Assessing Hedge Fund Mortality with Characterized Returns and Risks

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Abstract

The empirical characteristics and practical problems of hedge fund returns, such as nonnomality, serial correlation, misreporting and return smoothing practice, render financial models based on traditional mean-variance framework empirically weaker. In this paper, we apply orthogonal polynomial approximation (OPA) approach to identify risk-return measures which are used as explanatory variables to investigate their impacts on the mortality risk of hedge funds. We compare our approach with approaches based on higher return moments and expected shortfall in terms of predictive power for the probability of hedge fund mortality. Our results demonstrate that OPA approach has a greater predictive power than approaches used in previous research.

Key words: Hedge fund; Mortality risk; Orthogonal polynomial approximation; Risk-return measures;

JEL: C34, G23, G32

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I. Introduction

Hedge fund risks and returns exhibit unique features that differentiate them from other investment vehicles. It is well-known that hedge fund returns do not follow a normal distribution. Several studies report that hedge funds on average have negative skewness and excess kurtosis (Brooks and Kat, 2002; Anson, 2002; Kat, 2003; Lamm, 2003; and Brulhart and Klein, 2005). This option-like feature in hedge fund payoffs may due to heavily use of leverage, actively trade derivatives, or option-like dynamic trading strategies. Extensive research has been published exploring the risk and return characteristics of hedge fund over the last decade. This paper seeks to extend the current literature on hedge fund mortality risk by using a novel approach to identify hedge fund risk-return characteristics. In particular, we propose a way to decompose hedge fund returns into static and dynamic components to predict hedge fund failure.

The rapid growth and the associated high attrition rate of hedge funds in recent years have made financial markets more sensitive to shocks within hedge fund industry (Brown et al. 1999, Fung and Hsieh 2000, Getmanski et al. 2004, and Malkeral and Saha 2005). Not surprisingly there have been considerable interests shown by hedge fund academics on the investigation of mortality risk of hedge funds – see for example, Liang (2000) and Brown et al. (2001). These studies have identified the effects of various fund characteristics, governance arrangements and fee structure determinants on hedge fund survival. This includes, for example, management fees, incentive fees, high-water marks, leverage, lock-up periods, and assets under management (AUM).

Studies have shown that the impact of hedge fund risk and return are generally considered as most important factors on hedge fund mortality (Brown et al., 2001; Baquero et al., 2005; Baba and Goko, 2009; and Liang and Park, 2010). Empirical tests are conducted using different risk and return measures. For example, Liang (2000) uses average monthly returns over the fund's whole history, where risk is measured by standard deviation. Brown et al. (2001) find that funds with two consecutive years of negative returns exhibit lower survival probability, again using standard deviation as risk measure. Similarly, Baquero et al. (2005) find that funds with higher past returns are much more likely to survive based on the previous two-month fund returns. Baba and Goko (2009) extend the scope of fund mean returns thereby allowing higher unconditional return moments, i.e., variance, skewness, and kurtosis, in determining the risk of fund default. Liang and Park (2010) is the first paper to compares downside risk measures incorporating skewness and kurtosis in predicting hedge fund failure. They find Expected Shortfall (ES) is superior to standard deviation where standard deviation significantly underestimates the left-tail risk in hedge funds and ES has the highest explanative and predictive power.

The consensus to emerge from these studies is that the survival probability reflects historical return information. However, having focus on static or partial information of returns may create a biased aspect of return properties – as most of prior studies do – they are disadvantaged in their arbitrary measure specifications of fund returns and inability to capture the option-like features of hedge fund returns.

In addition, return smoothing practices are common in the hedge fund industry, partly due to trading in illiquid assets (Getmansky et al. 2004) and partly due to fund managers' intentionally misreporting returns (Bollen and Pool 2008, 2009), that is small positive returns significantly outnumbering small negative returns, leading to serial correlation in returns which can bias the risk-adjusted return measures. Furthermore, the "December Return puzzle" of Agarwal et al. (2011) shows that hedge funds tend to manage their reported returns upwards since their compensation depends on year-end performance. Agarwal et al. (2011) examine whether fund managers tend to report high returns when incentive fees are calculated. They find significant high reported returns in December and conclude mangers inflate returns upward in order to earn higher fee.

While it is impossible for hedge fund managers to walk away from illiquid assets (due to the large number of arbitrage opportunities) and not to 'manage' returns by mitigating good and bad surprises, the general trend of hedge fund returns over time is unlikely to be vulnerable to manipulation by managers. In this paper we propose a novel orthogonal polynomial approximation (OPA) approach to measure hedge fund returns. The classical statistical OPA approach, based on the whole history information, can provide a valid summary of the properties of fund returns and identify a number of measure components – its constant component measures the average level of returns; its first order component measures the linear trend; and its second order component measures the curvature. In particular OPA guarantees that the size of each component (constant level, linear trend, and quadratic) is independent of the others, i.e., its component provides unique information about the properties of hedge fund returns. Therefore, it may improve the validity of prior empirical research within the hedge fund risk-return measures domain.

The main contribution of this paper to the hedge fund literature resides in the proposed OPA measure. This approach has been used in many other areas such as Johnson et al. (2006) and Tang et al. (2014), where they apply OPA to derive information from speculative market price movement and financial customer attrition behaviour respectively. Nonetheless, it is the first time that OPA is tested in the context hedge fund research. The advantages of using OPA technique are: i) it uses the entire history of fund return information; ii) it can capture both the static and dynamic patterns of fund returns; and iii) derived return measures can use information based on fund reported returns more efficiently because these measures can capture fund returns exhibiting option-like features. Our work, therefore, complements empirical research that identifies and examines the effects of risk-return measures on mortality risk of hedge funds.

Our hedge fund data is obtained from the Lipper/TASS database. The sample contains 7,638 US dollar denominated hedge funds spanning for the period of January 1994 to July 2014. Using log-continuous hazard model, we contrast OPA approach with higher-moments mean-variance framework (HMMV) of Baba and Goko (2009) and mean-ES (MES) framework of Liang and Park (2010). Our results show that risk-return measure based on OPA approach has significant impacts on hedge fund mortality risk after controlling for fund-specific governance and fee structure characteristics. An increase in linear trend of hedge fund returns decreases fund mortality risk. We also find a large and positive change in returns, measure by quadric term, is negatively associated with mortality risk of hedge funds. The significance and signs of coefficients of return components and risk measures are consistent regardless whether we use all Live funds and Graveyard funds, or following Baquiro et al. (2005), only liquidated hedge funds in the Graveyard are deemed as failed funds, named Absolute Defunct Fund sample. Not all HMMV and MES measures are consistent with different fund samples, suggesting OPA can be used to predict the survival of hedge funds under difference circumstance whereas HMMV and MES cannot. In particular, this study shows that the quadratic terms of OPA can fully capture left-tail risk for which MES is aimed. We conclude that OPA approach can be treated as a generalization of MES approach.

