t} + \eta_{i,t} \tag{8}$$

where $Risk_{i,t}$ is the market beta of fund i in month t, measured by any of the four performance models defined by Eqs. (1)–(4) in Section 2.4, using net and gross daily data for the respective month. The coefficient on $Using_{i,t}$ in Panel B of Table 5 shows that option use leads to significantly lower market risk, as beta is reduced by 6.83 to 8.31 percentage points on average. The results hold for all four performance models and gross as well as net returns. More importantly, the coefficients for $Nonusing_{i,t}$ are insignificant and near-zero. Thus, the risk-reducing effect of option use is a direct effect. Hence, we conclude that mutual fund option use is not harmful for the financial system as it directly reduces systematic market risk.

As the performance enhancement coincides directly with reduced risk, our findings may be driven by other known phenomena like, e.g., the low beta anomaly shown by Frazzini and Pedersen (2014) or the low volatility anomaly documented by, e.g., Baker et al. (2011). To alleviate these concerns, we reestimate Eq. (7) including the funds' market betas from the Carhart (1997) model as additional control variable.[31] However, since our results in Panel B of Table 5 show that beta and option use are highly correlated, we orthogonalize beta and option use by regressing a fund's monthly beta on the $Using_{i,t}$ dummy. This way, $Orthogonalized\ beta_{i,t}$ captures any effects of beta on performance unrelated to option use, e.g. shifting of portfolio weights from high beta stocks to low beta stocks in order to capture the low beta anomaly.

Table 6 shows the results. The coefficient of $Orthogonalized\ beta_{i,t}$ is negative and significant with values around −0.0924, implying higher performance for funds investing in low beta stocks, consistent with the low beta anomaly. More importantly, the coefficients on $Using_{i,t}$ and $Nonusing_{i,t}$ are not affected by the inclusion of $Orthogonalized\ beta_{i,t}$ as they imply an outperformance of approximately 70 basis points p.a. Further, it is highly unlikely that the low beta anomaly is driving the relationship between option use and fund performance since it would imply that funds systematically shift portfolio weights from high beta stocks to low beta stocks whenever they start using options and vice versa when they stop using options. Alternatively, option user funds may try to capture the low beta anomaly by shorting options on high beta stocks not already part of their portfolio. However, Cici and Palacios (2015) as well as our results show that funds mainly use covered calls and thus do not use options to capture the low beta anomaly.[32] Hence, the positive relation between option use and fund performance is due to market timing, stock picking or capturing of option premiums. Thus, we conclude that performance differences are due to differential option use and not due to the low beta anomaly.

3.5. Hedging vs. speculation – panel analysis of option strategies

In the following, we analyze which option strategies predominantly drive the performance-enhancing effect documented in our performance tests and which option strategies drive the

[30] In additional analyses, we test whether this result holds for funds that exclusively use single stock options, as single stock options should exhibit more mispricing and picking potential compared with index options, due to market incompleteness (e.g., Guasoni et al., 2011). The results of this test are the same.

[31] Alternatively, we use the market beta from a CAPM model. The results are unchanged.

[32] See Table 7 in Section 3.5.

Table 6
Panel regressions of performance on option usage controlling for market beta.

	Gross		Net	
	Without nonusing	With nonusing	Without nonusing	With nonusing
Using	0.0074***	0.0076***	0.0074***	0.0076***
	(0.0028)	(0.0029)	(0.0028)	(0.0029)
Nonusing		0.0010		0.0010
		(0.0017)		(0.0017)
Orthogonalized beta	−0.0924***	−0.0924***	−0.0925***	−0.0925***
	(0.0217)	(0.0217)	(0.0217)	(0.0217)
Intercept	0.0923***	0.0925***	0.0922***	0.0924***
	(0.0237)	(0.0237)	(0.0236)	(0.0237)
Controls	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.08	0.08	0.08	0.08
N	231,641	231,641	231,641	231,641

This table reports panel regressions of fund performance on option usage controlling for market beta. The sample consists of actively managed U.S. domestic equity funds over the period 1998–2013. Fund performance and market beta are measured using the Carhart (1997) 4-factor model. Performance and market beta are calculated for each fund and month individually using daily gross and net return data and are winsorized at the 1% and 99% percentiles. Orthogonalized Beta is the intercept plus error terms from regressing a fund's monthly beta on the Using dummy. The option variable Using is one if a user fund invests in options in the respective month and zero otherwise. Nonusing is one if a user fund does not use options in the respective month and in all other cases zero. Control variables are as in Tables 3 and 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are 2-dimensionally clustered by fund and month to be consistent with regard to heterosedasticity, time-series correlation and cross-sectional correlation.

risk-reducing effect documented in our risk tests. To determine the sources of these effects, we run the following panel regressions, where monthly $Performance_{i,t}$ and $Risk_{i,t}$ measures, measured by Eqs. (1)–(4) using daily gross and net fund returns, are explained by monthly dummy variables indicating net long ($Long_{i,t}$) and short positions in options ($Short_{i,t}$), $Nonusing_{i,t}$ and control variables, including style- and time-fixed effects.[33] Standard errors are 2-dimensionally clustered by fund and month to be consistent with regard to heteroscedasticity, time-series correlation and cross-sectional correlation.

$$Performance_{i,t} = \varphi_0 + \varphi_1 Long_{i,t} + \varphi_2 Short_{i,t} + \varphi_3 Nonusing_{i,t} + \sum_{j=4}^{J} \varphi_j Controls_{j,t} + \eta_{i,t} \tag{9}$$

$$Risk_{i,t} = \varphi_0 + \varphi_1 Long_{i,t} + \varphi_2 Short_{i,t} + \varphi_3 Nonusing_{i,t} + \sum_{j=4}^{J} \varphi_j Controls_{j,t} + \eta_{i,t} \tag{10}$$

Panel A of Table 7 shows that the performance-enhancing effect of option use is mainly due to short positions in options based on Eq. (9). These show a positive and significant effect of 184 basis points p.a. on risk-adjusted performance (Carhart), an effect that is consistent for all performance models and return specifications. Long positions in options also have a positive but statistically insignificant impact on performance, except for Leland's alpha. This may be explained by the fact that Leland's (1999) model considers the skewness of fund returns, which corrects alphas on short positions downwards and alphas on long positions upwards. In summary, in months in which funds are net short in option positions they earn risk-adjusted returns between 100 and 200 basis points in excess of their nonusing peers, depending on the performance measure used. In addition, the

[33] Unreported statistics show that option users are net long in 19% of the using months and net short in 36% of the using months. In the remaining using months, they have net zero option positions and are treated as nonusing users. In additional tests, we exclude all net zero user fund months from the sample. The results are unchanged.

