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Do hedge funds dynamically manage systematic risk? ☆

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Defining systematic risk management (SRM) skill as persistently low fund systematic risk, we find evidence of time varying allocation of hedge fund management effort across the business cycle. In weak market states, skilled managers focus on minimization of systematic risk via dynamic reallocations across asset classes at the cost of fund alpha and foregoing market timing opportunities. As markets strengthen, attention shifts to asset selection within consistent asset classes. The superior performance of low systematic risk funds previously documented arises due to the superior asset selection ability of managers in strong market states. Incremental allocations by investors arise due to this superior performance and not due to recognition of SRM skill.

1. Introduction

Measuring investment manager skill and fund performance has been a topic of interest to academics dating back to the inception of the asset pricing literature. Since the early models of Jensen (1968), Sharpe (1966), and Treynor and Mazuy (1966), investment manager skill has been analyzed across two dimensions – asset selection and market timing. More recent work recognizes the dynamic and independent nature of both the asset selection and market timing dimensions of manager skill (Kacperczyk et al., 2014). It need not follow that a manager skilled in one dimension is necessarily skilled in the other. Mutual fund managers can create shareholder value via either channel and evidence suggests they allocate effort and attention independently to each dimension across the business cycle.

The self-reported value proposition of many hedge funds is to create alpha via asset selection skill while minimizing the exposure of the fund to systematic risk.[4] While an extensive literature examines the existence of asset selection skill in hedge fund managers, the second equally important systematic risk management skill (SRM) dimension has received relatively little attention.[5] Despite their declared objective of low systematic risk, Patton (2009) reports that

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[4] For example, Daniel Och, chairman and chief executive of Och-Ziff Capital Management, stated "Investors continue to actively seek access to investment managers that generate risk-adjusted returns which have a low correlation to the equity markets and consistently protect capital. We believe that this focus has led to increased allocations to the hedge fund industry in the first half of this year, and that this acceleration will continue," quoted in Ahmed, Azam, "Och-Ziff Quarterly Earnings rise 19%", *New York Times*, August 2, 2011.

[5] See, for example, Fung et al. (2008), Bali et al. (2014, 2013), Cao et al. (2013), Ramadorai (2012) and Sun et al. (2012) among many other who examine hedge fund performance. We discuss the more limited hedge fund systematic risk literature in detail below.

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approximately one quarter of "market neutral" hedge funds exhibit significant exposure to systematic risk. Similarly, a series of papers report that a significant portion of the variability in hedge fund returns can be explained by common risk factors.[6] These results suggest that akin to market timing, maintaining low systematic risk is an acquired skill not common to all hedge fund managers. Our objective is to examine the existence of SRM skill in the hedge fund industry.

We frame our analysis in the theoretical model of Titman and Tiu (2011) which can be viewed as a simplification of Treynor and Black (1973).[7] In the model, the hedge fund manager must allocate assets to create a mean–variance efficient portfolio by combining three investments: a risk-free asset (r_f), a publicly available index (F) and a proprietary strategy (A). The excess return to the portfolio is a function of the weight (w) placed on the index relative to the proprietary strategy given by $R - r_f = w_A(A - r_f) + w_F(F - r_f)$. Since the proprietary strategy consists of a long-short or similar strategy, its return is unrelated to the return of the publicly available index ($Corr(A, F) = 0$). In the Titman and Tiu (2011) model, there is no distinction between the manager's ability to select assets in the proprietary strategy and his ability to ensure that the strategy and the public index remain independent. Thus, more skilled managers allocate a greater proportion of fund assets to the proprietary strategy ($w_A > w_F$) and for these superior managers, low fund systematic risk arises indirectly via the allocation strategy. Specifically, superior funds are characterized as having low R^2 values in the regression of fund return on proxies for systematic risk.

In contrast, in this paper, we argue that managerial skill is multidimensional and inherently more complex. Specifically, we argue that managerial ability to maintain the independence condition (i.e. $Corr(A, F) = 0$) is separate from asset selection ability. In other words, the skill to select assets that are under and over-valued is different from the skill of maintaining low systematic risk and anticipating market conditions that may disrupt the long-short hedge. It is well understood that asset correlations vary over time and tend to increase in times of stress in financial markets.[8] Buraschi et al. (2014) show that hedge funds that achieve low systematic risk via implementation of long-short and arbitrage strategies incur significant correlation risk, resulting in low ex-post portfolio diversification and hedge effectiveness.[9] In a multidimensional covariance matrix, the effects of correlation shocks are not easily predicted. Hence, management of correlation risk entails broad reductions of portfolio reliance on long-short positions, with the potential of uncoupling the beta hedge. In this paper, we extend the analysis of Titman and Tiu (2011), allowing (and testing) for a separation in manager skill between asset selection and SRM. We analyze the prevalence and determinants of SRM skill and its consequences for fund performance and investor preferences. The typical definition of skill in the context of asset management is the ability, drawn from one's knowledge, experience, and training, to persistently achieve excellence in performance. In the context of stock picking and market timing, skill is associated with persistence in fund alpha.[10] In our setting, we associate SRM skill with persistence in low fund systematic risk.

To measure hedge fund systematic risk, we utilize a novel measure motivated by Pukthuanthong and Roll (2009) who analyze levels of world systematic risk across equity indexes for a broad sample of developed, emerging, and frontier countries. This approach has the advantage of enabling the joint consideration of a highly inclusive set of systematic risk factors within the confines of a limited number of degrees of freedom when estimating annual systematic risk with monthly fund returns. Specifically, we estimate the principal components (PC) of 251 assets and measure systematic risk as the R^2 value from the regression of hedge fund returns on those PCs.

We commence our analysis by examining how fund-level systematic risk exposure changes over time, both unconditionally, and conditional on market state. If systematic risk levels do not change over time or across the cross-section of funds, then an examination of persistence in systematic risk as a proxy for manager skill will be non-informative. Tracking the systematic risk quintile rank of each fund between years in a transition matrix, we find that on average, only 30% of funds remain in the same risk quintile over a two-year period. These results suggest that SRM skill, proxied by persistence in systematic risk, is a rare commodity processed by relatively few managers. Partitioning by market state, the levels of systematic risk and correlation risk both increase when markets weaken. However, the ability of fund managers to stay in their original quintile rankings does not appear to change across market states.

How do managers influence the systematic risk exposure of their funds? The actual asset transactions of hedge funds are largely unobservable. Like all financial intermediaries, hedge funds are required to disclose long equity positions to the Securities and Exchange Commission (SEC) quarterly in Form 13-F. However, holdings are reported by investment company (not by fund) and holdings of other assets and short positions are not disclosed. Given these limitations, we therefore examine time variation in factor loadings, focusing on the broadly utilized Fung and Hsieh (2004) seven factors. Mapping factor loadings over two-year periods, we show that loading variability is greatest for the equity risk, size spread, bond risk and credit risk factors. The standard deviation of the loading on these factors is typically two to three times the standard deviation on the other three factors. In other words, on average, managers appear to adjust exposure to equity risk, size spread, bond risk, and credit risk factors when managing the systematic risk exposure of their funds.

Which manager and fund types possess greater SRM skill? We find that the determinants of SRM skill can be loosely grouped into three categories. First, manager education and experience are both related to systematic risk persistence. Funds managed by better-educated managers (proxied by SAT score) and managed by more experienced managers have higher SRM skill. Similarly, larger and older funds which likely attract better qualified managers typically have higher SRM skill. Second, systematic risk is sensitive to fund distress indicators. SRM skill is lower for fund managers who manage funds with low investor flows, poor performance, and greater performance volatility, both at the fund and style level. Finally, correlation risk and market conditions both significantly drive SRM. Higher SRM funds have significantly lower correlation risk. This relation is accentuated in periods of stress in financial markets when asset correlations are more likely to shift away from historical correlation patterns.

How is SRM skill level related to fund performance? We initially relate alpha to systematic risk persistence, factor loading variability (to capture the magnitude of risk adjustment), correlation risk and controls. We find a weak positive relation (significantly weaker than documented in prior studies) between SRM skill and alpha, suggesting separation between the two skill sets. Low systematic risk does not appear to be associated with higher fund performance. We next partition the model by market state. If the two skills are inherently related, the relation between alpha and SRM should be reasonably time invariant. However, if the skills are

[6] See Avarmov et al. (2011), Fung and Hsieh (2004), Mitchell and Pulvino (2001), Aggarwal and Naik (2004) and Bollen (2013).

[7] Model details appear in Appendix A.

[8] See Bollerslev et al. (1988), Jorion (2000), Moskowitz (2003) and Engle and Sheppard (2006), among others.

[9] Buraschi et al. (2014) define correlation risk as the risk derived from unexpected changes in the correlation between the returns of different assets or asset classes.

[10] See, for example, Berk and Van Binsbergen (2015).

separate, we should observe a variation in the relation across time. We find that a positive relation between SRM skill and alpha holds only in the strong market state (the relation is twice as strong). This result suggests that manager attention shifts from asset selection to SRM across the cycle. Low systematic risk is maintained in weak market states at the cost of alpha. In the strong market state, managers allocate less attention to SRM and this re-allocation of attention results in significant alpha benefits.

Finally, we examine if investors value SRM skill. To address this issue, we partition the model by manager skill (managers who persistently remain in the bottom quintile of systematic risk relative to managers for whom the systematic risk quintile rank changes in each period). This model addresses whether in aggregate, the active attention allocation by SRM skilled managers benefits investors. The explanatory power of SRM skill for alpha is thrice as large for high SRM skill managers. The net benefits of active SRM appear to accrue only to high skill managers. For low skill managers, the cost of SRM by adjusting factor loadings exceeds the benefit, on average, by 1024 bps per annum. Turning to investor preferences, proxied by fund allocations, we find that investors appear to be unable to detect SRM skill or that it is of lower value relative to other fund factors. High SRM skill managers attract incrementally higher flow but this relation appears to arise due to asset selection skill as opposed to SRM skill. Flows to high SRM skill managers are significantly higher in the strong market state, suggesting investors are reacting to performance as opposed to rewarding low systematic risk in the weak market state when the systematic risk hedge is most valuable.