Second, based on our newly proposed risk-return measure, we examine other determinants of hedge fund failure. Our results indicate that funds with higher management fees and incentive fees are more likely to be liquidated. Longer redemption notice period, larger AUM decrease the hazard rate of fund mortality. Moreover, funds with RIAs are less likely to fail than non-RIA funds. Even though the HWM provision is not associated with the survival of hedge funds in full sample, it does reduce the real failure rate of hedge funds.

Third, we further conduct bootstrap simulation tests to compare the out-of-sample predictive power of OPA approach with HMMV and MES when using exactly the same number of risk-return measures, i.e., the constant and linear trend components for OPA and the average and expected value of loss for ES. Our bootstrap simulation test results show that OPA have the highest forecasting power of fund survival; MES comes the second and HMMV has the least forecasting power. Again, our tests are conducted for two samples: the full sample, and absolute defunct sample. The results are not subject to fund sample selection.

The remainder of the paper proceeds as follows. In section II we provide details of OPA approach. We also specify the hazard model to identify the impacts of risk-return measures and fund characteristics on fund mortality. The construction of risk-return measures and the description of our data on hedge fund characteristics are presented in section III. The empirical results are presented in section IV, while section V concludes.

II. Methodologies

The relationship between fund monthly returns and non-stochastic time can be represented by the following equation:

$$E(r \mid t) = \gamma_0 + \gamma_1 t + \gamma_2 t^2 + \cdots + \gamma_p t^p$$

$$Var(r \mid t) = \sigma^2$$

Direct estimation of $\gamma_0, \gamma_1, \cdots \gamma_p$ is problematic due to larger values of the sum of squares of powers of t, resulting large errors in matrix inversion, and re-estimate all previous estimates if a new term $\gamma_{p+1} t^{p+1}$ is added, resulting a new matrix inversion of size $(p+1) \times (p+1)$. However,

Based on monthly return values $\{(t(1), r(1)); \ldots; (t(n_k), r(n_k))\}$ for fund k with n months, a sequence of orthogonal polynomials $f_0, f_1, f_2, \ldots, f_p$ exists and satisfies

$$\sum_{l=1}^{n_k} f_h(t(l)) f_j(t(l)) = 0 \text{ for } \begin{cases} \text{h} = 1,2,\cdots,\text{p} \\ \text{j} = 1,2,\cdots \text{h-1} \end{cases}$$

$$\sum_{l=1}^{n_k} f_h(t(l)) = 0 \text{ for h} = 1,2,\cdots,\text{p}$$

where the *h*th-degree polynomial $f_h(t(l)) = c_{h,h}t^h + c_{h,h-1}t^{h-1} + \cdots + c_{h,1}t + c_{h,0}$. For fund returns, there is a unique set of coefficients a_0, a_1, a_2, $\cdots$, and a_p following:

$$r(l) = \sum_{h=0}^{p} a_h f_h(t(l))$$

The estimates of a_h can be seen as a valid summary of hedge fund returns and a_h can be found by least squares such that

$$\hat{a} = (f'f)^{-1} f'r \quad \text{and} \quad \text{var}\left(\hat{a}\right) = (f'f)^{-1}\sigma^2$$

$$\text{where } f'f = \begin{bmatrix} n_k & 0 & \cdots & 0 \\ 0 & \sum_{l=1}^{n_k} f_1^2(t(l)) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sum_{l=1}^{n_k} f_p^2(t(l)) \end{bmatrix} \quad \text{and} \quad f'r = \begin{bmatrix} \sum_{l=1}^{n_k} r_l \\ \sum_{l=1}^{n_k} r_1 f_1(t(l)) \\ \vdots \\ \sum_{l=1}^{n_k} r_1 f_p(t(l)) \end{bmatrix}$$

The advantage of the OPA approach is that the off-diagonal terms of matrix $f'f$ are all zero without involvement of matrix inversion and adding a new term does not change all previous estimates. That is

(1) $$\hat{a}_0 = \frac{1}{n_k}\sum_{l=1}^{n_k} r_l \quad \text{and} \quad \hat{a}_h = \frac{\sum_{l=1}^{n_k} r_h f_h(t(l))}{\sum_{l=1}^{n_k} f_h^2(t(l))} \quad h = 1,2,\cdots,p$$

As f_h are orthogonal, a_h signifies the size of the order h component in the return value. Because of the importance of the average returns suggested by previous research (Liang 2000), we let $f_0(t(n)) = f_0(1) = 1$ and $f_h(1) = 0$ for all $h \geq 1$, and make the level component a_0 equal to the average of returns.

This study also normalizes each f_h so that its leading term is simply t^h and let p = 2 so that the number of risk-return measures for OPA is equivalent to that of HMMV and MES. a_1 is the slope trend of the least squares regression line constrained to pass through $t((n_k), r(n_k))$ due to the importance of last month return values (Baquero et al. 2005). a_2 measures the monthly return curve curvature, i.e., it measures how quickly a tangent line turns into a curve. The values of a_0, a_1,, and a_2 are orthogonal and can be used to identify the effects of risk and return measures on the hedge fund mortality. Further details of OPA construction can be found in Wetherill (1981).

The mortality risk of the hedge fund is specified as a logarithm of a continuous-time hazard process which is given by

(2) $$\ln h_i(t) = \alpha + \tau T(t) + \beta X_i + \gamma Y_i$$

where $h_i(t)$ represents the hazard rate between the probability of default at time t over the cumulative probability of fund survival up to time t. $T(t)$ denotes the baseline hazard fund duration dependence, also known as piecewise-linear Gompertz, which is based on the transformation of the spell duration t, with three notes being used in this study, i.e., $T(t) = (\min[t, v_1], \max[0, \min[t - v_1, t - v_2]], \max[0, t - v_2])$. We set $[v_1 = 3 \text{ year}, v_2 = 6 \text{ year}]$. X represents the vector of exogenous fund governance and fee structure covariates based on previous literature concerning fund performance determinants which shift the baseline hazard. Y, which also shifts the baseline hazard rate, represents the vector of extracted risk-return measures, i.e., $Y = [a_0 \quad a_1 \quad a_2]$ for OPA-ES, $Y = [mean \quad std \quad skewness \quad kurtosis]$ for HMMV and $Y = [mean \quad es]$ for MES approaches respectively. es is the expected value of shortfall given the threshold VaR_α, that is $es = E[R_t \mid R_{t-1} > VaR_\alpha] = \frac{1}{\alpha}\int_{-\infty}^{VaR_\alpha} rf(r)dr$ and α is set to be 0.05. Given the log-hazard equation for fund failure, the baseline survival function for each fund is given by

(3) $$S_0(t) = \exp\{-\int_{t_0}^{t} \exp(\alpha \quad + \tau \ T(\upsilon))d\upsilon\}$$

where t_0 denotes the moment at which the fund becomes at risk for failure. The resulting survival function (i.e., the probability that the fund has not default yet at time t conditional on exogenous covariates X , is

(4) $$S_i(t, X_i, Y_i) = \exp\{-\int h(\upsilon)d\upsilon\} = \exp\{-\int_{t_0}^{t} \exp(\alpha \quad + \tau \ T(\upsilon))d\upsilon\}^{\exp\{\beta X_i + \gamma Y_i\}}$$

The conditional likelihood function for the hazard process is given by

(5) $$l_i^h(\varepsilon) = \{ \begin{matrix} S_i(t, X_i, Y_i) & \text{if fund is still alive at t} \\ S_i(t^l, X_i, Y_i) - S_i(t^u, X_i, Y_i) & \text{if fund defaults between } t^l \text{ and } t^u \end{matrix}$$

The full-information log-likelihood function is maximized using the Berndt et al. (1974) approach.