Table 7
Panel regressions of performance and market beta on net long and net short option usage.

	Gross				Net			
	Carhart	IOS	Leland	Bawa/ Lindenberg	Carhart	IOS	Leland	Bawa/ Lindenberg
Panel A: Performance								
Long	0.0042	0.0096	0.0094*	0.0074	0.0044	0.0062	0.0095*	0.0075
	(0.0056)	(0.0061)	(0.0057)	(0.0063)	(0.0056)	(0.0055)	(0.0057)	(0.0063)
Short	0.0184***	0.0207***	0.0129***	0.0124***	0.0184***	0.0183***	0.0128***	0.0124***
	(0.0038)	(0.0042)	(0.0036)	(0.0041)	(0.0038)	(0.0039)	(0.0036)	(0.0041)
Nonusing	0.0006	0.0004	0.0000	−0.0010	0.0006	0.0003	−0.0000	−0.0010
	(0.0017)	(0.0017)	(0.0015)	(0.0018)	(0.0017)	(0.0017)	(0.0015)	(0.0018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.07	0.04	0.10	0.08	0.07	0.10	0.10	0.08
N	231,641	231,641	231,634	231,641	231,641	231,641	231,634	231,641
Panel B: Market beta								
Long	−0.1326***	−0.1379***	−0.1157***	−0.1289***	−0.1326***	−0.1379***	−0.1157***	−0.1289***
	(0.0311)	(0.0404)	(0.0322)	(0.0426)	(0.0311)	(0.0404)	(0.0322)	(0.0426)
Short	−0.1055***	−0.1247***	−0.1039***	−0.0987***	−0.1055***	−0.1247***	−0.1039***	−0.0987***
	(0.0175)	(0.0192)	(0.0175)	(0.0192)	(0.0175)	(0.0192)	(0.0175)	(0.0192)
Nonusing	0.0068	0.0079	0.0055	0.0052	0.0068	0.0079	0.0055	0.0052
	(0.0061)	(0.0067)	(0.0069)	(0.0074)	(0.0061)	(0.0067)	(0.0069)	(0.0074)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.12	0.10	0.12	0.07	0.12	0.10	0.12	0.07
N	231,641	231,641	231,634	231,641	231,641	231,641	231,634	231,641

This table reports panel regressions of fund performance and market beta on net long and net short option usage. The sample consists of actively managed U.S. domestic equity funds over the period 1998-2013. Fund performance and market beta are measured using the Carhart (1997) 4-factor model, the Cremers et al. (2013) model plus an investable option strategy (IOS) factor based on the CBOE BuyWrite index, the Leland (1999) model and the Bawa and Lindenberg (1977) model. All performance measures and market betas are calculated for each fund and month individually using daily gross and net return data and are winsorized at the 1% and 99% percentiles. Panel A displays the results for performance and Panel B for market beta. The option variable Long is one if a user fund is net long in options in the respective month and zero otherwise. Short is one if a user fund is net short in options in the respective month and zero otherwise. Nonusing is one if a user fund does not use options in the respective month and in all other cases zero. Control variables are as in Tables 3 and 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are 2-dimensionally clustered by fund and month to be consistent with regard to heteroscedasticity, time-series correlation and cross-sectional correlation.

insignificant coefficient of $Nonusing_{i,t}$ confirms our findings from Section 3.4 that funds choosing not to use options do not exhibit economically meaningful outperformance.

Panel B in Table 7 reports the results for Eq. (10). The results indicate that the risk-reducing effect is mainly due to funds' long option positions. These reduce market beta significantly by 13.26 percentage points (Carhart), implying that funds use options to hedge market risk. Short positions in options also have a significant market risk-reduction effect of 10.55 percentage points. $Nonusing_{i,t}$ is insignificant thereby further demonstrating that it is the actual use of options which drives the reduction in systematic market risk and not an overall user effect. The results are consistent across all specifications.

Funds can only achieve lower systematic risk via long options if they purchase puts. This has the effect of indirectly selling exposure to the option's underlying asset. It is now logical to assume that option users' long positions in options are predominantly protective puts, as introduced by Merton et al. (1982). Furthermore, funds can only attain the risk-reducing effect documented for short positions in options if they write calls and thereby indirectly sell exposure to the option's underlying asset. As the SEC requires all short positions in options to be covered, the predominant short option strategy employed by option users must be a covered call strategy. Thus, option user funds use protective put

Table 8
Panel regressions of performance on net long and net short option usage controlling for market beta.

	Gross		Net	
	Without nonusing	With nonusing	Without nonusing	With nonusing
Long	−0.0007	−0.0006	−0.0005	−0.0004
	(0.0065)	(0.0065)	(0.0065)	(0.0065)
Short	0.0161***	0.0162***	0.0161***	0.0162***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)
Nonusing		0.0007		0.0007
		(0.0017)		(0.0017)
Orthogonalized beta	−0.0919***	−0.0919***	−0.0920***	−0.0920***
	(0.0217)	(0.0217)	(0.0217)	(0.0217)
Intercept	0.0914***	0.0915***	0.0913***	0.0914***
	(0.0236)	(0.0236)	(0.0236)	(0.0236)
Controls	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.08	0.08	0.08	0.08
N	231,641	231,641	231,641	231,641

This table reports panel regressions of fund performance on net long and net short option usage controlling for market beta. The sample consists of actively managed U.S. domestic equity funds over the period 1998–2013. Fund performance and market beta are measured using the Carhart (1997) 4-factor model. Performance and market beta are calculated for each fund and month individually using daily gross and net return data and are winsorized at the 1% and 99% percentiles. Orthogonalized Beta is the intercept plus error terms from regressing a fund's monthly beta on the Using dummy. The option variable Long is one if a user fund is net long in options in the respective month and zero otherwise. Short is one if a user fund is net short in options in the respective month and zero otherwise. Nonusing is one if a user fund does not use options in the respective month and in all other cases zero. Control variables are as in Tables 3 and 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are 2-dimensionally clustered by fund and month to be consistent with regard to heterosedasticity, time-series correlation and cross-sectional correlation.

strategies for hedging purposes in combination with covered calls to generate steady income through option premiums. This is also consistent with summary statistics in Cici and Palacios (2015) who, in sharp contrast to our clear and concise findings, find no significant effect of these option types on fund performance or risk. Finally, the near zero and insignificant coefficient of $Nonusing_{i,t}$ further confirms that the findings are a direct option effect so that both long and short positions in options are beneficial to investors.