2. Context

2.1. Related literature

Recent studies have typically used either correlation or factor models to measure fund exposure to systematic risk. As an example of the first class, Sun et al. (2012) suggest a measure of the distinctiveness of a fund's investment strategy based on the correlation of returns between peer funds and find that funds with more distinct portfolios realize superior performance. Among the second class, Fung and Hsieh (2004) develop a set of factors explaining hedge fund returns that subsequent papers have built on.[11]

The closest studies to our research question offer differing conclusions. As previously discussed, Titman and Tiu (2011) argue that superior hedge fund managers possess the joint ability to select assets and maintain low systematic risk. Managers form portfolios by allocating assets between a proprietary strategy and a publicly available index. Skilled managers allocate a greater proportion of assets to the proprietary strategy, resulting in low systematic risk for these funds. Titman and Tiu (2011) empirically test this theoretical prediction by ranking funds on the R^2 generated by regressing hedge fund returns on systematic factors and show that funds with *low* R^2s have higher information ratios, Sharpe ratios, and alphas. In addition, controlling for past performance, funds in the lowest R^2 quartile attract greater investment inflows and are able to charge higher fees. In sharp contrast, Bali et al. (2012) measure systematic risk as the standard deviation of residuals from factor models that include the Fama and French (1993), Carhart (1997), and Fung and Hsieh (2004) factors and show that systematic risk is positively related to the returns earned by the funds. Funds in the *highest* systematic risk quintile generate 6% higher average annual returns than funds in the lowest systematic risk quintile.

Both papers draw their inferences from the average characteristics of funds in systematic risk-ranked portfolios, where portfolios are formed over either the entire history of the fund or a reduced timeframe. A noteworthy limitation of this analysis is its static dimension. As we discuss below, hedge fund systematic risk ranks are highly variable over time. In our sample, the systematic risk quintile rank for over 70% of the funds changes each year by at least one rank. This variability obscures inferences that can be drawn from average systematic risk estimates. We extend the analysis in these papers by focusing on *persistence* in systematic risk, as opposed to the transitory level, and allow for the separation of asset selection from SRM skill.

2.2. Manager incentives

The self-stated mandates of Equity Hedge and Equity Market Neutral style hedge funds (EMN) are to minimize investor exposure to systematic factors.[12] Hence, we use persistence in systematic risk as our proxy for risk management skill. However, managers face a series of conflicting incentives which interact to make low systematic risk targets less appealing. For example, maintaining persistently low systematic risk requires managers to forego market timing opportunities. It is well understood in the mutual fund literature that active fund managers tilt their portfolios toward high beta stocks during up markets to take advantage of the superior returns earned by high beta stocks in these periods (Karceski, 2002). Return-chasing by retail investors, unable to distinguish between the proportion of returns that comes from the fund alpha and that which comes from its exposure to risk factors, increases portfolio flows and fees to these funds. EMN hedge funds may employ similar strategies, resulting in a limited or potentially positive relation between fund performance and systematic risk, particularly in strong market states.

In addition, choosing to consistently maintain low systematic risk regardless of market conditions entails taking on additional risk, particularly in down markets. Buraschi et al. (2014) show that hedge funds that achieve low systematic risk via implementation of long-short and arbitrage strategies incur significant correlation risk, resulting in low ex-post portfolio diversification and hedge effectiveness.[13] In a multi-dimensional covariance matrix, the effects of correlation shocks are not easily predicted. Hence, management of correlation risk entails broad reductions of portfolio reliance on long-short positions, with the potential of uncoupling the beta hedge. To the best of our knowledge, this paper is the first to consider the divergent incentives of joint minimization of systematic and correlation risk in the context of manager risk preferences. The extent to which investors are aware of and consider correlation risk in the context of EMN hedge funds has also never been explored.

3. Measuring systematic risk

As in the literature surveyed above, we utilize factor models to estimate fund exposure to systematic risk. The problem of identifying the factors to use in systematic risk factor models is non-trivial due to the large number of known and unknown potential factors and the limited degrees of freedom in each regression. To address this issue, we draw on Pukthuanthong and Roll (2009) who analyze levels of world systematic risk across equity indexes

[11] See for example, Sadka, 2010; Bali et al., 2011; Bollen and Whaley, 2009, or Patton and Ramadorai, 2013.

[12] Hedge funds employ a variety of investment strategies, not all of which are necessarily associated with the objective of low systematic risk. As discussed in more detail below, we focus our analysis on hedge funds in the equity market neutral and equity hedge styles which have the self-declared objective of low systematic risk. We refer to hedge funds of these two styles collectively as Equity Market Neutral (EMN).

[13] Buraschi et al. (2014) define correlation risk as the risk derived from unexpected changes in the correlation between the returns of different assets or asset classes.

for a broad sample of developed, emerging, and frontier countries. Specifically, they calculate the principal components (PC) of a global sample of country indexes and then regress daily country index returns on these global PCs, using the R^2 of that model to measure systematic risk. This approach has the advantage of using a comprehensive set of systematic risk factors within the confines of a limited number of degrees of freedom when estimating annual systematic risk with monthly fund returns. We obtain asset data from Datastream (see Appendix B for a summary). The list of 251 assets included in our PC estimates is as comprehensive as possible and is drawn from a survey of the hedge fund literature (see for example, Fung and Hsieh, 2004 or Titman and Tiu, 2011). For each calendar year, we calculate the covariance matrix of USD monthly returns for the 251 assets.[14] From this matrix, we compute eigenvectors and sort them from the smallest to the largest eigenvalue. The PCs are then estimated from returns in the subsequent calendar year. This process is repeated in each calendar year, ultimately resulting in 15 calendar years of monthly frequency, out-of-sample PCs.

As in Pukthuanthong and Roll (2009), we use the first 10 PCs as systematic risk factors. On average, these PCs explain approximately 99% of the variability in the returns of the considered assets. Our systematic risk proxy is the R^2 obtained from the regression of hedge fund returns on the 10 PCs:

$$\text{PC10}: R_{i,t} = \alpha_i + \sum_{n=1}^{10} \beta_{i,n} \text{PC}_{n,t} + \epsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is the return to fund i in month t and n denotes the PC estimated from the 251 assets described in Appendix B.

Titman and Tiu (2011) observe that in their sample, the portfolio of low R^2 funds (with low systematic risk exposure) has substantial volatility that cannot be explained by the common factors used in their model. Their evidence suggests that, although these funds have low correlations with the large group of common factors explored, the funds tend to be correlated with each other. Similarly, Bollen (2013) uses style factors as systematic risk proxies and finds that portfolios of funds with R^2 of zero in those models contain half the volatility of portfolios of other funds and thus have substantial systematic risk. These tests indicate the presence of an omitted systematic risk factor not captured by the style factors. In unreported tests, we calculate the correlation matrix of monthly residual values from the systematic risk model where the value-weighted index return to each hedge fund strategy is regressed on the first 10 principal components calculated from the 251 assets. The residual correlations are typically low, with an average value of 0.16 and only 9 of the 36 correlation values significantly differ from zero at the 5% level. These results suggest that the 10 principal components capture an omitted risk factor not captured in the Titman and Tiu (2011) models and highlight the importance of factor selection in multi-factor model estimates of systematic risk exposure.

Although the PC10 systematic risk measure in Eq. (1) is appealing given its ability to mitigate potential omitted variable bias induced by factor selection constraints, it has several limitations. First, estimation of annual systematic risk by relating 12 monthly returns to 10 PCs results in a model with one degree of freedom which may generate unstable estimates. Second, hedge funds often invest in illiquid securities for which market prices are not readily available, resulting in returns that appear smoother than true economic returns (Getmansky et al., 2004). Funds may also employ management strategies or invest in derivative assets that result in non-linear payoffs. Systematic risk proxies based on a linear underlying estimation may therefore systematically underestimate systematic risk for funds with these return features.

We address these issues by employing a second factor model which includes the first PC extracted from the asset list in Appendix B plus a proxy for the degree of return smoothing estimated from the Getmansky et al. (2004) model and a proxy for the importance of non-linear factors in fund returns, estimated as in Fung and Hsieh (2004).[15] Since the first PC explains 66% of the variability in the returns of the considered assets, it is a reasonable proxy for a systematic risk factor by itself.

$$\text{PC3}: R_{i,t} = \alpha_i + \beta_{1,i}\text{PC1}_t + \beta_{2,i}\theta_{0,i,t} + \beta_{3,i} NF_{i,t} + \epsilon_{i,t} \tag{2}$$

where PC1 is the first PC extracted from the assets in the Appendix, $\theta_{0,t}$ is an estimate for the degree of return smoothing and NF is an estimate of the importance of nonlinear factors to fund returns.

An inherent weakness in each of these models is the imposition of an annual horizon over which to estimate systematic risk. For example, a fund with high systematic risk at the start of the year, which adjusts its portfolio to low systematic risk in July will have moderate systematic risk for that year in our model. To address this issue, Bollen and Whaley (2009) employ a change-point analysis to estimate shifts in hedge fund systematic risk. However, as they note, the limited history of hedge funds allows only 1 change-point for each fund between 1994 and 2005. To ensure the imposition of annual systematic risk estimates is not biasing our results, we replicate our analysis using alternative horizons of 1.5 and 2 years for all three models described above. These models provide similar degrees of freedom to prior papers – for example, Titman and Tiu (2011) include 5 risk factors in stepwise regression models using monthly return observations and two-year windows. We obtain similar results (unreported) for the alternative horizons and reach the same conclusions.

A further limitation of our approach is our assumption that managers implement long-short portfolio strategies with financial assets. Alternative investment strategies exist that could generate low systematic risk based on our proxy but require little SRM skill. For example, a fund holding 100% cash, a fund that invests in lottery tickets or a fund that invests in far out-of-the-money put options on the SP500 would have near zero systematic risk. As the true portfolio holdings of hedge funds are unobservable, we cannot exclude the presence of such strategies in our sample.