III. Sample and Data Description

The hedge fund data used in our analysis are obtained from the Lipper/TASS database for the period extending from January 1994 to July 2014. This period suffers less survivorship bias because the TASS database starts reporting information on hedge fund mortality after 1994 (Fung and Hsieh, 2000). We only consider those funds that reported in US Dollar. We drop those funds that do not report any AUM or have missing characteristics. This results in a final sample of 7,638 US dollar denominated funds. The TASS database classifies hedge funds into two categories: Live and Graveyard, in which there are 1,832 live funds and 5,906 graveyard funds in the two respective categories. The Lipper/TASS classifies Graveyard funds into seven sub-categories: (i) fund liquation; (ii) fund no longer reporting; (iii) unable to contact; (iv) closed to new investment; (v) merged into another fund; (vi) program closed; (vii) unknown. Ackermann et al. (1999) argue that those funds that no longer report their performance or are closed to new investment should not be classified as defunct because of poor performance, but rather because they have no need to attract additional capital. Consequently, in later analysis we form the sample by only selecting defunct funds in categories (i), while the number of live funds remains the same. We repeat all analysis for this sub-sample of hedge funds – denoted as the 'Absolute Defunct'.

The control variables

The control variables included in our analyses follows prior research (for example, Brown et al., 2001; Goetzmann et al., 2003; Panageas and Westfield, 2009; and Agarwal et al., 2009), the variables such as management fees, incentive fees, high-water marks, leverage, lock-up periods, register independent advisor (RIA) and asset under management (AUM) are included in our analyses in order to control for determinants that have been shown to influence the performance of hedge funds. Our analyses also controls fund investment styles, i.e., convertible arbitrage, dedicated short bias, equity market neutral, event driven, fixed income arbitrage, funds-of-funds, global macro, long/short equity hedge, and the rest styles. Among these investment styles, since funds-of-funds accounts for the highest proportion 28%, we create a dummy variable of value 1 if funds-of-funds and zero otherwise.

[Insert Table 1 here]

Table 1 presents the descriptive statistics for both Live and Graveyard funds over the sample period. The average (median) duration of live funds is 10.02 (9.01) years, longer than the average duration of Graveyard funds, which is 6.71 (5.51) years. A Logrank test for the differences across the two groups for the survival duration shows that the differences are significant (p_value = 0.000). The median monthly self-report return for live funds is 0.62% larger than that of defunct funds being 0.55%. The mean monthly self-reported return of live funds is 0.68%, slightly larger than 0.64% for defunct funds. However, the mean Sharpe Ratio for live funds is 0.94 (0.65%/0.72%) significantly larger than 0.47(0.64%/1.37%) for defunct funds. This suggests that those funds taking higher risks to achieve maximum returns tend to immature early. Similar findings are also exhibited for return-smoothing adjusted returns (For details see Section IV, B). It is noted that Sharpe Ratio which is calculated based on return-smoothing adjusted returns for default funds is 0.42 (0.45%/1.05%) is smaller than that based on self-reported returns. The remaining variables of Table 1 give a summary of statistics for control variables used in the analysis. Most control variables exhibit considerable cross-sectional variation due to high standard deviation relative to mean values.

IV. Empirical Results

A. Effects of Risk-Return Measures and Control Variables

Table 2 and Table 3 present the results from estimating log-continuous hazard models for hedge fund risk-returns based on OPA, HMMV and MES approaches using full sample as well as a "Absolute Defunct" sample. Hedge funds drop from the database for various reasons. According to the Lipper TASS Graveyard funds classification, hedge fund were delisted because of being liquated, funds no longer reporting, unable to contact, closed to new investment, merger into another fund, program closed or for unknown reasons. Hodder et al. (2014) indicate that funds with poor prior performance and no clearly stated delisting reason had a significantly negative estimated mean delisting return, suggesting that a shock to their returns "tips them over the edge" and leads to delisting. Funds fall into other categories in graveyard may not real dead. We therefore reestimate all hazard models to allow only those funds fall into liquidation category. All specifications control for the same fund governance and fee structure characteristics and all are estimated by the maximum likelihood estimation.

[Insert Tables 2 and 3 here]

We are particularly interested in the effects for the vector of coefficients of identified risk-return measures on hedge fund mortality risk. Across all columns in Table 2, data reveals that average size of fund returns vary negatively with the mortality risk of hedge funds. Specifically, the coefficients on fund mean returns are negative and significant across the three approaches, ranging from -0.7320 (OPA), -0.3406 (HMMV), to -0.2822 (MES). The economic magnitudes are meaningful, in that a 1% increase in monthly returns is associated with an approximately 51.90%, 28.87%, and 24.59% decline for fund mortality risk respectively when other explanatory variables are fixed, confirming the findings of Liang (2000), Amin and Kat (2003), Brown et al. (2001), and Baquero et al. (2005). For OPA estimation results, the coefficient on the slope trend a_1 , capturing the linear relationship between fund returns and mortality risk, takes value of -0.2488 $(t = -23.8)$. This effect is both statistically and economically significant, suggesting that a one percent increase in linear trend of monthly returns is associated with fund mortality hazard decline of 21.98%. This finding indicates that fund investors should focus not only on historical average fund returns but also on the general linear trend movements in fund monthly return performance.

Fung and Hsieh (2001) suggest that hedge fund returns cannot be completely explained by linear-factor models, since hedge fund returns tend to exhibit option-like features: large and positive returns are associated with the best- and worst-performing months of world stock markets. Given that hedge fund returns tend to be nonlinear due to using dynamic trading strategies and use of derivatives, the quadratic component a_2 is capable of capturing the nonlinear measure of hedge fund returns. More so, a hedge fund with large changes (either positive or negative) in returns can be considered as more volatile than other funds. Therefore a_2 also reflects the riskiness of hedge fund returns. Our results show that a one percent increase of return quadratic change is positively associated with the mortality risk of hedge funds by 19.03 percent $\left(\gamma_{a_2} = 0.1742 t = 73.5\right)$.

In comparison, the significance, sign and magnitudes of the coefficients of identified risk-return measures remain unchanged in Table 3 when more restrict sample are selected. It underscores the importance and relevance of derived information. Together, these results imply that, when investigating the effects of fund performance on mortality risk, the linear trend and nonlinear properties of fund returns is as important as the average historical returns. To take full advantage of the flexibility of OPA, more information about fund returns can be identified if higher orders of a_h in the return values are added.