In further tests similar to Table 6, we test if the findings for the performance impact of long and short positions are driven by systematic differences in systematic market risk between user and nonuser funds by including $Orthogonalized\ beta_{i,t}$ in Eq. (9). The results in Table 8 indicate that our results are not driven by the low beta anomaly thereby further supporting our conclusion that performance and risk effects are directly driven by option use.

3.6. *Matched comparison analysis and test for self-selection bias*

As shown in our summary statistics on option use in Table 1 and as indicated by Almazan et al. (2004), most funds are formally permitted to use options, but only a relatively small fraction of them make use of this permission. Hence, our results may suffer from a self-selection bias. Our summary statistics in Table 2 show that users and nonusers of options differ significantly with respect to many fund characteristics. Therefore, we employ a propensity score matching analysis similar to Chen et al. (2013) where we match each user fund to its twenty nearest neighbor nonuser funds. From these twenty nearest neighbors we construct an equally-weighted nonuser control portfolio to account for idiosyncrasy. Then we compare the user fund alphas according to Eqs. (1)–(4) and the nonuser control portfolio alphas via paired mean comparison tests.

Table 9 reports the results for the matched comparison of performance, where in Panel A the matching is based on all fund characteristics as in Evans et al. (2015), i.e. manager tenure, fund size,

Table 9
Matched comparison analysis of performance between option users and nonuser control portfolios.

	Gross				Net			
	Carhart	IOS	Leland	Bawa/ Lindenberg	Carhart	IOS	Leland	Bawa/ Lindenberg
Panel A: All control variables								
User	0.0066	0.0118	0.0065	0.0059	−0.0072	−0.0021	−0.0074	−0.0079
Control group	0.0017	0.0067	0.0016	0.0018	−0.0119	−0.0069	−0.0119	−0.0117
Difference	0.0049***	0.0051***	0.0049***	0.0041**	0.0047***	0.0048***	0.0045***	0.0038***
Panel B: All control variables plus market beta								
User	0.0066	0.0118	0.0065	0.0059	−0.0072	−0.0021	−0.0074	−0.0079
Control group	0.0016	0.0066	0.0015	0.0014	−0.0120	−0.0071	−0.0121	−0.0122
Difference	0.0050***	0.0052***	0.0050***	0.0045***	0.0048***	0.0050***	0.0047***	0.0043**
Panel C: All control variables plus market beta and nonsurvivor dummy								
User	0.0066	0.0118	0.0065	0.0059	−0.0072	−0.0021	−0.0074	−0.0079
Control group	0.0024	0.0070	0.0023	0.0023	−0.0114	−0.0067	−0.0114	−0.0114
Difference	0.0042***	0.0048***	0.0042***	0.0036**	0.0041**	0.0049***	0.0040**	0.0038**

This table reports a matched comparison analysis of fund performance between option users and nonuser control portfolios. The sample consists of actively managed U.S. domestic equity funds over the period 1998–2013. Fund performance and market betas are measured using the Carhart (1997) 4-factor model, the Cremers et al. (2013) model plus an investable option strategy (IOS) factor based on the CBOE BuyWrite index, the Leland (1999) model and the Bawa and Lindenberg (1977) model. Performance and market beta are calculated for each fund individually using monthly gross and net return data and are winsorized at the 1% and 99% percentiles. User funds are defined as funds that use any kind of option at least once during their existence. The equally-weighted nonuser control portfolios portfolio are constructed from the twenty nearest neighbor funds based on propensity scores. In Panel A, the matching is based on the fund characteristics used in Tables 3 and 4. In Panel B, the matching additionally uses a funds market beta. In Panel C, the matching additionally uses the market beta plus a dummy variable indicating if the fund is a nonsurvivor or not. Statistical significance of the differences is based on two-sided, paired mean comparison tests. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

turnover and expense ratio, load dummy, age, cash holdings as a fraction of TNA, and net investor flow. The performance difference between users and nonusers is positive and significant around 49 basis points p.a. (Panel A, gross, Carhart) which is also economically relevant. In Panel B, the matching algorithm uses the funds' market betas according to Eqs. (1)–(4) in addition to the characteristics used in Panel A as another test that any interdependence between performance and risk, i.e. the low beta anomaly (Frazzini and Pedersen, 2014), drives our findings. The results are similar to those in Panel A supporting the robustness of our main findings to the low-beta anomaly.

In Panel C, the matching algorithm uses a dummy indicating if the fund is a nonsurvivor in addition to the characteristics and the market beta used in Panel B to test if any survivorship bias drives our findings. Carhart et al. (2002) and Rohleder et al. (2011) show that survivors outperform nonsurvivors. Our main findings show that users outperform nonusers. Thus, any systematic relation between survival and option use could drive our results. Descriptive statistics in Table 2 show that user and nonuser funds disappear at the same rate (34.31% vs. 35.64%) indicating no such relation. The results of the matched comparison analysis confirm this notion as the difference between users and nonuser control funds remains positive, statistically significant and with 42 basis points p.a. (Carhart, gross) also economically relevant. Overall, the results are robust across all specifications and performance models, so that the matched comparison analysis confirms that our results are not driven by any self-selection bias.

Similarly, Table 10 reports the matched comparison regarding market beta, where in Panel A the matching is based on all fund characteristics. In Panel B, the matching is based on fund characteristics plus alpha. In Panel C, the matching is based on fund characteristics plus alpha and the non-survivor dummy. The results clearly confirm that the user funds have significantly reduced market beta if we explicitly control for fund characteristics. The difference is around −0.0355 percentage points (Panel A, Carhart, gross) and consistent for all specifications, except the Bawa/Lindenberg measure. Overall, we consider this proof that our main results are robust.

Table 10
Matched comparison analysis of market beta between option users and nonuser control portfolios.