We quantify high SRM skill as managers who maintain their fund in the bottom quintile of systematic risk over a 3-year window. Correspondingly, low SRM skill managers change systematic risk rank in each year of the 3-year window. Admittedly, our selection of 3-year windows is ad hoc but is motivated by the short time series of our sample and the desire to allow time variation in SRM skill. Despite the self-stated mandate to maintain low systematic risk, it is possible that a manager skilled in SRM would choose to employ a market timing strategy, varying fund systematic risk across the cycle. Our measure of SRM skill would overlook such managers. Presumably EMN hedge fund investors invest in this asset class for the properties of low systematic risk and these preferences would create manager incentives to maintain low systematic risk. Prior analysis suggests that funds with lower systematic risk are rewarded with higher flows (Titman and Tiu, 2011). We re-examine the relation between investor preferences and systematic risk below and examine if managers with transitory

[14] Given the range of assets held by hedge funds, we opt for an inclusive set of assets in the principal component analysis but recognize that inclusivity comes potentially at the cost of precision. For example, Johnstone and Lu (2009) argue that eigenvalues and eigenvectors estimated from large, singular covariance matrices are noisy. It should be noted that noise in the eigenvector estimates, if anything, biases against our results. For robustness, we replicate our analyses with smaller asset sets (for example, the set of assets utilized by Pukthuanthong and Roll (2009)) and find qualitatively similar results.

[15] Titman and Tiu (2011) utilize the Getmansky et al. (2004) and Fung and Hsieh (2004) factors for the same purpose.

systematic risk have market timing ability to validate our proxy for SRM skill.

4. Data

We obtain hedge fund data from the Center for International Securities and Derivatives Markets (CISDM) and TASS Lipper. Although there is a substantial overlap between the two data providers, they do track different funds, and so we utilize the combined datasets after excluding duplicates. Although hedge fund data is available starting in January 1990, we restrict our sample to January 1996 to December 2010, as prior to 1996, the data to estimate correlation risk (discussed in detail below) is unavailable. Data from both providers includes both active and defunct funds and thus is survivorship bias free during our period of analysis. We focus on Equity Market Neutral and Equity Hedge (EMN) strategy funds. As previously discussed, hedge funds employ a variety of strategies and not all strategies necessarily target low systematic risk. Thus, our analysis focuses on funds for which low systematic risk is a stated objective.[16] We also exclude fund of funds, multi-strategy funds, funds with non-US dollar returns, and funds which report only gross returns. To control for potential backfill bias, we follow Aggarwal and Jorion (2010) and exclude funds with a back-fill period greater than 180 days.[17]

Table 1 presents summary statistics for the hedge funds included in our sample, reported separately for the two styles considered in the analysis. On average, funds in our sample manage 271 million USD in assets, charge management fees of 1.3% and incentive fees of 17%. The life of a fund in our sample is, on average, 57 months or 4.75 years, which reflects the rapid growth in the industry in the later portion of our sample, rather than a high failure rate of funds.

5. Systematic risk persistence

To motivate our use of the persistence of systematic risk as a proxy for manager skill, we first examine how persistent systematic risk levels are across time and across the cross-section of funds. If systematic risk levels are reasonably time invariant, or move in tandem across funds, then an examination of persistence in systematic risk as a proxy for manager skill will be non-informative. To measure time series variation in systematic risk, we estimate annual systematic risk by fund from 1996 to 2010 using Eq. (1) and form systematic risk quintile ranks.[18] Table 2 reports the transition matrix of systematic risk ranks formed either annually or bi-annually. The R^2 proxy for systematic risk ranges from an average value of 83% for the highest quintile to 17% for the lowest quintile, with the values decreasing in a monotonic fashion between quintiles. The range in mean R^2 values suggests that the sorts are capturing meaningful differences in systematic risk across quintiles.

On average, only 27% of funds remain in the same systematic risk quintile rank between years (gray shaded cells reflect the percentage of funds that remained in each rank). Annual persistence in systematic risk rank is higher for high systematic risk funds (36% remain in the highest quintile) relative to low systematic risk funds (20% of funds remain in the low quintile rank). Extending the analysis to a two-year horizon produces similar results. On average, 29% of funds remain in the same quintile rank two years later.

Table 1
Summary of hedge fund characteristics.

	Equity hedge	Equity market neutral	Aggregate
Return	13.58	10.17	13.09
Total net assets (Mil. $)	284.98	190.14	271.23
Management fee (%)	1.18	1.70	1.26
Incentive fee (%)	16.33	17.56	16.51
Redemption notice (days)	39.03	34.44	38.36
Lockup (months)	3.42	3.77	3.47
Fund age (months)	57.19	56.13	57.04
No. funds	1132	192	1324

This table reports summary statistics for the hedge fund sample. Each variable is reported by style included in the sample over the timeframe of January 1996 to December 2010 (180 observations). Average end-of-month values are reported. Management and incentive fees are measured as a percentage of total net assets at year end. The redemption period is defined as the sum of the redemption and advanced notice periods required for investors to redeem shares and the subscription period is defined as the delay between investing in the fund and the purchase being processed. Lockup is the period during which investors are not allowed to redeem shares after purchase. Fund age is measured from the date of fund inception.

Fewer funds remain in the highest quintile rank between the one- and two-year horizons (36% relative to 30%). However, the number of funds that remained in the bottom quintile increases over the two-year horizon (20% relative to 41%) suggesting that 21% of funds drop out of the bottom quartile in the first year and return in the second year.

To provide an assessment of the influence of macroeconomic factors on systematic risk ranks, we partition the one year transition matrix into terciles based on market state, proxied by the DEF spread (only the bottom and top terciles are reported).[19] Annual DEF spread values are calculated as the mean end-month values of the difference between an AA and BB ranked corporate bond index in each year. On average, 29% of funds remain in the same systematic risk quintile year over year in the strong market state (low DEF tercile) relative to 33% of funds remaining in the same tercile in the weak market state (high DEF tercile). Consistency in systematic risk rank persistence across market states suggests that systematic risk shifts are either predominantly random or driven by fund-level factors.

A potential issue with the analysis in Table 2 is that the rank process fails to capture the stability of the absolute level of systematic risk. In other words, the risk of a given fund may remain constant and it is the change in risk of the comparison funds which causes the fund to change rank. To address this issue, in Fig. 1, we separately form ranks annually and across the entire sample in one sort. The entire sample sort benchmarks the systematic risk of the fund in each year to a constant benchmark as opposed to the relative benchmark of risk of comparison funds in each year. Our results are similar between the two sorts. In the annual sorting method, on average 24%, 30%, and 46% do not change rank, change 1 rank, or change more than 1 rank, respectively. In the entire sample sorting method, the comparison average values are 24%, 26%, and 49%. The similarity of these results suggests the quintile shifts in risk arise due to changes in fund-level risk and not time-varying benchmarks.

To provide an alternative perspective, we examine how systematic risk levels and correlation risk are related to market state. Table 3 reports average systematic and correlation risk levels by DEF tercile. Consistent with trends noted in equity markets, we find that a greater proportion of EMN hedge fund returns are

[16] Our results are similar if all hedge fund styles are included in the sample and after including style fixed effects in the panel regressions. Approximately 50% of the total hedge fund sample consists of EMN style funds.

[17] We obtain similar results and reach the same conclusions if funds with back-fill periods greater than 180 days are included in the sample.

[18] We obtain similar results if the alternative systematic risk proxy (defined in Eq. (2)) is used.

[19] We also obtain similar results if market state is alternatively proxied by the TED spread.

Table 2
Systematic Risk Transition Matrix.

		Mean R^2 (%)	Systematic risk quintile rank$_{T+1}$ (Year 1)					Systematic risk quintile rank$_{T+2}$ (Year 2)					Systematic risk quintile rank$_{T+1}$ low DEF tercile$_T$ (strong markets)					Systematic risk quintile rank$_{T+1}$ high DEF tercile$_T$ (weak markets)				
			High	4	3	2	Low	High	4	3	2	Low	High	4	3	2	Low	High	4	3	2	Low
Systematic Risk Quintile Rank$_T$	High	83	36.34	24.14	7.79	12.58	19.15	29.86	16.07	13.50	25.72	14.85	30.70	22.19	21.28	15.62	10.21	39.23	12.18	12.64	20.63	15.32
	4	69	30.05	27.14	16.11	12.16	14.54	16.18	30.56	13.48	24.97	14.82	39.50	28.56	9.30	14.01	8.63	27.85	35.62	13.13	9.26	14.14
	3	53	15.48	28.09	22.91	10.16	23.36	19.40	28.79	29.85	9.49	12.47	11.00	22.23	20.72	13.60	32.44	15.94	31.37	30.62	7.76	14.31
	2	35	7.32	5.93	35.79	27.75	23.20	18.89	18.95	29.82	15.57	16.77	9.24	12.14	31.10	31.77	15.75	4.82	13.26	28.15	27.30	26.47
	Low	17	10.81	14.71	17.39	37.35	19.74	15.67	5.64	13.35	24.24	41.09	9.55	14.89	17.59	24.99	32.98	12.17	7.56	15.45	35.05	29.76
	Mean of shaded cells						26.78					29.39					28.95					32.51

This table reports, for each systematic risk quintile, the percentage of funds that remain in the same quintile and the fractions that transition to other quintiles in year $T+1$ or $T+2$. Funds which enter the sample in year $T+1$ or $T+2$ are excluded. The one year transition matrix is additionally bifurcated, focusing on periods when DEF is the in bottom (strong market) or top tercile (weak market). Systematic risk is calculated as the R^2 from the annual frequency model: $R_{i,t} = \alpha_i + \sum_{n=1}^{10} \beta_{i,n} \mathrm{PC}_n + \epsilon_{i,t}$ where $R_{i,t}$ is the return to fund i in month t and n denotes the PC estimated from the 251 assets described in Appendix B. The mean R^2 for each quintile is reported in year T. The annual value of the DEF spread is calculated as the mean of the end-of-month values of the difference between AA and BB corporate bond index yields within each year. Tercile sorts of are formed from the annual mean values, resulting in three partitions of seven years. The shaded cells report the percentage of funds that remained in each quintile between periods.