Turning to HMMV model of Baba and Goko (2009) and MES model of Liang and Park (2010), results confirms that fund return is negatively associated with hedge fund failure while return volatility and ES are positively related to fund mortality risk. In particular, the hazard rate is 6.63 (exp(1.8923)) times the hazard if left-tail risk increases by one percent $\left(\gamma_{ES} = 1.8923 t = 8.39\right)$ However, HMMV model is very sensitive to sample selection. Baba and Goko (2009) find that funds with lower skewness in returns have higher liquidation probabilities while kurtosis has no impact on fund liquidation. In contrast to their finding, we find kurtosis has a point estimate of 0.0153 $\left(t = 101\right)$, suggesting funds are more likely to fail when fund returns exhibit fat tails. The coefficients of skewness are not consistent in two samples with significant positive loading in Table 2, negative loading in Table 3.

The coefficients for the baseline log-hazard are all statistically significant in all periods. For OPA estimation, the mortality risk for the first three years rises sharply, i.e., the hazard after three years is 4.53 times the hazard at the time when the fund started $\left(\tau_1 = 1.5111, t = 27.0\right)$, after which the mortality rate declines between year three and year six, a decline of approximating 5.13 percent per year $\left(\tau_2 = -0.0527, t = -3.65\right)$. Subsequently the failure rate rises only modestly after the sixth year by about 2.2 percent per year $(\tau_3 = 0.0210, t = 5.33)$. The estimated baseline hazard also shows similar patterns with respect to the significance and magnitude for both HMMV and MES estimations.

Regarding governance and fee structure control variables, we find incentive fees, redemption notice period, lock-up period, RIA and AUM have significant impact on hedge fund mortality risk. In particular, the significance and estimated signs for these explanatory variables are consistent across various estimations and samples. For the OPA estimation, the coefficient for the management fees and incentive fees variable are positive and significant at 1% level, $(\beta_{man} = 6.0917, t = 3.95)$ and $(\beta_{inc} = 1.7604, t = 9.30)$, respectively, suggesting management fees and incentive fees increase the hazard rate of fund mortality. It has been suggested that hedge fund incentive fee structure is more akin to a bonus schedule in that it limits downside risk for the fund manager. As such, managers would choose a riskier investment profile (Starks 1987). This result is consistent with Brown et al. (2001) and Baquero et al. (2005), who suggest that high incentive fees encourage fund managers to take more risks due to the convexity of compensation structure. This finding also supports Dangle et al. (2008) argument that fund risk increases with the proportional fee charged by fund managers.

The coefficient of the high-water mark and leverage are insignificant in Table 2, but significantly negative in Table 3 $(\beta_{hwm} = -0.1771, t = -6.67, \beta_{lev} = -0.0660, t = -2.03)$, indicating the HWM provision and leverage reduce real failure rate of hedge funds. With respect to the covariate lock-up period, our results indicate that a longer lock-up $(\beta_{loc} = 0.0508, t = 4.14)$ can increase the mortality-hazard rate of funds. This result lends support to the argument proposed in Baba and Goko (2009) that investors dislike less liquidity, so the longer the locked-up period the less likely they are to invest, which in turn destabilizes fund management. However, the lock-up period has no impact on attrition rate in liquidation only fund sample. Longer redemption period can significantly reduce fund hazard rate

$(\beta_{red} = -0.0528, t = -5.95)$. This is consistent with expectations that a longer redemption period provides greater managerial freedom and results in longer survivorship. RIA provides advice and monitoring service to funds thus reducing the liquidation risk of hedge funds $(\beta_{ria} = -0.2969, t = -6.87)$. Fund size is negatively associated with mortality risk, indicating that funds with larger and more stable assets are less likely to be liquidated $(\beta_{aum} = -0.1391, t = -54.1)$. Similar patterns also appear for HMMV and MES estimations.

B. Robustness checks

We address several issues related to the robustness of the results. As presented in prior section, we re-conduct survival analysis for three different risk-return approaches using a subsample consisting of Live funds and liquidation category funds in Graveyard. Results are presented in Table 3.

The main variable of interest is hedge fund return measure. The survival analysis and model comparisons presented in previous section are based on hedge fund monthly self-reported returns. As noted, deliberate misreporting and return-smoothing cause potentially severe erosion in risk transparency, which can have consequences on investors' predicting of the relationship between hedge fund performance and liquidation risk. The return smoothing technique is proposed to deal with hedge fund illiquidity exposure. In the second robustness check, we first apply Getmansky et al. (2004)'s approach to estimate monthly smoothing adjusted returns. Then apply OPA based on smoothing adjusted returns to examine whether OPA is sensitive to modified returns. The main results are reported in Table 4, while Table 5 presents the results using "Absolute Defunct" subsample.

[Insert Table 4 and Table 5 here]

In all cases, the sign and significance of the coefficients on the key risk-return measures estimated by OPA remain the same. The results confirm that the findings are robust irrespective of how we treat and use of different samples. Most of variables show the same hazard direction with only a few exceptions such as management fees and HMV.

The third robustness check is to compare the information that can be captured by OPA and MES approaches by adding additional risk measure to OPA. Our propose approach is inspired by the fact that OPA can capture not only static return, but also linear trend and the return changing pattern. To some extent, the quadratic term captures hedge fund return volatility or tail risk. We therefore add ES as a measure of downside risk alongside with OPA measures and repeat the survival analysis, which is reported in Table 6, in which the survival analysis is conducted based on the full and absolute defunct samples. In each sample, two model estimations are conducted, in which Model 1 includes quadratic component, a_2, while Model 2 does not include a_2 in the estimation. Since the estimation results for full and absolute defunct samples display similar patterns, our analysis only focus on the results of full sample. Model 1 of Table 6 shows that the sign and significance of OPA component measures are indistinguishable from our estimation results on $[a_0 \quad a_1 \quad a_2]$ in Table 2, indicating that including the ES measure leaves the set of coefficients of OPA measures unaffected. In contrast to the finding for ES in Table 2, the estimated sign of ES coefficient reversed from positive to negative, indicating ES measure could be related with one of OPA measure components. We then calculate the correlation value between the quadratic component, a_2, and ES and the correction value is 0.492 indicating that these two measures might contain similar information about the risks of hedge funds. As expected, the correlation between Linear trend of OPA, a_1, with ES is very low, -0.006. Therefore, in Model 2, we exclude a_2 from the estimation and the estimation results show that the coefficient for ES is positive $(\gamma_{ES} = 1.9355 t = 8.48)$, almost the same empirical magnitude as that in Table 2. Together, these estimates imply that when estimating the impact of return measures on fund mortality risk, the ES measure is, on the margin, only as important as the quadratic component a_2 of OPA approach. This indicates that ES approach can be a special case for OPA approach in that all information in ES can be approximated by using OPA while information in OPA could not be incorporated in ES.