	Gross				Net			
	Carhart	IOS	Leland	Bawa/ Lindenberg	Carhart	IOS	Leland	Bawa/ Lindenberg
Panel A: All control variables								
User	0.9584	0.9198	0.9593	0.9942	0.9584	0.9198	0.9593	0.9939
Control group	0.9919	0.9791	0.9921	1.0136	0.9919	0.9792	0.9921	1.0133
Difference	−0.0335**	−0.0593***	−0.0328**	-0.0194	−0.0335**	−0.0594***	−0.0328***	−0.0194
Panel B: All control variables plus performance								
User	0.9584	0.9198	0.9593	0.9942	0.9584	0.9198	0.9593	0.9939
Control group	0.9884	0.9743	0.9889	1.0133	0.9877	0.9739	0.9880	1.0124
Difference	−0.0300**	−0.0545***	−0.0296**	−0.0191	−0.0293**	−0.0541***	−0.0287**	−0.0185
Panel C: All control variables plus alpha and nonsurvivor dummy								
User	0.9584	0.9198	0.9593	0.9942	0.9584	0.9198	0.9593	0.9939
Control group	0.9888	0.9754	0.9892	1.0133	0.9887	0.9752	0.9891	1.0133
Difference	−0.0304**	−0.0556***	−0.0299**	−0.0191	−0.0303**	−0.0554***	−0.0298**	−0.0194

This table reports a matched comparison analysis of market beta between option users and nonuser control portfolios. The sample consists of actively managed U.S. domestic equity funds over the period 1998–2013. Fund performance and market betas are measured using the Carhart (1997) 4-factor model, the Cremers et al. (2013) model plus an investable option strategy (IOS) factor based on the CBOE BuyWrite index, the Leland (1999) model and the Bawa and Lindenberg (1977) model. Performance and market beta are calculated for each fund individually using monthly gross and net return data and are winsorized at the 1% and 99% percentiles. User funds are defined as funds that use any kind of option at least once during their existence. The equally-weighted nonuser control portfolios portfolio are constructed from the twenty nearest neighbor funds based on propensity scores. In Panel A, the matching is based on the fund characteristics used in Tables 3 and 4. In Panel B, the matching additionally uses a funds performance. In Panel C, the matching additionally uses performance plus a dummy variable indicating if the fund is a nonsurvivor or not. Statistical significance of the differences is based on two-sided, paired mean comparison tests. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

3.7. The effects of heavy vs. light option usage on performance and market risk

To further test our main finding that the performance-enhancing effect and the risk-reducing effects are direct effects of option usage and not driven by any other fund characteristic, we now distinguish between light and heavy option use. Specifically, in our first specification we define heavy users as funds which use options more frequently over time, i.e. for an above median number of months. Similarly, light users are funds which use options for a below median number of months. This definition is only applicable in the cross-section (Eqs. (11) and (12)). Alternatively, we define heavy users as funds which use options more intensively, i.e. holding above median absolute dollar amounts in options (long + short). Similarly, light users are funds which hold below median absolute dollar amounts in options. This definition is applicable in both cross-sectional (Eqs. (11) and 12) as well as panel (Eqs. (13) and (14)) analyses.

If the effects we find in our main analysis are direct effects of option use, we expect that the effect should be more pronounced for heavy users compared to light users. To test this, we run cross-sectional regressions where the dependent variables $Performance_i$ and $Risk_i$ are explained by the dummy variables $Heavy_i$ and $Light_i$ as well as fund specific control variables. Standard errors are heteroscedasticity consistent based on White (1980) estimator.

$$Performance_i = \varphi_0 + \varphi_1 Heavy_i + \varphi_2 Light_i + \sum_{j=3}^{J} \varphi_j Controls_j + \eta_i \tag{11}$$

$$Risk_i = \varphi_0 + \varphi_1 Heavy_i + \varphi_2 Light_i + \sum_{j=3}^{J} \varphi_j Controls_j + \eta_i \tag{12}$$

The results for our first specification of user intensity based on the frequency of option use over time are presented in Table 11. Regarding the performance effect of option use, the results indicate

Table 11
Cross-sectional regressions of performance and market beta on heavy and light option use defined by the frequency of usage over time.

	Gross				Net			
	Carhart	IOS	Leland	Bawa/ Lindenberg	Carhart	IOS	Leland	Bawa/ Lindenberg
Panel A: Performance								
Heavy	0.0047**	0.0043**	0.0047**	0.0051**	0.0047**	0.0042**	0.0047**	0.0050**
	(0.0021)	(0.0021)	(0.0021)	(0.0023)	(0.0021)	(0.0021)	(0.0021)	(0.0022)
Light	0.0041**	0.0038**	0.0041**	0.0028	0.0042**	0.0039**	0.0041**	0.0029
	(0.0017)	(0.0017)	(0.0017)	(0.0018)	(0.0017)	(0.0017)	(0.0017)	(0.0018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.08	0.08	0.08	0.07	0.09	0.09	0.09	0.08
N	2576	2576	2576	2441	2576	2576	2576	2441
Panel B: Market beta								
Heavy	−0.0618***	−0.0923***	−0.0613***	−0.0470**	−0.0619***	−0.0924***	−0.0614***	−0.0473**
	(0.0145)	(0.0156)	(0.0144)	(0.0186)	(0.0145)	(0.0156)	(0.0144)	(0.0186)
Light	−0.0002	−0.0119	0.0003	0.0037	−0.0002	−0.0118	0.0003	0.0037
	(0.0093)	(0.0098)	(0.0093)	(0.0123)	(0.0093)	(0.0098)	(0.0093)	(0.0123)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.15	0.15	0.15	0.10	0.15	0.15	0.15	0.10
N	2576	2576	2576	2441	2576	2576	2576	2441

This table reports cross-sectional regressions of performance and market beta on heavy and light option usage according to the frequency of usage over time. The sample consists of actively managed U.S. domestic equity funds over the period 1998–2013. Fund performance is measured using the Carhart (1997) 4-factor model, the Cremers et al. (2013) model plus an investable option strategy (IOS) factor based on the CBOE BuyWrite index, the Leland (1999) model and the Bawa and Lindenberg (1977) model. All performance measures are calculated for each fund individually using monthly gross and net return data and are winsorized at the 1% and 99% percentiles. Panel A displays the results for performance and Panel B for market beta. The dummy variable Heavy is one if a user fund uses any kind of option in an above median number of months and zero otherwise. The dummy variable Light is one if a user fund uses any kind of option in a below median number of months and zero otherwise. All variables are averages over time for each individual fund. Control variables are as in Tables 3 and 4. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively. Heteroscedasticity consistent standard errors are given in parentheses (White, 1980).

that funds which use options more frequently have slightly higher additional performance compared to light users (e.g., 47 vs. 41 basis points p.a. for Carhart, gross). Regarding the risk effect of option use, the results show very clearly that funds which use options more frequently have a very strong and significant risk reduction, while funds using options seldomly show no significant reduction of market beta (e.g., −6.18 vs. −0.02 percentage points for Carhart, gross). These results are robust for all specifications and performance models.