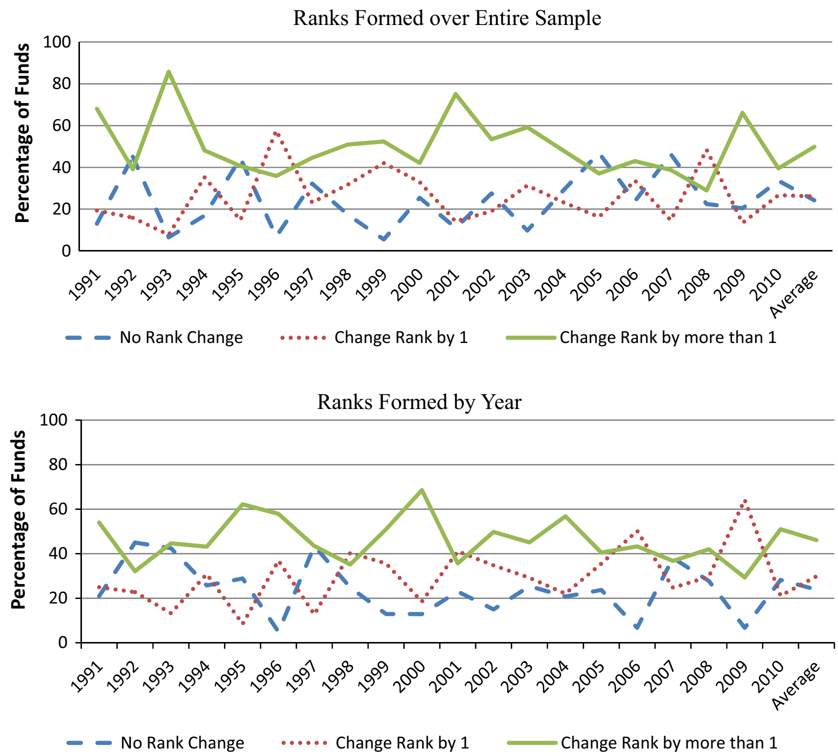

Fig. 1. This figure shows the proportion of the hedge fund sample that changes its systematic risk quintile rank by year. Proportions are reported for three groups; (1) funds which maintain the same quintile rank from the prior year ($\Delta Q = 0$), (2) funds which increase or decrease their quintile rank by one position (abs$\Delta Q = 1$) and (3) funds which increase or decrease their quintile ranks by more than one position (abs$\Delta Q < 1$). Systematic risk quintile ranks are formed separately across the entire sample and within each year. Systematic risk is calculated as previously defined using the PC10 model (Eq. (1)).

Table 3
Systematic and correlation risk.

DEF tercile (market state)	Systematic risk	Correlation risk
Low (Strong)	0.4409	0.1064
Medium	0.4544	0.1531
High (Weak)	0.6509	0.1638
H–L	0.2100***	0.0574***
	(0.0031)	(0.0013)

This table reports the relation between market conditions and average hedge fund systematic and correlation risk, across time partitions defined by market state proxied by the DEF spread. Systematic risk is calculated as the R^2 from the annual frequency model: $R_{i,t} = \alpha_i + \sum_{n=1}^{10} \beta_{i,n} \mathrm{PC}_n + \epsilon_{i,t}$ where $R_{i,t}$ is the return to fund i in month t and n denotes the PC estimated from the 251 assets described in Appendix B. Correlation risk is measured as the fund return loading on the correlation risk factor estimated as in Buraschi et al. (2014). DEF spread partitions are formed as defined in Table 2. Mean risk values for each tercile are reported, followed by the difference between the third and first tercile means (H–L). The p-value from the t-test of the difference in means is reported in brackets below each difference.
*** Significance at the 1% level. None of the variables are significant at the 5% or 10% levels.

explained by global risk proxies during times of financial stress. In other words, EMN hedge funds become more integrated with global markets precisely when diversification effects are most needed by investors. Specifically, average R^2 value increases by 21% between periods of low and high DEF.

As previously discussed, hedge fund managers must also consider correlation risk when choosing the optimal systematic risk level for a fund. As correlation risk increases in weak market states, the noted increase in systematic risk may reflect a managerial reaction to correlation risk. To measure fund-level correlation risk, we estimate return loadings on the correlation risk factor as estimated in Buraschi et al. (2014). Specifically, the correlation risk factor is measured as the spread in implied and realized correlations for stocks in the S&P 500 index using derivative contract prices. Over our sample period of 1996–2010, the correlation risk factor has a mean value of −12.18, with a median of −8.22 and standard deviation of 19.54. These values are reasonably consistent with the estimates in Buraschi et al. (2014) of −10.96, −7.92, and 16.78, respectively, which they estimate from 1996 to 2008.[20] In aggregate, factor loading on the correlation risk factor increases by 54% between low and high periods of DEF. This result reflects a significant increase in EMN hedge fund correlation risk as broad market conditions deteriorate and highlights the challenges faced by managers in managing systematic risk. It should be recognized that the increase in correlation risk is muted by any adjustments the fund manager has made to mitigate correlation risk by increasing the systematic risk of the fund. Here again, trends are broadly consistent, or perhaps stronger, for funds in the equity market neutral style.

To summarize these results, systematic risk ranks are highly variable, with typically less than 30% of funds remaining in the same rank year over year. Average systematic risk levels increase during periods of stress in financial markets, which coincide with increases in correlation risk. This trend potentially arises due to active management of systematic risk by managers who alter the hedge position of the fund to reduce its exposure to correlation risk. These results lead us to one of two conclusions: (1) Either maintaining stable systematic risk is challenging and a skill that is potentially a rare commodity or (2) managers forego systematic risk stability to avail of market timing opportunities.

6. The dynamic management of systematic risk

Precisely how do EMN hedge fund managers adjust the risk exposure of their funds? How do these approaches vary between high and low skill managers? To answer these questions, we examine time series variation in hedge fund loadings on the Fung and Hsieh (2004) factors. We chose these factors as they are commonly utilized in fund performance models as benchmarks for assets commonly held by hedge funds with non-linear payoffs. These factors capture a broad spectrum of the assets we consider in Appendix B. We do not utilize the PCs from Eq. (1) in this setting as we seek to identify tangible, easily interpreted risk exposures which vary over the cycle. We show that variation of these factors is indeed related to persistence in fund systematic risk further in the paper.

We calculate factor loadings over two-year periods, starting in 1996 and concluding with a three-year period spanning 2008–2010. Panel (a) of Table 4 reports the time series of factor loadings estimated as a pooled OLS regression of all funds in the sample. Of the seven factors, the equity market, size spread, bond market, and credit spread factors have the largest absolute loading size and it is for these factors that the largest variability in loading is observed (typically twice the loading and variability on the other three factors). These results suggest that managers typically vary exposure to these factors when seeking to vary the systematic risk of their funds.

The analysis in Panel (a) of Table 4 is provided to motivate and provide context for our primary analysis which examines variation in SRM between high and low skilled managers. To facilitate this analysis, we calculate the same factor loadings by fund and then calculate the cross-sectional standard deviation of factor loadings between high and low SRM skill subsets. Our measure of systematic risk skill is motivated by Table 2. We define high skill managers as those which maintain their fund in the bottom systematic risk quintile over the prior three-year period since these managers have fulfilled the self-stated fund mandate of EMN hedge funds to maintain low systematic risk exposure. In contrast, for low SRM managers, the systematic risk quintile rank of the fund changes in each of the prior three years. The skill classification updates annually. Thus, our definition allows hedge fund managers to transition across skill classifications over time.

Panel (b) of Table 4 reports the results, reporting the cross-sectional standard deviation of the four factor loadings (equity, size, bond, and credit spread) with the largest absolute size in Panel (a), segmented both by manager skill and market state (proxied by the DEF spread). Results for the other three loadings are typically much smaller and insignificant. The focus of our analysis is on the bottom frame of Panel (b), which reports the difference in cross-sectional factor loading standard deviation between high and low skill managers.

In the strong market state (low DEF), we observe a higher level of consistency in factor loadings among high relative to low skill managers (lower standard deviation in factor loadings). As market conditions deteriorate (transition from low to high DEF), we observe that this relation reverses. The difference in standard deviation of factor loadings between high and low skill managers is positive and significant for each of the primary factors except the bond factor (t-statistic 1.58). Thus, in periods of stress in financial markets when correlation risk and systematic risk passively increase, the standard deviation of factor loadings for high skill managers typically increases dramatically while those of low skill managers typically shrinks as dramatically. This suggests that in weak markets, skilled hedge fund managers are more active in seeking mechanisms to manage both risks and typically take positions different from their peers while unskilled managers herd.

7. Determinants of systematic risk management skill

We now examine the determinants of SRM skill and the characteristics of high SRM skill managers. Table 5 reports cross-sectional logit models where the dependent variable is an indicator variable set to 1 if the fund has remained in the bottom quintile of systematic risk over the prior three years. This proxy for SRM skill is used throughout the remainder of the paper. As determinant variables, we consider variability in Fung and Hsieh 7-factors, correlation risk and manager and fund characteristics. Factor loading variability and correlation risk are as previously defined in Tables 3 and 4. Following Li et al. (2011), as a proxy for either intelligence or education of the fund manager, we use the composite SAT score from the *U.S. News and World Report* and the *Princeton Review* of 2003 of the undergraduate college that the fund manager attended. We also use the number of years the fund manager has worked as a proxy for management experience or career concerns (*Work Experience*). Both variables are reported in TASS. As in Li et al. (2011), we exclude manager age and tenure (which are also reported by TASS) from our analysis as age is missing for over half of the dataset and tenure is highly correlated (0.95) with work experience.[21] The fund-level determinants are as previously described in Table 4.

The fund characteristics variables we consider include fund age in years, fund size measured by total net assets, annual return, the standard deviation of monthly returns over the prior year, fund flow defined as:

$$Flow_{i,t} = (TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t}))/TNA_{i,t-1} \quad (3)$$

where TNA is total net assets to fund i at the end of year t and R is the fund return, the natural logarithm of the required minimum initial investment, an indicator variable equal to 1 if the fund uses leverage in its investment strategy, and the lengths of the lockup, redemption, and subscription periods (in days). The redemption period is defined as the sum of the redemption and advance notice periods required for investors to redeem shares and the

[20] S&P 500 derivative data was obtained from Optionmetrics and commences in 1996. Thus, as previously discussed, by necessity we limit the analysis in the paper to the period of 1996–2010.