To summarize, these results support the view that the identified risk-return measures have a potentially significant effect on the mortality risk of hedge funds. We find that, in addition to static risk-return measures such as return moments and expected shortfall, dynamic measures may also be both relevant and important factors in explaining the mortality risk of hedge funds. The results are also robust to the use of different samples of hedge funds, mitigating the concern that the identified risk-return measures are contaminated by fund mortality definition changes, return smoothing problem or missing downside risk measure. While these results are informative, further investigations among OPA, HMMV and MES are needed. In the next subsection, we draw stronger conclusions from comparing predictive power for the three approaches.

C. Bootstrap simulation comparison of derived return measure, unconditional return moments and expected shortfall risk-returns

The use of HMMV and MRS as measures to investigate the impact of returns on hedge fund survivorship is straightforward. However, these two approaches may not capture all the dynamic return information. Therefore, we compare the out-of-sample forecasting ability of these two approaches' with our OPA in assessing the validity of derived risk-return measures. We conduct non-parametric bootstrap simulations to avoid the predictive power imbedded in fortunate selection of the training and validation datasets. We use Efron's (1981) algorithm to conduct non-parametric bootstrap simulations for censored data. Details of bootstrap simulation procedures are presented as follows:

i. We sample with replacement from the original data to obtain a new bootstrap sample. Note that some funds can be selected more than once in this new sample, or possibly not at all.

ii. We next randomly and equally split-off the new bootstrap sample into training and validation samples (50% and 50%).

iii. The training sample is then used to estimate the hazard model with OPA, HMMV and MES respectively. With the relevant estimated coefficients, we calculate bootstrap predicted survival probabilities for each fund using the new validation sample data. To do so, we first need to calculate the Nelson-Aalen estimate of the baseline cumulative hazard function, considering there are *n* funds, among which there are *r* distinct default times and $n-r$ right-censored survival times. Then the baseline cumulative hazard function for $H_0(t)$ is obtained as

$$H_0(t) = -\log S_0(t) = \sum_{j=1}^{J} \frac{e_j}{\sum_{l \in R(t_j)} \exp\left(\hat{\beta} x_l + \gamma Y_l\right)}$$

for $t_J \le t < t_{J+1}$, $J = 1,2,\cdots,r-1$, where $S_0(t)$ is the baseline survivor function, $R(t_j)$ is the group of funds that are still alive at a time just prior to t_j, x_l and Y_l are the vector of explanatory variables and derived return measures for the l^{th} fund, respectively. e_j is the number of events at the j^{th} ordered event time, $j = 1,2,\cdots,r$. We then obtain the approximate conditional probability of surviving through the interval $(t, t+h)$ for fund *i* in the sample (Here we let $h = 1$ year)

$$\tilde{P}_i(t, t+h) = \exp\left[-\{H_0(t+h) - H_0(t)\} \exp\left(\hat{\beta} x_i + \gamma Y_i\right)\right]$$

Using the bootstrap replicates of predictive survival probabilities, we calculate the area under the ROC curves (AUC), which is a commonly used summary measure of predictive power. The value for the area under the ROC curve closing to 1 indicates perfect predictive power and 0.5 indicates the same accuracy as a random guess.

iv. We replicate steps i through iii 1,000 times.

[Insert Figures 1 and 2 here]

Figure 1 presents a bootstrap comparison of the ROC curve results for a one-year-forward horizon and comparing the out-of-sample predictive power for risk-return measures generated with OPA, HMMV and MES with the same control fund characteristic variables. The comparison is based on full sample. The OPA model with the derived return measure performs better than HMMV and MES models. The average area-under-curve (AUC) values for OPA, HMMV and MES are 0.6328, 0.6084 and 0.6123, respectively. OPA has the highest predictive power at all false positive rates. The gains are high at low false positive rates, decreasing proportionally with false positive rates. At upper false positive rates three approaches are almost identical.

Recall that we define fund failure in two ways: Graveyard funds and liquidation only funds. As we now have a modified sample – Absolute Defunct – by including live funds and liquidation funds only, we apply OPA approach to compute AUC value (AUC=0.6784, presented in Figure 3) using this sample to be compared with our full sample set (AUC=0.6328, presented in Figure 1). Clearly OPA has stronger power in predicting 'real failure' of hedge funds.

To demonstrate that OPA approach better captures the characteristics of hedge fund returns, we provide a comparison of the same predictive power curve using OPA based on fund directly reported returns and smoothing adjusted returns generated by Getmansky et al. (2004)'s approach. The test is repeated for Absolute Defunct sample.

[Insert Figures 2 and 3 here]

The result in Figure 2 shows that OPA based on raw return (AUC = 0.6328) has higher predictive power than OPA based on smoothing adjusted return (AUC = 0.5939). Again the gains are larger at the lower end of false positive rate spectrum. The gap narrows in the intermediate range and disappears in the high rate spectrum. Similar patterns also appear for real defunct hedge fund sample. These two comparisons suggest that OPA captures more information contained in monthly fund returns that cannot be captured by Getmansky (2004)'s return smoothing method, suggesting OPA can used to better deal with hedge fund unique return properties.

As further confirmation of our results to address the same impacts of ES and a_2, two further comparisons of out-of-sample predictive power between OPA and OPA-ES are conducted and are shown in Figures 4 and 5, respectively. This time OPA only includes two components, a_0 and a_1, so that both OPA and MES have the same number of measures. By direct comparison of OPA with a_0 and a_1 to MES with *mean* and *ES*, it is possible to justify the additional predictive power provided by OPA. At all false positive rates, OPA and OPA-ES yield almost the same predictive power for full sample and Absolute Defunct sample. This suggests that OPA can be served as a useful risk-return framework due to its flexibility to incorporate higher order of components. The main reason that OPA is able to out-perform HMMV and MES is due to the derived risk-return measures using static and dynamic information from the entire history of fund returns when compared with HMMV and MES. Furthermore, the results cannot only be attributed to more number of risk-return measures being used for OPA.

V. Conclusions

In this paper, we conduct the survival analysis of hedge fund over the period from January 1994 to December 2014. Nonetheless, risk and return are two unique features of hedge funds due to the fact that hedge funds heavily use leverage and actively trade derivatives. While previous studies use either average return, this study proposes a return measure capture both static and dynamic return information. Three risk-return measures are compared: OPA, HMMV and MES. The OPA approach is particularly appropriate for this study since the hedge fund returns are determined by certain number of orthogonal components in order to capture the whole history of both static and dynamic return information hedge fund returns are divided into constant, linear and quadric components in order to capture both static and dynamic return information.