The results for our second specification based on absolute dollar amounts in options are presented in Table 12. The results show that funds with higher absolute dollar amounts in options have a distinctively higher additional performance compared to funds with smaller absolute dollar amounts in options (e.g., 97 vs. 18 basis points p.a. for Carhart, gross). Regarding the risk effect of option use, the results show that heavy and light option users have similar reductions in market beta (e.g., −3.58 vs. −4.62 percentage points for Carhart, gross). These results are robust for all specifications and performance models.

In addition to the cross-sectional tests, we also run panel regressions where the dependent variables $Performance_{i,t}$ and $Risk_{i,t}$ are explained by the option dollar amount based option user dummy variables $Heavy\ use_{i,t}$, $Light\ use_{i,t}$ and dummy $Nonusing_{i,t}$ as well as fund specific control variables including time- and style-fixed effects. Standard errors are 2-dimensionally clustered by fund and month to be consistent with regard to heteroscedasticity, time-series correlation and cross-sectional correlation.

$$Performance_{i,t} = \varphi_0 + \varphi_1 Heavy_{i,t} + \varphi_2 Light_{i,t} + \varphi_3 Nonusing_{i,t} + \sum_{j=4}^{J} \varphi_j Controls_{j,t} + \eta_{i,t} \quad (13)$$

Table 12
Cross-sectional regressions of performance and market beta on heavy and light option use defined by the intensity of option use.

	Gross				Net			
	Carhart	IOS	Leland	Bawa/ Lindenberg	Carhart	IOS	Leland	Bawa/ Lindenberg
Panel A: Performance								
Heavy	0.0097***	0.0083***	0.0097***	0.0089***	0.0096***	0.0082***	0.0096***	0.0087***
	(0.0021)	(0.0022)	(0.0021)	(0.0023)	(0.0021)	(0.0021)	(0.0021)	(0.0023)
Light	0.0018	0.0024	0.0018	0.0019	0.0019	0.0023	0.0019	0.0020
	(0.0024)	(0.0024)	(0.0024)	(0.0027)	(0.0024)	(0.0024)	(0.0024)	(0.0026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.08	0.08	0.08	0.07	0.09	0.09	0.09	0.08
N	2576	2576	2576	2441	2576	2576	2576	2441
Panel B: Market beta								
Heavy	−0.0358**	−0.0672***	−0.0360**	−0.0258	−0.0358**	−0.0672***	−0.0360**	−0.0258
	(0.0158)	(0.0170)	(0.0158)	(0.0197)	(0.0158)	(0.0170)	(0.0158)	(0.0197)
Light	−0.0462***	−0.0705***	−0.0453***	−0.0240	−0.0463***	−0.0706***	−0.0454***	−0.0244
	(0.0157)	(0.0166)	(0.0156)	(0.0200)	(0.0157)	(0.0166)	(0.0156)	(0.0200)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.15	0.14	0.15	0.10	0.15	0.14	0.15	0.10
N	2576	2576	2576	2441	2576	2576	2576	2441

This table reports cross-sectional regressions of performance and market beta on heavy and light option usage according to the intensity of usage. The sample consists of actively managed U.S. domestic equity funds over the period 1998–2013. Fund performance is measured using the Carhart (1997) 4-factor model, the Cremers et al. (2013) model plus an investable option strategy (IOS) factor based on the CBOE BuyWrite index, the Leland (1999) model and the Bawa and Lindenberg (1977) model. All performance measures are calculated for each fund individually using monthly gross and net return data and are winsorized at the 1% and 99% percentiles. Panel A displays the results for performance and Panel B for market beta. The dummy variable Heavy is one if a user fund is holding an above median dollar amount in options (long+short) on average and zero otherwise. The dummy variable Light is one if a user fund is holding a below median dollar amount in options (long+short) on average and zero otherwise. All variables are averages over time for each individual fund. Control variables are as in Tables 3 and 4. ***. **. * indicate significance at the 1%, 5%, and 10% level, respectively. Heteroscedasticity consistent standard errors are given in parentheses (White, 1980).

$$Risk_{i,t} = \varphi_0 + \varphi_1 Heavy_{i,t} + \varphi_2 Light_{i,t} + \varphi_3 Nonusing_{i,t} + \sum_{j=4}^{J} \varphi_j Controls_{j,t} + \eta_{i,t} \tag{14}$$

The results are presented in Table 13 and show that heavy option use leads to higher additional performance compared to light use (e.g., 164 vs. 104 basis points p.a. for Carhart, gross) while the effect for nonusing is near zero as in all other panel regressions before. Heavy use also leads to a higher reduction of market beta compared to light option use (e.g., −14.07 vs. −8.94 percentage points for Carhart, gross). These results are robust for all specifications and performance models.

Overall, the comparison between different user types regarding their option usage behavior confirms and strengthens our previous finding that option use has a direct positive effect on performance and a direct reducing effect on systematic market risk.

3.8. Tests for endogeneity in the relation between performance and option use

Our main findings concerning the relationship between option use and performance may be spurious if the analysis suffers from endogeneity due to a significant opposite relationship between past performance and option use, e.g., based on tournament behavior in the mutual fund industry. In this context, various studies, such as Brown et al. (1996), Busse (2001), Kempf and Rünzi (2008) and Schwarz (2011), show that mutual funds tend to change their risk taking behavior as a reaction to inferior performance. Likewise, mutual funds might employ hedging instruments after periods of good performance to secure their winner status. Alternatively, they might employ speculative instruments to boost performance after periods of inferior performance to rid themselves of their loser status.

Table 13
Panel regressions of performance and market beta on heavy and light option use defined by the intensity of option use.