[21] Chevalier and Ellison (1999) show that the number of years worked is a better proxy for manager experience than tenure.

Table 4
The dynamic management of systematic risk.

Factor	1996–1997	1998–1999	2000–2001	2002–2003	2004–2005	2006–2007	2008–2010	Mean	St. dev.
Panel (a)									
Bond trend-following	0.178	0.096	−0.002	−0.021	0.010	0.081	−0.024	0.048	0.088
Currency trend-following	0.175	−0.011	0.210	0.066	0.100	0.052	0.001	0.085	0.090
Commodity trend-following	0.223	−0.055	0.230	0.204	−0.011	−0.055	0.059	0.066	0.119
Equity	0.580	0.563	0.441	0.171	−0.206	0.257	0.041	0.243	0.303
Size spread	0.498	0.478	0.339	0.074	0.271	0.275	−0.057	0.246	0.150
Bond	−0.532	−0.889	−0.173	−0.401	−0.085	0.045	−0.025	−0.316	0.356
Credit spread	−1.015	−0.685	−0.035	−0.479	−0.334	−0.250	−0.169	−0.375	0.260

DEF tercile	Equity	Size spread	Bond	Credit spread
Panel (b)				
High SRM skill managers				
Low (Strong)	0.436	3.427	2.819	2.144
Medium	1.813	5.197	2.364	15.738
High (Weak)	13.753	25.054	2.948	49.767
High–Low	13.317**	21.627***	0.129	47.623***
	(2.06)	(4.14)	(0.75)	(4.49)
Low SRM skill managers				
Low (Strong)	17.391	45.005	2.577	59.935
Medium	1.478	18.041	6.595	25.343
High (Weak)	0.312	8.270	0.408	2.477
High–Low	−17.079***	−36.735***	−2.169	−57.458***
	(3.29)	(4.45)	(1.67)	(3.74)
Low–High SRM skill managers				
Low (Strong)	−16.956	−41.578***	0.242	−57.791***
	(2.41)	(3.80)	(0.56)	(4.72)
Medium	0.334	−12.844**	−4.231	−9.606
	(1.07)	(2.60)	(1.62)	(1.26)
High (Weak)	13.441**	16.784**	2.540	47.290***
	(2.66)	(2.42)	(1.33)	(3.81)
High–Low	30.396***	58.362***	2.298	105.081***
	(2.79)	(3.93)	(1.58)	(7.26)

This table reports the time series and cross-sectional standard deviation of hedge fund return loading on the Fung-Hsieh (2000) 7 factors. Factor loadings are estimated over 2 year periods using monthly hedge fund returns. Panel A summarizes the factor loadings by period and the mean and standard deviation of the estimated loadings. Panel B summarizes the standard deviation of factor loadings across funds, segmented by high and low SRM skill and the DEF spread (as previously defined). SRM skill is proxied by the standard deviation of the R^2 over the prior three years from the annual regression of fund return on the 10 PCs estimated from the assets listed in Appendix B (Eq. (1)). High and Low skill managers are proxied by funds that remain in the lowest quintile of systematic risk over the prior three years (high skill) relative to funds that change quintile rank in each of the prior three years (low skill). The bottom frame of Panel B reports the difference in cross-sectional standard deviation of factor loading between high and low skill managers, with t-test statistics reported in brackets.

** Significance at the 5% levels.

*** Significance at the 1% level. None of the variables are significant at the 5% or 10% levels.

subscription period is defined as the delay between investing in the fund and the purchase being processed. Finally, we include fund fee attributes, including the management and incentive fee and an indicator variable equal to 1 if the fund has a high water mark provision. Average style return and flow are included to capture style effects on systematic risk. To capture barriers to flow, we also include an indicator variable equal to 1 if the fund is active or open to new investment at the end of 2010. Since TASS reports static fee data in each data release, to build the time-series of fees for each fund, we access multiple end-of-year releases of the database. As multiple database releases were not available for the CISDM dataset, funds unique to that data provider are excluded from the fund-level analysis. Although TASS commenced reporting lockup and high water mark data in 2002, this data is available in CISDM from the start of the dataset. Therefore, we use the CISDM dataset to fill lockup and high water mark values missing in the TASS dataset for overlapping funds. Funds in the TASS dataset that closed prior to 2002 and which do not overlap with the CISDM dataset are excluded. We obtain the same results using the full TASS dataset, excluding the lockup and high water mark controls. In all the time-series panel regressions in the paper, standard errors are clustered by time and fund family.

Given the high level of consistency in results, we focus our discussion on model (2). We first note a positive and significant association between equity risk, credit risk, and bond risk factor loading volatility and manager skill, suggesting that high skill managers more commonly vary these factors when managing systematic risk. The relation with the size spread factor loading is also positive but not significant. Correlation risk and correlation risk standard deviation is typically lower in funds managed by high skill managers and this relation is more pronounced in weak market states when DEF is higher (positive and significant relation between manager skill and the interaction of correlation risk and DEF).

Turning to fund manager characteristics, we find that managers with high SRM skills tend to be better educated and be more experienced (positive relation with SAT Score and work experience). Older and larger funds tend to have higher skilled managers, consistent with the observed relations with manager characteristics. We also find a positive relation between fund performance and manager skill. Systematic risk levels are more persistent for funds that have realized higher prior performance, performance persistence, and greater investment inflows. The same relations are observed at the style level. Persistence in systematic risk is more likely following higher style level returns and inflows of investment at the style level. Funds with longer subscription periods and higher initial investment requirements typically have higher skill managers. Finally, higher incentive fees are positively associated with SRM skill.

A possible interpretation of these results is that managers that have performed well (and have attracted high flows) in the past have more leeway when it comes to managing systematic risk. In

Section 9, we show that investors appear to react to fund performance rather than to persistence in systematic risk. Managers who have performed poorly in the past are unlikely to be given leeway to manage systematic risk.

8. SRM skill and hedge fund performance

Thus far, we have explored the how persistent are levels of hedge fund systematic risk, the channels through which managers influence the systematic risk of their funds and managerial and fund characteristics associated with persistence in low systematic risk. We now return to the question of independence in asset selection and SRM skill and the association between SRM skill and hedge fund performance. We seek to understand if asset selection and SRM skill are indeed joint attributes associated with a select subset of superior fund managers or whether the skill sets are independent. To model this relation, we relate hedge fund performance (measured as annual Fung and Hsieh (2004) 7-factors alphas) to factor loading variability, an indicator variable for SRM skill set to 1 if the manager remained in the bottom quintile of systematic risk for three years (as previously defined), correlation risk and its standard deviation and controls.[22] We include the factor loading variability variables to capture the relation between active SRM and fund performance. As active SRM triggers trading costs and the intangible cost of engaging manager attention away from asset selection, we expect a negative relation between fund performance and proxies for the level of SRM. The variables in the models are standardized (mean = 0, STD = 1) to ensure comparability. The test of interest is whether high SRM skill managers create value for investors via active SRM (i.e. is the sum of the coefficients on factor loading volatility and the SRM skill indicator greater than 0). As the relations between fund performance and the control variables are well understood in the extant literature, control variable coefficients are suppressed in the results reported in Table 6 in the interest of brevity. Coefficients related to correlation risk are reported as this variable is not considered as broadly in the hedge fund literature.

Focusing first on the full sample model, on average, active SRM factor loading revisions, is a drag on fund performance. The relation between alpha and the four factor loading volatility variables is either negative (for equity risk and credit risk) or insignificant (size spread and bond risk). To provide a sense of economic magnitude, a joint one standard deviation shift in the four factor standard deviation variables relates to a 1.7% reduction in annual fund alpha. Consistent with Titman and Tiu (2011) but in contrast to Bali et al. (2012), we find a positive association between SRM skill and fund performance. However, when the net benefit to investors is considered (sum of the factor loading volatility and SRM skill coefficients) the relation weakens 3-fold.

To further test the independence of SRM and asset selection skill, we partition the model into market state terciles (proxied by DEF as in prior models).[23] If asset selection and SRM skill are joint characteristics of superior fund managers, the relation between fund performance and SRM skill should be time invariant. However, if the two skills are independent, the relation should be time varying as SRM skill is more difficult and requires greater allocation of attention in weak market states when correlation risk is increasing and historic correlation patterns become less informative for realized correlations. The relation between SRM skill and fund performance is positive in both the positive and negative market state while the relation between active SRM and performance is negative. However, the sum of the coefficients is positive only in the strong market state. These results are consistent with time variation in manager attention allocation to tasks. In the weak market state, managers with SRM skill allocate greater attention to SRM to the detriment of fund alpha. In the strong market state, managers appear to allocate greater effort to asset selection and generate substantial benefits for investors.

To provide a sense of scale, on average, high skill managers generate a net benefit of 1971 bps per annum in the strong market state relative to no statistically significant net benefit in the weak market state. These results are in line with Kacperczyk et al. (2014) who propose a measure of mutual fund manager skill based on the manager's ability to shift the weight of his attention between market timing in recessions and asset selection in booms. In the hedge fund setting, high skill managers allocate attention much in the same way, but focus on maintaining low systematic risk in recessions, as opposed to seeking to exploit the recovery via portfolio beta adjustments. Similarly, Glode (2011) argues that mutual fund managers exert greater effort in weak market states at which times investors are willing to pay higher rents and their market utility of consumption is higher.

Finally, to capture the net benefit of SRM skill to investors across market states, we partition the model by SRM skill.[24] High skill managers are as previously defined, we label a fund as managed by a low SRM skill manager if the quintile of systematic risk changes for the fund in each of the prior three years. The coefficient for systematic risk is three times the magnitude for high relative to low skilled managers (−0.34 vs. −0.12) and this difference is statistically significant at the 1% level. In other words, the net benefits of active SRM accrue only to high skilled managers. For the low skill managers, the cost of systematic risk management by adjusting factor loadings exceeds the benefit by almost two fold (−0.29 vs. −0.17, reflecting a net loss of −0.18, which relates on average to 832 bps per annum). Interestingly, the sensitivity of fund performance to correlation risk and correlation risk volatility is higher for high skill managers. This result further illustrates the inherent conflict when jointly seeking to minimize both systematic and correlation risk and points to further costs associated with minimization of systematic risk by high skill managers.