Though HMMV and MES approaches have the advantage of permitting a straightforward analysis of the impact of hedge fund returns on survival, they have deficiencies in their inability to capture the option-like features of hedge fund returns. We show that the OPA approach we applied in this study does a better job – it has greater predictive power than those used in previous studies, such as Baba and Goko (2009) and Liang and Park (2010). We further apply bootstrap simulations to conduct one-year-head and three-year-ahead forecasting tests, and provide evidence on the predictive gains associated with the OPA return measures. The main benefit of a derived return measure that has higher predictive power over unconditional return moments or dynamic lagged returns is that the OPA approach utilises more of the information content based on reported hedge fund returns. These results should be of interest to hedge fund investors regarding the efficiency of using relevant information.

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Table 1: Cross-Sectional Hedge Fund Characteristics

This table presents the descriptive statistics for the sample of cross-sectional hedge fund characteristics used in our analysis. The sample is based on Lipper/TASS database over the period from 1994 to 2014. Duration is defined as fund's time to failure or still alive at the censoring date. Self-report return is the fund monthly report returns. Adjusted-return is estimated using Getmansky et. al. (2004)'s return-smoothing approach. Management fee is proportional (typically between 1-2%) to the total asset. Incentive fee is the term in the compensation contract which gives managers a percentage of any positive returns. High-water mark (HWM) is a dummy variable that equals one if the fund has a water mark provision and zero otherwise. Leverage is a dummy variable which equals one if the fund employs leverage and zero otherwise. Lock-up period refers to the time during which the invested money cannot be withdrawn. Notice Redemption period is the notice period before investors will receive their capital back. RIA indicates whether the hedge fund has become registered with investment advisers.

	Live funds			**Graveyard funds**		
Characteristics	**Mean**	**Median**	**Std.**	**Mean**	**Median**	**Std.**
Duration (year)	10.02	9.006	5.747	6.710	5.507	4.198
Self-reported return (%)	0.680	0.620	0.720	0.641	0.550	1.370
Smoothing-adjusted return (%)	0.451	0.405	0.474	0.449	0.384	1.050
Management fee (%)	1.428	1.500	0.006	1.472	1.500	0.007
Incentive fee (%)	14.31	20.00	8.376	15.85	20.00	7.497
HWM (%)	68.54	100.0	46.44	60.66	100.0	48.85
Leverage (%)	53.15	100.0	0.499	57.89	100.0	49.37
RNPeriod (day)	40.57	30.00	34.88	35.84	30.00	30.19
Lock-up (month)	3.349	0.000	6.769	3.181	0.000	6.358
RIA(%)	18.62	0.000	38.92	9.425	0.000	29.22
AUM (log)	17.65	17.83	2.065	17.07	17.17	1.856

Table 2: Tests of The Effects of Risk-Return Measures and Control Variables on Mortality Risk Using Raw Returns – Full Sample

This table presents the estimation results of hazard regression of hedge fund morality risk on risk-return measures: $[a_0 \quad a_1 \quad a_2]$ of OPA, $[mean \quad std \quad skewness \quad kurtosis]$ of HMMV and $[mean \quad es]$ of MES approaches. The specifications include control variables for hedge funds governance and fee structure characteristics: investment style dummy (D1), management fees (Mgnt fees), incentive fees (Inctv fees), high water mark (HWM), leverage, redemption notice period (RNPeriod), lock-up period (Lock-up), register independent advisor (RIA), asset under management (AUM). The sample extends from January 1994 to July 2014. The estimation results are obtained by maximum likelihood estimation. Figures marked with '***', '**' and '*' are significant at the 1%, 5% and 10% levels respectively.

	OPA		HMMV		MES	
Variables	**Coefficient**	**t-value**	**Coefficient**	**t-value**	**Coefficient**	**t-value**
Risk-return measures						
a_0	-0.7320***	-8.37				
a_1	-0.2488***	-23.8				
a_2	0.1742***	73.5				
Mean			-0.3406***	-31.4		
Std			0.4640***	9.61		
Skewness			0.1707***	8.73		
Kurtosis			0.0153***	101		
Mean					-0.2822***	-27.2
ES					1.8923***	8.39
Control variables						
Constant	-2.6761***	-16.7	-4.2262***	-26.9	-3.1897***	-20.1
Spline0-3	1.5111***	27.0	1.7264***	31.1	1.3972***	25.1
Spline3-6	-0.0527***	-3.65	-0.1613***	-11.6	-0.1044***	-7.26
Spline6+	0.0210***	5.33	0.0221***	5.98	0.0114**	2.64
D1	-0.1981***	-5.40	-0.1508***	-4.83	-0.1526***	-4.22
Mgnt fees	6.0917***	3.95	-0.0885	-0.06	0.1467	0.08
Inctv fees	1.7604***	9.30	1.0813**	6.37	1.4666***	7.27
HWM	0.0038	0.14	0.0706**	2.70	0.0088	0.29
Leverage	0.0088	0.35	-0.0525**	-2.29	-0.0096	-0.37
RNPeriod	-0.0528***	-5.95	-0.0214**	-2.46	-0.0348***	-3.68
Lock-up	0.0508***	4.14	0.0600***	5.66	0.0549***	4.46
RIA	-0.2969***	-6.87	-0.3519***	-9.47	-0.3208***	-7.67
AUM	-0.1391***	-54.1	-0.1414***	-58.4	-0.1396***	-53.4
Log Likelihood	-21113.98		-22252.73		-21644.78	

Notes: D1 is dummy variable. D1 equals to 1 if investment style is fund of funds and zero otherwise.

Table 3: Tests of The Effects of Risk-Return Measures and Control Variables on Mortality Risk Using Raw Returns – Absolute Defunct Sample

This table presents the estimation results of hazard regression of hedge fund morality risk on risk-return measures: $[a_0 \quad a_1 \quad a_2]$ of OPA, $[mean \quad std \quad skewness \quad kurtosis]$ of HMMV and $[mean \quad es]$ of MES approaches. The specifications include control variables for hedge funds governance and fee structure characteristics: investment style dummy (D1), management fees (Mgnt fees), incentive fees (Inctv fees), high water mark (HWM), leverage, redemption notice period (RNPeriod), lock-up period (Lock-up), register independent advisor (RIA), asset under management (AUM). The sample extends from January 1994 to July 2014. The estimation results are obtained by maximum likelihood estimation. Figures marked with '***', '**' and '*' are significant at the 1%, 5% and 10% levels respectively.