	Gross				Net			
	Carhart	IOS	Leland	Bawa/ Lindenberg	Carhart	IOS	Leland	Bawa/ Lindenberg
Panel A: Performance								
Heavy	0.0164***	0.0175***	0.0142***	0.0139***	0.0164***	0.0155***	0.0142***	0.0139***
	(0.0045)	(0.0051)	(0.0041)	(0.0044)	(0.0045)	(0.0045)	(0.0041)	(0.0044)
Light	0.0104**	0.0159***	0.0090**	0.0074*	0.0105**	0.0124***	0.0090**	0.0074*
	(0.0041)	(0.0047)	(0.0040)	(0.0044)	(0.0041)	(0.0042)	(0.0040)	(0.0044)
Nonusing	0.0007	0.0004	0.0000	−0.0009	0.0006	0.0003	0.0000	−0.0010
	(0.0017)	(0.0017)	(0.0015)	(0.0018)	(0.0017)	(0.0017)	(0.0015)	(0.0018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.07	0.04	0.10	0.08	0.07	0.10	0.10	0.08
N	231,641	231,641	231,634	231,641	231,641	231,641	231,634	231,641
Panel B: Market beta								
Heavy	−0.1407***	−0.1593***	−0.1314***	−0.1341***	−0.1407***	−0.1593***	−0.1314***	−0.1341***
	(0.0261)	(0.0318)	(0.0265)	(0.0335)	(0.0261)	(0.0318)	(0.0265)	(0.0335)
Light	−0.0894***	−0.0992***	−0.0847***	−0.0846***	−0.0894***	−0.0992***	−0.0847***	−0.0846***
	(0.0157)	(0.0168)	(0.0160)	(0.0173)	(0.0157)	(0.0168)	(0.0160)	(0.0173)
Nonusing	0.0067	0.0077	0.0054	0.0051	0.0067	0.0077	0.0054	0.0051
	(0.0061)	(0.0067)	(0.0069)	(0.0074)	(0.0061)	(0.0067)	(0.0069)	(0.0074)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.12	0.10	0.12	0.07	0.12	0.10	0.12	0.07
N	231,641	231,641	231,634	231,641	231,641	231,641	231,634	231,641

This table reports panel regressions of fund performance and market beta on heavy and light option usage according to the intensity of usage. The sample consists of actively managed U.S. domestic equity funds over the period 1998–2013. Fund performance and market beta are measured using the Carhart (1997) 4-factor model, the Cremers et al. (2013) model plus an investable option strategy (IOS) factor based on the CBOE BuyWrite index, the Leland (1999) model and the Bawa and Lindenberg (1977) model. All performance measures and market betas are calculated for each fund and month individually using daily gross and net return data and are winsorized at the 1% and 99% percentiles. Panel A displays the results for performance and Panel B for market beta. The dummy variable Heavy is one if a user fund is holding an above median dollar amount in options (long+short) in a given month and zero otherwise. The dummy variable Light is one if a user fund is holding a below median dollar amount in options (long+short) in a given month and zero otherwise. Nonusing is one if a user fund does not use options in the respective month and in all other cases zero. Control variables are as in Tables 3 and 4. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are 2-dimensionally clustered by fund and month to be consistent with regard to heterosedasticity, time-series correlation and cross-sectional correlation.

To test for such behavior, we run pooled panel probit regressions based on semi-annual observations of all user funds where the binary dependent $Option_{i,t}$ variables are explained with lagged performance and control variables as well as time and style fixed effects. $Performance_{i,t\text{-}1}$ is calculated as Carhart's (1997) alpha (Eq. (1)) using daily returns. Standard errors are 2-dimensionally clustered by fund and month to be consistent with regard to heteroscedasticity, time-series correlation and cross-sectional correlation.

$$Option_{i,t} = \varphi_0 + \varphi_1 Performance_{i,t-1} + \sum_{j=2}^{J} \varphi_j Controls_{j,t} + \eta_{i,t} \tag{15}$$

Specifically, we use three different specifications of Eq. (15). In our first specification, we employ the binary option variable $Using_{i,t}$, defined as in Section 2.3, to assess the effect of past performance on the unconditional probability of using options. Further, we examine if our results are driven by the effect of performance on changes in usage behavior. Thus, in our second specification, we assess funds' probabilities of starting to use options as a reaction to past performance. For this, the binary option variable $Positive\_usage\_change_{i,t}$ is one if a fund changes its using behavior from nonusing during

Table 14
Semiannual panel probit regressions of option usage on lagged performance as tests for endogeneity.

	Gross			Net		
	$Using_t$	Positive usage $change_t$	Negativ usage $change_t$	$Using_t$	Positive usage $change_t$	Negativ usage $change_t$
$Performance_{t-1}$	0.0348	−0.0032	−0.0593**	0.0345	−0.0037	−0.0601**
	(0.0654)	(0.0267)	(0.0255)	(0.0654)	(0.0268)	(0.0256)
Manager $tenure_{t-1}$	−0.0000	−0.0008	−0.0001	−0.0000	−0.0008	−0.0001
	(0.0030)	(0.0005)	(0.0005)	(0.0030)	(0.0005)	(0.0005)
Log Tna_{t-1}	−0.0067	0.0016	0.0024*	−0.0067	0.0016	0.0024*
	(0.0084)	(0.0014)	(0.0013)	(0.0084)	(0.0014)	(0.0013)
$Turnover_{t-1}$	0.0116	0.0005	0.0003	0.0116	0.0005	0.0003
	(0.0075)	(0.0012)	(0.0009)	(0.0075)	(0.0012)	(0.0009)
Expense $ratio_{t-1}$	8.8593***	0.9817*	1.0942**	8.8920***	0.9814*	1.0343**
	(2.8456)	(0.5167)	(0.4864)	(2.8452)	(0.5145)	(0.4879)
Load $dummy_{t-1}$	0.0098	−0.0044	−0.0021	0.0098	−0.0044	−0.0021
	(0.0342)	(0.0058)	(0.0054)	(0.0342)	(0.0058)	(0.0054)
Age_{t-1}	−0.0005	0.0002	−0.0000	−0.0005	0.0002	−0.0000
	(0.0014)	(0.0002)	(0.0002)	(0.0014)	(0.0002)	(0.0002)
$Cash_{t-1}$	0.1806*	0.0062	0.0242	0.1806*	0.0062	0.0242
	(0.0985)	(0.0218)	(0.0202)	(0.0985)	(0.0218)	(0.0202)
Net $flow_{t-1}$	0.0138	−0.0343	0.0271	0.0139	−0.0342	0.0271
	(0.0750)	(0.0350)	(0.0211)	(0.0750)	(0.0350)	(0.0211)
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.06	0.04	0.05	0.06	0.04	0.05
N	9959	9018	9339	9959	9018	9339

This table reports semiannual panel probit regressions of option usage behavior on lagged fund performance to test for endogeneity. The sample consists of actively managed U.S. domestic equity funds over the period 1998–2013. Fund performance and market beta are measured using the Carhart (1997) 4-factor model. Performance and market beta are calculated for each fund and semiannual reporting period individually using daily gross and net return data and are winsorized at the 1% and 99% percentiles. The binary dependent variable $Using_t$ is one if a user fund invests in options in the respective period and zero otherwise. $Positive\_usage\_change_{i,t}$ is one if a user fund changes its using behavior from nonusing in the semiannual period t-1 to using in t and zero otherwise. Similarly, $Negative\_usage\_change_{i,t}$ is one if a user fund changes its using behavior from using in t-1 to nonusing in t and zero otherwise. Control variables are as in Tables 3 and 4 and lagged one semiannual reporting period ($t-1$). ***, **, * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are 2-dimensionally clustered by fund and month to be consistent with regard to heterosedasticity, time-series correlation and cross-sectional correlation.