9. Investor sensitivity to fund systematic risk

Next we examine the extent to which investors recognize and value dynamic management of hedge fund systematic risk. To proxy for investor preferences, we use fund flow which we relate to factor loading volatility, SRM skill, and correlation risk, and control variables. The analysis is reported in Table 7. As in Table 6, in the interest of brevity, we do not report coefficient values for the control variables and the variables in the models are standardized (mean = 0, STD = 1) to ensure comparability.

Focusing first on the full sample model, investors appear to understand that active factor management is a drag on fund performance, preferring funds with low factor loading volatility. Specifically, the coefficients on equity risk and credit risk (the same factors that most strongly influenced performance) are negative and significant at the 10% level (t-statistics 2.17 and 1.75, respectively). To provide a sense of economic magnitude, a joint one standard deviation shift in the four factor loading volatility variables is related to a 0.9% reduction in annual flow. Hedge fund investors appear to recognize SRM skill, rewarding high skill managers with incremental flow (coefficient value of 0.28, t-statistic 3.97 on the SRM skill indicator variable).

[22] We obtain similar results and reach the same conclusions utilizing alternative proxies for fund performance including fund returns in excess of the style average, Sharpe Ratio and Information Ratio.

[23] Similar results are obtained if TED is used as an alternative proxy for market state.

[24] We obtain similar results and reach the same conclusions in Tables 6 and 7 if funds which undergo a manager change in the three year period of skill identification are excluded from the sample.

Table 5
Fund level determinants of systematic risk.

Dependent variable	Systematic risk management skill$_t$	
Model	(1)	(2)
Equity Risk St. Dev.$_{t-1}$	0.17***	0.23***
	(3.08)	(3.09)
Size Spread St. Dev.$_{t-1}$	0.07	0.05
	(1.60)	(1.10)
Bond Risk St. Dev.$_{t-1}$	0.08**	0.08
	(2.25)	(1.44)
Credit Risk St. Dev.$_{t-1}$	0.11**	0.11
	(2.08)	(1.72)
Market characteristics		
Correlation Risk$_{t-1}$	−0.08	−0.15**
	(1.54)	(2.60)
DEF$_{t-1}$		0.31***
		(3.82)
DEF × Correlation Risk$_{t-1}$		0.25***
		(3.40)
Correlation Risk Standard Dev.$_{t-1}$	−0.18**	−0.18**
	(2.53)	(2.45)
Fund manager characteristics		
SAT Score	0.13**	0.15***
	(2.28)	(2.92)
Work Experience$_{t-1}$	0.17**	0.14**
	(2.29)	(2.49)
Fund characteristics		
Fund Age$_{t-1}$	0.13**	0.17***
	(2.21)	(3.00)
Fund Size$_{t-1}$	0.30***	0.37***
	(4.20)	(4.43)
Fund Return$_{t-1}$	0.43	0.43**
	(1.74)	(2.08)
Fund Return St. Deviation$_{t-1}$	−0.09**	−0.10**
	(2.17)	(2.06)
Fund Flow$_{t-1}$	0.26***	0.30***
	(4.08)	(4.06)
Log Initial Investment	0.14**	0.16***
	(2.07)	(2.99)
Leverage Indicator	−0.01	−0.01
	(0.87)	(0.71)
Lockup Period	0.00	0.00
	(0.25)	(0.39)
Redemption Period	−0.02	−0.02
	(1.59)	(1.07)
Subscription Period	0.16**	0.20***
	(2.59)	(3.25)
High Water Mark Indicator	0.14**	0.12**
	(2.42)	(2.65)
Management Fee$_{t-1}$	0.01	0.01
	(0.37)	(0.44)
Incentive Fee$_{t-1}$	0.05	0.16***
	(1.21)	(3.03)
Style Return$_{t-1}$	0.08	0.11*
	(1.74)	(1.88)
Style Flow$_{t-1}$	0.45***	0.42***
	(5.15)	(4.86)
Active Indicator	0.33	0.35
	(1.14)	(1.60)
Open to Investment Indicator	0.01	0.01
	(0.31)	(0.28)
Pseudo R^2	19.01	22.28
Number of observations	2509	2509

This table reports logit, time-series, panel regression results of annual fund-level SRM skill related to determinant variables. The dependent variable is an indicator variable set to 1 (otherwise zero) for funds that have remained in the bottom systematic risk quintile over the prior three years (as defined in Table 4). Systematic risk is calculated as previously defined in Table 4 using the PC10 model (Eq. (1)). Factor loading variability, DEF and correlation risk are as defined in Tables 3 and 4. Considered manager characteristics include *SAT Score*: the composite SAT score from the U.S. News and World Report and Princeton Review and *Work Experience*: the number of years the manager as worked. Fund characteristics considered include: *Fund Age*: the number of years since fund inception, *Fund Return* and *Fund Return Standard Deviation* measured using monthly returns in the prior year, *Fund Size* measured by total net assets (TNA), *Fund Flow* calculated as $(TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t}))/TNA_{i,t-1}$ where *TNA* is total net assets to fund *i* at the end of year *t* and *R* is fund return, *Initial Investment*: the minimum investment required to initially invest in the fund, *Leverage Indicator*: an indicator variable equal to one if the fund uses leverage in its positions, annual management and incentive fee and the number of days in the lockup, redemption and subscription periods and an indicator variable equal to one if the fund has a high water mark provision to charge the incentive fee, average return and flow to funds in the same style as fund *i*, and indicator variables equal to 1 if the fund is still active or open to new investment at year-end 2010. Standardized regression coefficient values are reported with associated *t*-statistics reported in parentheses. Standard errors are clustered by fund family and the models include style and year fixed effects.
* Significance at the 10% levels.
** Significance at the 5% levels.
*** Significance at the 1% level.

To capture incremental sensitivity to systematic risk during periods of financial stress, we partition the sample using terciles of the market condition proxy DEF (as previously defined). Investor sensitivity to factor loading volatility and systematic risk is remarkably similar across market states, with the exception that investors place greater emphasis on credit risk in weak market states.

As in the performance analysis, dynamic risk management yields a net benefit to the fund in terms of incrementally higher flow only in the strong market state. Rationally, investors would be expected to favor low systematic risk in weak market states when the systematic risk hedge is most likely fund value enhancing and investor marginal utility of consumption is higher (Glode, 2011). The stronger preference for low systematic risk in the strong market state suggests that investors are reacting to fund performance as opposed to continuity in fund systematic risk levels. Partitioning the model between high and low SRM skill managers, we find a stronger relation between fund flow and systematic risk for high skill managers. This result potentially suggests that more savvy investors are able to select high SRM skill managers and these investors are more prone to monitor and react to the systematic risk level of the fund.

10. Market timing by hedge funds

As previously discussed, a potential issue with our proxy for SRM skill is its dependence on the self-stated mandate by hedge funds to maintain low systematic risk. Our skill proxy overlooks managers with SRM skill who abandon this mandate and instead seek to time the market, delivering low systematic risk in weak market states and realizing the performance benefits of a high beta position in strong market states. Evidence regarding the ability of hedge funds to time the market is mixed. For example, Chen and Liang (2007) examine the market-timing ability of funds from the self-described market-timing style. In their sample from 1994 to 2005, they find evidence of market-timing ability at both the fund and aggregate levels. In contrast, Fung et al. (2002) find that global hedge fund managers do not show market-timing ability in their 1994–2000 sample of 115 funds and Chen (2007) finds limited evidence of market-timing ability across nine hedge fund styles.

To test the market-timing ability of hedge fund managers, we first categorize each fund in our sample as a market-timing or stable fund. Market-timing funds are funds which shift from the top to the bottom tercile of systematic risk (or vice versa) at least twice during the timeframe of our sample. The remaining funds are classified as stable (i.e. having consistent systematic risk rankings). Approximately 39% of the funds in our sample are classified as market-timing funds. We then estimate the Henriksson–Merton (1981) market-timing model (HM model) separately for market-timing and stable funds:

$$r_{p,t} = \alpha + \sum_{j=1}^{K} \beta_j \phi_{j,t} + \gamma r_{m,t} S_t + \varepsilon_t \tag{4}$$

Table 6
Performance and dynamic systematic risk management.

	Dependent variable: alpha (%)				
	Full sample	DEF partitions		Skill partitions	
		Weak market	Strong market	High	Low
Equity Risk St. Dev.$_{t-1}$	−0.11*	−0.12**	−0.07	**−0.07****	**−0.15*****
	(1.82)	(2.69)	(1.70)	(2.39)	(2.76)
Size Spread St. Dev.$_{t-1}$	−0.03	−0.02	−0.04	−0.04	−0.04
	(0.91)	(0.40)	(1.02)	(0.70)	(0.54)
Bond Risk St. Dev.$_{t-1}$	0.04	0.03	0.04	0.03	0.04
	(0.68)	(0.35)	(0.74)	(0.56)	(1.00)
Credit Risk St. Dev.$_{t-1}$	−0.12	**−0.16****	**−0.05****	−0.09**	−0.14**
	(2.37)	(2.14)	(2.01)	(2.29)	(2.53)
Systematic Risk$_{t-1}$				**−0.34*****	**−0.12****
				(4.37)	(2.35)
SR Management Skill$_{t-1}$	0.32***	**0.18****	**0.43*****		
	(4.33)	(2.34)	(5.46)		
Correlation Risk$_{t-1}$	−0.05	−0.07*	−0.01	−0.09*	−0.02
	(1.17)	(1.70)	(0.70)	(1.93)	(0.39)
Correlation Risk St. Deviation$_{t-1}$	−0.14**	−0.11**	−0.18***	**−0.19*****	**−0.10****
	(2.70)	(2.70)	(2.97)	(3.12)	(2.13)
Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	26.95	27.74	25.12	29.23	23.36
Sum of Factor Std. Coef.	−0.22	−0.28	−0.12	−0.17	−0.29
Skill or abs. Systematic Risk Coef.	0.32	0.18	0.43	0.34	0.12
Sum	0.10**	−0.09*	0.31***	0.17***	−0.18***
t-Statistic	(2.15)	(1.91)	(3.87)	(2.85)	(2.83)
Number of observations	2825	972	442	619	2206

This table reports time-series regression results of hedge fund alpha estimates on factor loading volatility, systematic risk or systematic risk management skill and correlation risk. The dependent variable is the annual fund alpha calculated using the Fung and Hsieh (2004) 7 factor model. Systematic risk is calculated as previously defined using the PC10 model (Eq. (1)) and systematic risk management skill as is defined in Table 5. Equity Risk St. Dev., Size Spread St. Dev, Bond Risk St. Dev and Credit Risk St. Dev. are the standard deviation of hedge fund return loading on each risk factor. Factor loadings are calculated annually and the standard deviation is calculated over three year windows. Market condition and manager skill partitions are calculated as defined in Table 5. The fund characteristic variables considered in Table 5 are included in each model as controls, but are suppressed in the interest of brevity. In each model standard errors are clustered by fund family and year and style fixed effects are included. Standardized coefficient estimates are reported with associated *t*-statistics reported in parentheses. In the weak and strong market models, coefficient pairs that are statistically different from each other appear in bold face.