	OPA		HMMV		MES	
Variables	**Coefficient**	**t-value**	**Coefficient**	**t-value**	**Coefficient**	**t-value**
Risk-return measures						
a_0	-0.9629***	-11.4				
a_1	-0.3480***	-38.6				
a_2	0.2834***	123				
Mean			-0.6325***	-41.3		
Std			0.9913***	43.8		
Skewness			-0.0156***	-7.57		
Kurtosis			0.0204***	107		
Mean					-0.4687***	-21.5
ES					2.1596***	8.14
Control variables						
Constant	-2.1219***	-9.29	-3.9791***	-17.1	-2.7220***	-11.6
Spline0-3	1.5660***	19.7	1.6436***	20.5	1.6106***	20.0
Spline3-6	-0.0887***	-4.50	-0.1526***	-7.27	-0.1641***	-7.80
Spline6+	0.0620***	17.9	-0.0114*	-1.65	0.0132**	2.08
D1	-0.1741***	-3.91	-0.2619***	-6.03	-0.2637***	-5.29
Mgnt fees	14.801***	18.2	3.6854**	2.24	0.8042	0.32
Incentive fees	1.6807***	6.87	1.6419***	6.23	2.0742***	6.54
HWM	-0.1771***	-6.67	-0.0997**	-2.89	-0.1575***	-3.83
Leverage	-0.0660**	-2.03	-0.0575*	-1.77	0.0010	0.03
RNPeriod	-0.0795***	-8.24	-0.0569***	-4.87	-0.0938***	-7.68
Lock-up	0.0014	0.08	0.0508***	3.76	0.0011	0.05
RIA	-0.4223***	-6.92	-0.4800**	-9.17	-0.4317***	-6.96
AUM	-0.1446***	-44.0	-0.1469***	-34.1	-0.1930***	57.2
Log Likelihood	-10626.08		-10986.33		-10466.85	

Notes: D1 is dummy variable. D1 equals to 1 if investment style is fund of funds and zero otherwise.

Table 4: Tests of The Effects of Risk-Return Measures and Control Variables on Mortality Risk Using Smoothing Adjusted Returns – Full Sample

This table presents the estimation results of hazard regression of hedge fund morality risk on risk-return measures: $[a_0 \quad a_1 \quad a_2]$ of OPA, $[mean \quad std \quad skewness \quad kurtosis]$ of HMMV and $[mean \quad es]$ of MES approaches. The specifications include control variables for hedge funds governance and fee structure characteristics: investment style dummy (D1), management fees (Mgnt fees), incentive fees (Inctv fees), high water mark (HWM), leverage, redemption notice period (RNPeriod), lock-up period (Lock-up), register independent advisor (RIA), asset under management (AUM). The sample extends from January 1994 to July 2014. The estimation results are obtained by maximum likelihood estimation. Figures marked with '***', '**' and '*' are significant at the 1%, 5% and 10% levels respectively.

	OPA		HMMV		MES	
Variables	**Coefficient**	**t-value**	**Coefficient**	**t-value**	**Coefficient**	**t-value**
Risk-return measures						
a_0	-1.7189***	-12.9				
a_1	-0.0776***	-13.6				
a_2	0.0821***	23.7				
Mean			-0.2770***	-13.9		
Std			0.0415***	6.67		
Skewness			-0.1613***	-5.80		
Kurtosis			-0.0266***	-8.15		
Mean					-0.2390***	-12.6
ES					0.2553***	8.77
Control variables						
Constant	-2.9129***	-17.5	-3.1241***	-19.2	-3.1137***	-19.1
Spline0-3	1.4357***	25.6	1.2499***	22.4	1.2748***	22.8
Spline3-6	-0.1094***	-7.62	-0.0850**	-5.86	-0.0916***	-6.29
Spline6+	0.0042	1.00	0.0066	1.54	0.0072	1.61
D1	-0.0813**	-2.28	-0.0901**	-2.36	-0.0888**	-2.32
Mgnt fees	0.5471	0.44	0.8275	0.47	2.5478	1.35
Inctv fees	1.1802***	5.67	1.3204***	5.94	1.4565***	6.51
HWM	0.0506*	1.76	0.0353	1.16	0.0165	0.54
Leverage	-0.0318	-1.22	-0.0220	-0.83	-0.0131	-0.49
RNPeriod	-0.0235**	-2.59	-0.0171*	-1.77	-0.0303***	-3.12
Lock-up	0.0446***	3.62	0.0445***	3.62	0.0467***	3.78
RIA	-0.3127***	-7.28	-0.3204***	-7.54	-0.3183***	-7.54
AUM	-0.1331***	-40.9	-0.1299***	-38.8	-0.1374***	-42.7
Log Likelihood	-21559.16		-21531.15		-21548.20	

Notes: D1 is dummy variable. D1 equals to 1 if investment style is fund of funds and zero otherwise.

Table 5: Tests of The Effects of Risk-Return Measures and Control Variables on Mortality Risk Using Smoothing Adjusted Returns – Absolute Defunct Sample

This table presents the estimation results of hazard regression of hedge fund morality risk on risk-return measures: $[a_0 \quad a_1 \quad a_2]$ of OPA, $[mean \quad std \quad skewness \quad kurtosis]$ of HMMV and $[mean \quad es]$ of MES approaches. The specifications include control variables for hedge funds governance and fee structure characteristics: investment style dummy (D1), management fees (Mgnt fees), incentive fees (Inctv fees), high water mark (HWM), leverage, redemption notice period (RNPeriod), lock-up period (Lock-up), register independent advisor (RIA), asset under management (AUM). The sample extends from January 1994 to July 2014. The estimation results are obtained by maximum likelihood estimation. Figures marked with '***', '**' and '*' are significant at the 1%, 5% and 10% levels respectively.

	OPA		HMMV		MES	
Variables	**Coefficient**	**t-value**	**Coefficient**	**t-value**	**Coefficient**	**t-value**
Risk-return measures						
a_0	-4.7838***	-32.5				
a_1	-0.1222***	-23.4				
a_2	0.1221***	37.5				
Mean			-0.4380***	-29.5		
Std			0.0737***	30.8		
Skewness			-0.2890	-6.71		
Kurtosis			-0.0389***	-6.46		
Mean					-0.4303***	-29.1
ES					0.1029***	4.13
Control variables						
Constant	-2.3052***	-9.53	-3.0638***	-12.9	-3.0542***	-12.8
Spline0-3	1.4711***	18.1	1.3662***	17.3	1.3619***	17.2
Spline3-6	-0.1291***	-6.08	-0.1181***	-5.50	-0.1233***	-5.71
Spline6+	-0.0254***	-3.55	-0.0214**	-2.95	-0.0230***	-3.07
D1	-0.1095**	-2.18	-0.0930*	-1.68	-0.0940*	-1.71
Mgnt fees	2.1001	0.93	0.13378	0.05	2.1378	0.85
Inctv fees	2.0331***	6.84	2.1270***	6.43	2.1241***	6.34
HWM	-0.1424***	-3.71	-0.1434***	-3.31	-0.1521***	-3.46
Leverage	-0.0237	-0.62	-0.0125	-0.31	-0.0185	-0.46
RNPeriod	-0.0794***	-6.67	-0.0657***	-4.79	-0.0765***	-5.57
Lock-up	0.0019	0.09	-0.0093	-0.45	-0.0070	-0.34
RIA	-0.4081***	-6.08	-0.4079***	-5.90	-0.4088***	-5.94
AUM	-0.1493***	-29.0	-0.1504***	-28.0	-0.1557***	-30.2
Log Likelihood	-10467.99		-10402.86		-10435.44	

Notes: D1 is dummy variable. D1 equals to 1 if investment style is fund of funds and zero otherwise.