N-SAR filing period $t-1$ to using in period t and zero otherwise. In the third specification, we assess funds' probability of ceasing to use options as a reaction to past performance by employing the binary option variable $Negative\_usage\_change_{i,t}$, which is one if a user fund changes its using behavior from using in t-1 to nonusing in t and zero otherwise.

Table 14 presents marginal effects at the mean. The results for $Using_{i,t}$ indicate that past performance has no significant effect on a user fund's probability of subsequently using options, which is clear evidence against endogeneity. The marginal effect of past performance on $Positive\_usage\_change_{i,t}$ is also statistically insignificant, indicating that past performance does not affect user funds' probability of starting to use options. The marginal effect of past performance on $Negative\_usage\_change_{i,t}$ is negative and significant, indicating that lower past performance leads to a higher probability that a user fund stops using options. This is consistent with tournament behavior as it implies higher risk-taking. However, this result only explains nonusage but not usage. Overall, the pooled panel probit analyses present evidence against endogeneity in the relationship between performance and option use and further supports our main findings that option use leads to direct benefits for mutual funds and their investors.[34]

[34] In additional tests, we estimate the panel regressions of our main analysis, explaining performance and risk on a semiannual basis using lagged option and control variables to circumvent problems associated with endogeneity. The results are qualitatively the same as in our main analysis.

4. Further tests and robustness checks

4.1. Leverage effect

Performance, as measured by linear regression models, is a function of systematic risk. Hence, any non-zero alpha can be scaled up or down the security market line using leverage (e.g., Rudd and Clasing, 1988). In the case of mutual funds, a manager who generates a non-zero alpha could increase or decrease it by leveraging the alpha generating holdings. As options are levered investments in the underlying asset, the performance-enhancing effect of using options could be a consequence of the leverage effect inherent in options. To rule out this explanation, we run our cross-sectional and panel regressions using the 'manipulation proof performance' measure proposed by Goetzmann et al. (2007). The results are qualitatively the same as in our main analysis. Thus, the leverage effect cannot explain our results.

4.2. Market timing

Classic market timing approaches, such as Treynor and Mazuy (1966) model, are often criticized because any loadings on the squared market factor intended to measure timing-activity could also reflect other sources of nonlinearity such as options (e.g., Jagannathan and Korajczyk, 1986). Using the reverse argumentation, option users' market timing activities may influence our findings regarding the effect of option use on performance and risk. Therefore, in additional analyses, we include Treynor and Mazuy (1966) market timing term in Carhart (1997) model. The results are the same as in our main analysis.

To further control for conditional market timing based on publicly available information, we also recalculate performance and risk measures using Carhart (1997) model where the market beta is time varying conditional on the information variables proposed by Ferson and Schadt (1996). The results are qualitatively the same as in our main analysis. Thus, market timing also cannot explain our results.

4.3. Alternative measures of risk

In our main analysis, we measure risk using the market beta from either of the four performance models. However, the results regarding the risk-reducing effects of option use might be spurious if risk is simply shifted to other components of risk. Therefore, in additional tests, we run alternative cross-sectional regressions similar to Eq. (6) and panel regressions similar to Eq. (8), using total risk measured by funds' standard deviation of returns instead of beta. The results are similar to those in our main analysis.

To further examine if any of the higher moments in returns can explain the risk-reducing effect of option use, we estimate Regressions (6) and (8), using skewness and kurtosis instead of market beta. The effect on skewness is negative, while that on kurtosis is positive, although these effects are not statistically significant at conventional levels. Overall, the use of alternative risk measures and higher moments of the return distribution cannot explain the results in our main analysis, lending further confidence to the validity of our main results.

4.4. Market environments

Our sample period, from 1998 to 2013, covers two major stock market crashes and three major stock market booms. Thus, these market environments may drive our results if option use or the success of option strategies differs significantly between booms and crashes. For example, option usage for hedging (speculation) may be more pronounced during crashes (booms). Therefore, we perform our cross-sectional and panel regressions on separate sub-samples based on boom periods and crash periods, which we define following Chalmers et al. (2013). Our results are qualitatively the same in both sub-samples, indicating that different stock market environments do not drive the results of our main analysis.

To further control for changing relations between performance and option use as well as market risk and option use over time, we also run regressions based on the standard Fama and MacBeth (1973) approach. In addition, this also controls for the large sample size of our panel regressions. The results for Using vs. Nonusing as well as Long vs. Short are as in our main analysis, show high levels of statistical as well as economic significance and are thus robust.

4.5. Alternative performance models

To rule out that our choice of the Carhart (1997) model as our baseline model drives our results, we estimate fund performance and risk using both the CAPM (Jensen, 1968) and Fama and French (1993) model as our baseline models. Additionally, as premiums on illiquid securities could influence performance, we also employ Carhart (1997) model augmented with the traded market illiquidity factor from Pástor and Stambaugh (2003). Moreover, Cremers et al. (2013) argue that Fama and French (1993) factors suffer from several biases, especially that they produce non-zero alphas on average. Therefore, in addition to the index-based 4-factor model we use with our IOS factor, we also use the index-based 7-factor model of Cremers et al. (2013). The respective results are similar to those in our main analysis.

5. Conclusion

We show via cross-sectional and panel data analyses that the use of options by mutual funds yields higher risk-adjusted performance. Moreover, option use produces significantly lower systematic risk because mutual funds use options mainly for hedging strategies and not for speculation. Thus, mutual fund option use is beneficial to investors and does not pose risk for the financial system in general.