* Significance at the 10% levels.
** Significance at the 5% levels.
*** Significance at the 1% level.

Table 7
Investor sensitivity to dynamic systematic risk management.

	Dependent variable: flow$_t$				
	Full sample	DEF		Skill	
		Weak market	Strong market	High	Low
Equity Risk St. Dev.$_{t-1}$	−0.10**	−0.13**	−0.07*	**−0.05****	**−0.16*****
	(2.17)	(2.38)	(1.99)	(2.03)	(3.68)
Size Spread St. Dev.$_{t-1}$	0.06	0.05	0.05	0.05	0.06
	(1.40)	(1.53)	(1.03)	(0.86)	(0.68)
Bond Risk St. Dev.$_{t-1}$	0.02	0.02	0.03	0.01	0.04
	(0.42)	(0.99)	(0.83)	(0.37)	(1.21)
Credit Risk St. Dev.$_{t-1}$	−0.08*	−0.11**	−0.07*	−0.10*	−0.08**
	(1.75)	(2.19)	(1.75)	(1.95)	(2.02)
Systematic Risk$_{t-1}$				**−0.24*****	**−0.09****
				(3.30)	(2.05)
SR Management Skill$_{t-1}$	0.28***	**0.17*****	**0.41*****		
	(3.97)	(3.20)	(5.36)		
Correlation Risk$_{t-1}$	−0.07	−0.07	−0.07	−0.05	−0.09*
	(1.33)	(1.58)	(1.67)	(1.26)	(1.85)
Correlation Risk St. Deviation$_{t-1}$	−0.12*	−0.10	−0.13**	**−0.19****	**−0.07***
	(1.78)	(1.49)	(2.56)	(2.54)	(1.88)
Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	28.58	24.86	30.07	30.75	25.95
Sum of Factor Std. Coef.	−0.10	−0.16	−0.06	−0.09	−0.14
Skill or abs. Systematic Risk Coef.	0.28	0.17	0.41	0.24	0.09
Sum	0.18***	0.01	0.35***	0.15**	−0.04
t-Statistic	(2.81)	(0.39)	(4.50)	(2.44)	(1.21)
Number of observations	2825	972	442	619	2206

This table reports time-series panel regression results of hedge fund flow related to hedge fund systematic and correlation risk. All independent variable are as previously defined. The fund characteristic variables considered in Table 5 are included in each model as controls, but are suppressed in the interest of brevity. In each model standard errors are clustered by fund family and year and style fixed effects are included. Standardized coefficient estimates are reported with associated *t*-statistics reported in parentheses. In the weak and strong market models, coefficient pairs that are statistically different from each other appear in bold face.

* Significance at the 10% levels.
** Significance at the 5% levels.
*** Significance at the 1% level.

where r_p is the excess return on the equal-weighted portfolio of market-timing or stable funds, ϕ are the Fung and Hsieh (2004) factors as previously described ($K = 7$), r_m is the excess return to the Fama and French (1993) market factor, and S is an indicator variable equal to one when the market factor is positive and is otherwise equal to zero. We find that neither the stable or market-timing funds have market-timing ability. The market-timing coefficient (γ) is positive for both groups, 0.21 versus 0.16 for stable vs. market-timers but both coefficients are not statistically significant (t-statistics of 1.85 and 1.71, respectively). Partitioning the model by financial market state yields similar results (i.e. neither group exhibits significant market-timing ability and the size of market-timing coefficient is similar between the groups). We find similar results in the aggregate sample, free of market-timer partitions.

We undertake a series of robustness checks. First, we replicate the market timing analysis utilizing the Treynor and Mazuy (1966) market timing test, utilizing the Fung and Hsieh (2004) 7-factor model, and reach the same conclusions. Second, we replicate the market-timing model (Eq. (4)) adjusting for potential bias associated with using monthly return data when timing decisions can be made at the daily frequency as described in Goetzmann et al. (2000):

$$r_{p,t} = \alpha + \sum_{j=1}^{K} \beta_j \varnothing_{j,t} + \gamma P_{m,t} S_t + \varepsilon_t \tag{5}$$

$$P_{m,t} = \left[\left(\prod_{\tau \epsilon month(t)}^{t} \max\{1 + r_{m,\tau}, 1 + r_{f,\tau\}} \right) - 1 \right] - r_{m,t}$$

where r_f is the risk-free return. Using this alternative market-timing test specification again yields similar results. These results lead to two possible conclusions. First, broadly hedge fund managers do not possess market timing skill or managers with SRM skill forgo market timing opportunities. Regardless, the results suggest that SRM skill is absent in the set of managers with variable fund systematic risk, providing validation of our proxy for SRM skill.

11. Conclusions

Hedge funds commonly market themselves as delivering alpha while controlling the level of systematic risk. In this paper, we investigate the dynamic risk management ability of hedge fund managers. Our results point to time varying allocation of effort by skilled hedge fund managers. During market downturns, systematic risk commonly increases as the returns to unrelated assets become increasingly correlated. In weak market states, skilled managers focus on maintaining low systematic risk via active adjustments to return factor loadings. The allocation of effort to this activity comes at the costs of fund alpha. In times of strengthening market states, skilled hedge fund managers forego market timing opportunities, maintaining low systematic risk. In strong market states, skilled managers generate incremental alpha to low skill managers via superior asset selection ability.

Appendix A. Summary of the Titman and Tiu (2011) theoretical model

In the model, the manager forms a mean–variance efficient portfolio from three assets, a risk-free asset, a publicly available index (F) and a proprietary strategy (A) for which:

$$E[F - r_f] = \mu > 0, \quad std[F] = \sigma;$$
$$E[A - r_f] = \alpha > 0, \quad std[A] = TE;$$
$$Corr(A, F) = 0$$

Define w_F and w_A as the weights allocated by the manager to the index and proprietary strategy. The excess return to the strategy is then defined as $R - r_f = w_A(A - r_f) + w_F(F - r_f)$. The Sharpe ratio for the fund is given by:

$$SR_{(w_A, w_F)} = \frac{E[R - r_f]}{std[R]} = \frac{\alpha + \beta\mu}{\sqrt{TE^2 + \beta^2\sigma^2}} \tag{A1}$$

where $\beta = w_F/w_A$.

To maximize the SR, the manager solves:

$$\max_{w_F, w_A} SR(w_F, w_A) \tag{A2}$$

The solution to Eq. (A2) is given by:

$$\begin{cases} \beta^* = \mu/\sigma^2 \\ w_F^* = \beta^* w_A^* \end{cases} \tag{A3}$$

and the SR of the optimal portfolio is:

$$SR^* = \sqrt{\left(\frac{\alpha}{TE}\right) + \left(\frac{\mu}{\sigma}\right)^2} \tag{A4}$$

To estimate the systematic risk exposure of the fund, $R - r_f$ can be regressed on F. From the above model, superior managers for which $F > A$ will allocate greater portfolio weight to F ($w_F > w_A$), thus systematic risk is indirectly decreasing with manager skill in generating the proprietary strategy.

Appendix B. Principal component asset sample summary

This Appendix summarizes the assets included in the global principal component analysis.

B.1. Global equity indexes

An index with the designation "RI" is a total return index (with reinvested dividends). The designation "PI" denotes a pure price index.

Country	Index identification	DS mnemonic	Country	Index identification	DS mnemonic
Australia	AUSTRALIA-DS MARKET	TOTMAU$(RI)	Netherlands	NETHERLAND-DS Market	TOTMKNL(RI)~U$
Austria	AUSTRIA-DS Market	TOTMKOE(RI)~U$	New Zealand	NEW ZEALAND-DS MARKET	TOTMNZ$(RI)
Belgium	BELGIUM-DS Market	TOTMKBG(RI)~U$	Norway	NORWAY-DS MARKET	TOTMNW$(RI)
Brazil	BRAZIL BOVESPA	BRBOVES(PI)~U$	Pakistan	KARACHI SE 100	PKSE100(PI)~U$
Canada	S&P/TSX COMPOSITE INDEX	TTOCOMP(RI)~U$	Philippines	PHILIPPINE SE I(PSEi)	PSECOMP(PI)~U$
Chile	CHILE GENERAL (IGPA)	IGPAGEN(PI)~U$	Portugal	PORTUGAL PSI GENERAL	POPSIGN(PI)~U$

(*continued*)