Previous research on mutual fund option use has not offered such clear evidence, as most studies suffer from severe data limitations. By contrast, we base our analysis on a large and comprehensive sample of the SEC's mandatory N-SAR filings. We thereby contribute to several streams of mutual fund research. Specifically, we add to the literature on the benefits of mutual fund derivative use by showing a performance-enhancing and risk-reducing effect of option use based on both gross returns and net returns. Furthermore, we contribute to the literature on mutual fund option investment strategies. Consistent with covered call strategies for income generation, we show that mutual funds' short positions are the main drivers of the performance-enhancing effect adding 184 bp per year. On the other hand, consistent with protective put strategies for hedging, long option positions are the predominant contributors to the risk-reducing effect of options. Finally, we contribute to the literature on performance measurement in general by introducing a new 5-factor IOS-model, which controls for option exposure in mutual fund returns, using a feasible option strategy based on actually traded investment alternatives, in the spirit of Cremers et al. (2013).

Overall, this paper helps answer the vital question of whether derivative use by mutual funds is beneficial to mutual funds and their investors, an issue raised in a concept paper by the SEC in 2011, currently leading to the preparation of new regulations by the SEC to limit risk posed to the financial system or the broader economy by mutual fund option usage. Our results indicate that such fears are unjustified, as mutual fund option usage directly enhances risk-adjusted performance and reduces systematic risk.

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2015 Annual Meeting of the Financial Management Association in Orlando, the Research Seminars at the University of Sydney and the University of Auckland, and the 2015 Australasian Finance and Banking Conference in Sydney. We acknowledge financial support by the Research Center Global Business Management of the University of Augsburg. All remaining errors are our own.

Appendix. CRSP/N-SAR matching and data screening

The same methodology to preprocess the data and a similar corresponding Appendix is used in Rohleder et al. (2015). From the SEC's EDGAR online database, we obtain 106,357 individual N-SAR-filings for the period from 1998 to 2013 in unformatted text format, which we parse into a formatted table, using regular expressions under Linux. In addition, we extract ticker symbols from the header sections of the filings. To construct our final dataset, we merge this table with the funds in the CRSP database. Unfortunately, there is no common identifier in CRSP and N-SAR. Even worse, in N-SAR, there is no consistent fund identifier over time. Although the general instructions of the SEC urge registrants to use consistent information, the company identification key (CIK) and series numbers change over time for a substantial number of funds. Consequently, we match N-SAR and CRSP using the funds' names for each reporting date. For entries where ticker information is available in both CRSP and N-SAR filings, we additionally use the ticker symbols to match the funds. To improve our matching accuracy, we clean fund names in CRSP and N-SAR by hand, i.e., by deleting special characters such as ',' and ':' and standardize abbreviations (e.g., 'Small CP' or 'Small Capitalization' becomes 'Small Cap'). Furthermore, as fund name entries in N-SAR are often erroneous, we correct them manually. We conduct the actual matching of fund names with Winkler's (1990) Jaro-Winkler string distance metric, as implemented in the SimMetrics open source library. In tests with our database, we find the Jaro-Winkler algorithm to be superior to other string matching techniques in the SimMetrics library regarding speed and matching accuracy.

Because algorithmic string matching techniques may lead to false positive matches, we manually check all matches for plausibility. In the following step, we clean the match sample from further false positives, as in Chen et al. (2013). We rigorously discard from our sample all funds with discrepancies of more than 10% for net assets reported in N-SAR and CRSP in more than 25% of the reported months.

Table A.1
Comparison of the CRSP/NSAR matched sample and the NSAR-only samples by year.

Panel A: matched CRSP/NSAR sample							Panel B: CRSP-only sample					
Year	Funds	TNA	Expense ratio	Turnover ratio	Age	Excess return	Funds	TNA	Expense ratio	Turnover ratio	Age	Excess return
1998	438	1812	0.0126	0.9460	8.75	0.0213	1734	993	0.0128	0.9310	8.6470	0.0152
1999	876	1608	0.0126	0.9910	8.65	0.0387	1908	1114	0.0129	1.0100	8.7940	0.0244
2000	1028	1559	0.0127	1.0610	8.40	0.0012	2132	1209	0.0131	1.1150	8.8280	0.0012
2001	1143	1217	0.0131	1.1720	8.66	−0.0048	2270	966	0.0133	1.2400	9.0220	−0.0053
2002	1334	947	0.0134	1.2300	8.97	−0.0185	2379	800	0.0136	1.2470	9.4020	−0.0188
2003	1426	926	0.0137	1.1450	9.38	0.0244	2456	785	0.0139	1.1680	9.8120	0.0242
2004	1508	1102	0.0135	1.0010	9.84	0.0113	2470	983	0.0137	1.0060	10.3100	0.0101
2005	1853	1157	0.0129	0.8960	10.54	0.0073	2539	1074	0.0131	0.9370	10.4900	0.0059
2006	1933	1189	0.0123	0.8340	10.52	0.0106	2632	1172	0.0126	0.8950	10.5700	0.0104
2007	1979	1303	0.0117	0.8450	10.80	0.0050	2668	1298	0.0120	0.9010	10.8000	0.0052
2008	1994	1044	0.0114	0.8830	11.31	−0.0376	2665	1073	0.0116	0.9130	11.2300	−0.0372
2009	1964	799	0.0112	1.0010	11.87	0.0239	2629	842	0.0114	1.0240	11.7700	0.0231
2010	1940	979	0.0112	0.8950	12.33	0.0160	2547	1041	0.0113	0.9220	12.3100	0.0154
2011	1905	1134	0.0109	0.7870	12.70	−0.0004	2525	1183	0.0109	0.7970	12.7600	−0.0003
2012	1810	1243	0.0106	0.7570	13.72	0.0123	2380	1274	0.0105	0.7600	13.5500	0.0122
2013	1645	1567	0.0104	0.7290	14.70	0.0233	2248	1611	0.0104	0.7280	14.6400	0.0239

This table compares average fund characteristics for two samples of actively managed domestic equity funds by year during the period 1998–2013. Panel A shows the relevant variables for funds with entries in both the N-SAR filings and the CRSP mutual fund database. Panel B shows the relevant variables for funds available in the CRSP mutual fund database. All variables are taken from the CRSP mutual fund database.

Table A.1 presents cross-sectional statistics of fund characteristics for both the matched N-SAR/CRSP sample and the complete actively managed domestic equity fund universe from CRSP to check for any systematic biases in our sample. However, no significant differences in the main fund characteristics are found. Thus, we conclude that our sample is representative of the universe of all active U.S. domestic equity funds.

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