Country	Index identification	DS mnemonic	Country	Index identification	DS mnemonic
Czech Republic	CZECH REP.-DS NON-FINCIAL	TOTLICZ(RI)~U$	Singapore	SINGAPORE-DS MARKET EX TMT	TOTXTSG(RI)~U$
Denmark	MSCI DENMARK	MSDNMKL(RI)~U$	South Africa	SOUTH AFRICA-DS MARKET	TOTMSA$(RI)
France	FRANCE-DS Market	TOTMKFR(RI)~U$	South Korea	KOREA SE COMPOSITE (KOSPI)	KORCOMP(PI)~U$
Germany	DAX 30 PERFORMANCE	DAXINDX(RI)~U$	Spain	MADRID SE GENERAL	MADRIDI(PI)~U$
India	INDIA BSE (100) NATIONAL	IBOMBSE(PI)~U$	Sri Lanka	COLOMBO SE ALLSHARE	SRALLSH(PI)~U$
Ireland	IRELAND-DS MARKET	TOTMIR$(RI)	Sweden	OMX STOCKHOLM (OMXS)	SWSEALI(PI)~U$
Israel	ISRAEL TA 100	ISTA100(PI)~U$	Switzerland	SWITZ-DS Market	TOTMKSW(RI)~U$
Italy	ITALY-DS MARKET	TOTMIT$(RI)	Taiwan	TAIWAN SE WEIGHTED	TAIWGHT(PI)~U$
Japan	TOPIX	TOKYOSE(RI)~U$	Thailand	THAILAND-DS MARKET	TOTMTH$(RI)
Jordan	AMMAN SE FINANCIAL MARKET	AMMANFM(PI)~U$	Turkey	ISE TIOL 100	TRKISTB(PI)~U$
Malaysia	KLCI COMPOSITE	KLPCOMP(PI)~U$	United Kingdom	UK-DS MARKET	TOTMUK$(RI)
Mexico	MEXICO IPC (BOLSA)	MXIPC35(PI)~U$	United States	S&P 500 COMPOSITE	S&PCOMP(RI)~U$
Morocco	MOROCCO SE CFG25	MDCFG25(PI)~U$	Zimbabwe	ZIMBABWE INDUSTRIALS	ZIMINDS(PI)

B.2. Currencies

Albanian Lek	Colombian Peso	Icelandic Krona	Nigerian Naira	Surinamese Dollar
Algerian Dinar	Comorian Franc	Indian Rupee	Norwegian Krone	Swedish Krona
Angolan Kwanza	Congo (DRC) Francs	Indonesian Rupiah	Omani Rial	Swiss Franc
Argentine Peso	Croatian Kuna	Irish Punt or Pound	Pakistani Rupee	Taiwanese Dollar
Australian Dollar	Cyprian Pound	Israeli Sheqel	Papua New Guinean Kina	Tanzanian Shilling
Austrian Schilling	Czech Koruna	Italian Lira	Paraguayan Guarani	Thai Baht
Azerbajanian Manat	Danish Krone	Japanese Yen	Peruvian Nuevo Sol	Tongan Pa'anga
Bahraini Dinar	Dominican Peso	Jordanian Dinar	Philippine Peso	Trinidad & Tobago Dollar
Bangladeshi Taka	Dutch Guilder	Kazakh Tenge	Polish Zloty	Tunisian Dinar
Belarusian Ruble	East Caribbean Dollar	Kenyan Shilling	Portuguese Escudo	Turkish Lira
Belgian Franc	Ecuadorian Sucre	Korean Won	Qatari Riyal	Ugandan Shilling
Belizean Dollar	Egyptian Pound	Kuwaiti Dinar	Romanian Leu	Ukrainian Hryvnia
Bermudian Dollar	Estonian Kroon	Latvian Lat	Russian Federation Rouble	United Arab Emirates Dirham
Bolivian Boliviano	Euro	Lebanese Pound	Samoan Tala	United Kingdom Pound
Bosnia-Herzegovina Dinar	Fijian Dollar	Lithuanian Lita	Saudi Arabian Riyal	United States Dollar
Botswana Pula	Finnish Markka	Luxembourg Franc	Serbian Dinar	Uruguayan Peso
Brazilian Real	French Franc	Malawian Kwacha	Sierra Leonean Leone	Vanuatuan Vatu
Brunei Darussalam Dollar	Gambian Dalasi	Malaysian Ringgit	Singaporean Dollar	Venezuelan Bolivar
Bulgarian Lev	Georgian Lari	Maltese Lira	Slovak Koruna	Vietnamese Dong
Burundian Franc	German Mark	Mauritanian Ouguiya	Slovenian Tolar	Zambian Kwacha
C.F.P. Franc	Ghanaian Cedi	Mauritian Rupee	Solomon Islands Dollar	Zimbabwean Dollar
Canadian Dollar	Greek Drachma	Mexican Peso	South African Rand	
Cayman Islands Dollar	Guinean Franc	Moroccan Dirham	Spanish Peseta	
Chilean Peso	Hong Kong Dollar	Mozambican Metical	Special Drawing Right	
Chinese Yuan Renminbi	Hungarian Forint	New Zealand Dollar	Sri Lankan Rupee	

B.3. Bond Indexes

Name	DS mnemonic	Market	Source	Currency
BD BENCHMARK 10 YEAR DS GOVT. INDEX	BMBD10Y	Germany	Datastream	Euro
BARCLAYS EURO AGGREGATE (E)	LHAGGBE	International	Barclays Capital	Euro
BARCLAYS EURO AGG GOVERNMENT (E)	LHAGOVE	International	Barclays Capital	Euro
IBOXX EURO OVERALL INDEX ALL MATS.	IBEURAL	Overall	iBoxx	Euro
IBOXX EURO SOVEREIGN EZONE ALL MATS	IBSEZAL	Sovereign	iBoxx	Euro
IBOXX EURO SUB-SOV. SUPRA.ALL MATS.	IBSUPAL	Sub-Sovereign	iBoxx	Euro
IBOXX EURO CORP. ALL MATS	IBCRPAL	Corporate	iBoxx	Euro
EMU BENCHMARK 10 YR. DS GOVT. INDEX	BMEM10Y	EMU	Datastream	Euro
FR BENCHMARK 10 YEAR DS GOVT. INDEX	BMFR10Y	France	Datastream	Euro
IT BENCHMARK 10 YEAR DS GOVT. INDEX	BMIT10Y	Italy	Datastream	Euro
JP BENCHMARK 10 YEAR DS GOVT. INDEX	BMJP10Y	Japan	Datastream	Japanese Yen
BARCLAYS ASIA PACIC JAPAN ISSUERS	LHAPJAP	International	Barclays Capital	Japanese Yen
BARCLAYS ASIA PACIC JAPANESE TSY.	LHAPJTY	International	Barclays Capital	Japanese Yen
UK BENCHMARK 10 YEAR DS GOVT. INDEX	BMUK10Y	United Kingdom	Datastream	United Kingdom Pound
IBOXX £ SOVEREIGN ALL MATURITIES	IB£SOAL	United Kingdom	iBoxx	United Kingdom Pound
IBOXX £ IBoxx United Kingdom Sterling	IB£CRAL	Collateralised	iBoxx	United Kingdom Pound
IBOXX £ CORP. ALL MATS.	IB£CSAL	Corporate	iBoxx	United Kingdom Pound
IBOXX £ NON-GILTS ALL MATURITIES	IB£GNAL	Non-Gilts	iBoxx	United Kingdom Pound
BOFA ML UK GILTS ALL MAT (Â£)	MLUKALÂ£	United Kingdom	Merrill Lynch	United Kingdom Pound
US BENCHMARK 10 YEAR DS GOVT. INDEX	BMUS10Y	United States	Datastream	United States Dollar
BARCLAYS US TREASURY BELLWETHERS 3M	LHTBW3M	United States	Barclays Capital	United States Dollar
BARCLAYS US TREASURY BELLWETHERS 2Y	LHTBW2Y	United States	Barclays Capital	United States Dollar
BARCLAYS US TREASURY BELLWETHERS 30Y	LHTBL30	United States	Barclays Capital	United States Dollar
BARCLAYS US AGG GOVERNMENT	LHGOVBD	United States	Barclays Capital	United States Dollar
BARCLAYS US AGGREGATE	LHAGGBD	United States	Barclays Capital	United States Dollar
BARCLAYS US TREASURY	LHUSTRY	United States	Barclays Capital	United States Dollar
BOFA ML TRSY MASTER ($)	MLGTRSA	United States	Merrill Lynch	United States Dollar
BOFA ML US MORT MASTER ($)	MLMORTM	United States	Merrill Lynch	United States Dollar
BARCLAYS PAN-EUR. AGG (E)	LHPANAE	International	Barclays Capital	Euro
JPM EU EMBI GLB DIVS COMPOSITE	JPMETOC	International	JP Morgan	Euro
JPM GBI BROAD ALL MATS. (LOC)	JGGBALC	Global Broad	JP Morgan	n/a
JPM GBI GLOBAL ALL MATS. (LOC)	JGGIALC	Global	JP Morgan	n/a
BOFA ML GLOBAL GVT INDEX ($)	MLGGALM	International	Merrill Lynch	United States Dollar
CGBI WBIG OVERALL NON-US$ ($)	SBWBX$$	Overall	Citigroup	United States Dollar
CGBI USBIG OVERALL BROAD INV.GRADE	SBBIGBI	Overall	Citigroup	United States Dollar

B.4. Commodities

We include 27 different commodity futures. Our data on Brent Crude Oil is from the Intercontinental Exchange (ICE), Live Cattle, Feeder Cattle, Lean Hogs is from Chicago Mercantile Exchange (CME), Corn, Soybeans, Soy Meal, Soy Oil, Wheat is from Chicago Board of Trade (CBOT), WTI Crude Oil is from New York Mercantile Exchange (NYMEX), Gold, Silver is from New York Commodities Exchange (COMEX), and Cotton, Coffee, Cocoa, Sugar is from New York Board of Trade (NYBOT). We also include the Goldman Sachs commodity index (GSCI).

B.5. Real estate

We include the value weighted real estate investment trust (REIT) index from the Center for Research in Securities Prices and the Shiller housing index from Datastream (US S&P/CASE-SHILLER HOME PRICE INDEX – 10-CITY COMPOSITE NADJ).

B.6. Hedge fund factors

We include the seven Fung and Hsieh (2004) hedge fund factors: Bond Trend Following Factor, Currency Trend Following Factor, Commodity Trend Following Factor, Equity Market Factor, Size Spread, Bond Market Factor, Credit Spread Factor and Emerging Market Risk Factor provided on David Hsieh's webpage.

B.7. Domestic equity factors

In addition to the domestic equity factors collected from David Hsieh's website, we also include the return to the Russell 3000 and NASDAQ indexes from Datastream, the 3 Fama French factors and the Momentum factor collected from Ken French's website.

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