Table 6: Tests of The Effects of OPA and ES on Mortality Risk Using Raw Returns – Full and Absolute Defunct Samples

This table presents the estimation results of hazard regression of hedge fund morality risk on risk-return measures: $\left[a_0 \quad a_1 \quad a_2\right]$ of OPA, [*es*] of MES approaches. The specifications include control variables for hedge funds governance and fee structure characteristics: investment style dummy (D1), management fees (Mgnt fees), incentive fees (Inctv fees), high water mark (HWM), leverage, redemption notice period (RNPeriod), lock-up period (Lock-up), register independent advisor (RIA), asset under management (AUM). The sample extends from January 1994 to July 2014. The estimation results are obtained by maximum likelihood estimation. Figures marked with '***', '**' and '*' are significant at the 1%, 5% and 10% levels respectively.

	Full Sample				**Absolute Defunct Sample**			
	Model 1		**Model 2**		**Model 1**		**Model 2**	
Variables	**Coefficient**	**t-value**	**Coefficient**	**t-value**	**Coefficient**	**t-value**	**Coefficient**	**t-value**
Risk-return measures								
a_0	-1.2731***	-17.4	-1.9951***	-19.1	-1.4386***	-17.3	-4.0945***	36.2
a_1	-0.2314***	-28.7	-0.0801***	-3.30	-0.3357***	-46.4	-0.1569***	-4.82
a_2	0.2312***	140			0.2979***	134		
ES	-1.4078***	-30..3	1.9355***	8.48	-1.534***	-26.4	2.3039***	8.81
Control variables								
Constant	-2.9648***	-18.4	-3.1756***	-20.1	-0.9882***	-4.64	-2.6021***	-11.1
Spline0-3	1.7201***	30.8	1.3882***	25.0	1.1685***	15.3	1.5019***	18.7
Spline3-6	-0.0981***	-7.37	-0.1080***	-7.50	-0.0475**	-2.41	-0.1374***	-6.40
Spline6+	0.0799***	37.6	0.0095**	2.18	0.0768***	25.2	-0.0168**	-2.27
D1	-0.1540***	-5.15	-0.1360***	-3.78	-0.1122*	-2.61	-0.2033***	-3.94
Mgnt fees	8.5961***	8.28	0.3629	0.21	14.886***	20.4	2.1823	0.81
Inctv fees	1.1040***	7.29	1.3671***	6.84	1.7499***	7.84	1.9797***	6.01
HWM	-0.0034	-0.16	0.0142	0.47	-0.1861***	-7.80	-0.1475***	-3.39
Leverage	-0.1005***	-4.58	-0.0128	-0.49	-0.1163***	-3.55	0.0011	0.03
RNPeriod	-0.0550***	-7.60	-0.0353***	-3.74	-0.0597***	-6.16	-0.0816***	-6.34
Lock-up	0.0623***	5.84	0.0507***	4.11	0.0111	0.62	0.0021	0.11
RIA	-0.3396***	-9.30	-0.3173***	-7.61	-0.4901**	-2.61	-0.4034***	6.33
AUM	-0.1301***	-47.5	-0.1410***	-55.0	-0.1521***	-47.4	-0.1891***	-53.7
LogLikelihood	-21441.45		-21682.57		-10760.84		-10474.60	

Notes: D1 is dummy variable. D1 equals to 1 if investment style is fund of funds and zero otherwise

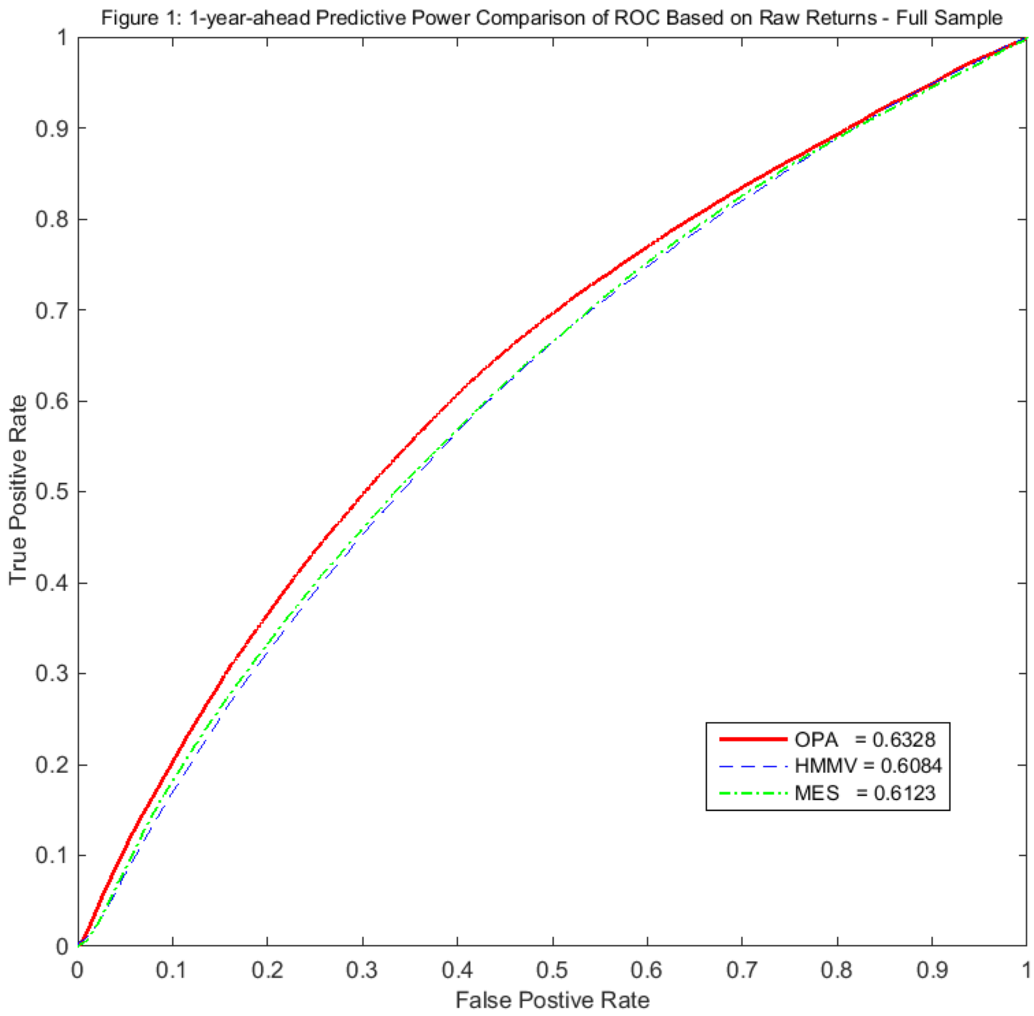
Figure 1: 1-year-ahead Predictive Power Comparison of ROC Based on Raw Returns - Full Sample
True Positive Rate
False Postive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
OPA = 0.6328
HMMV = 0.6084
MES = 0.6123

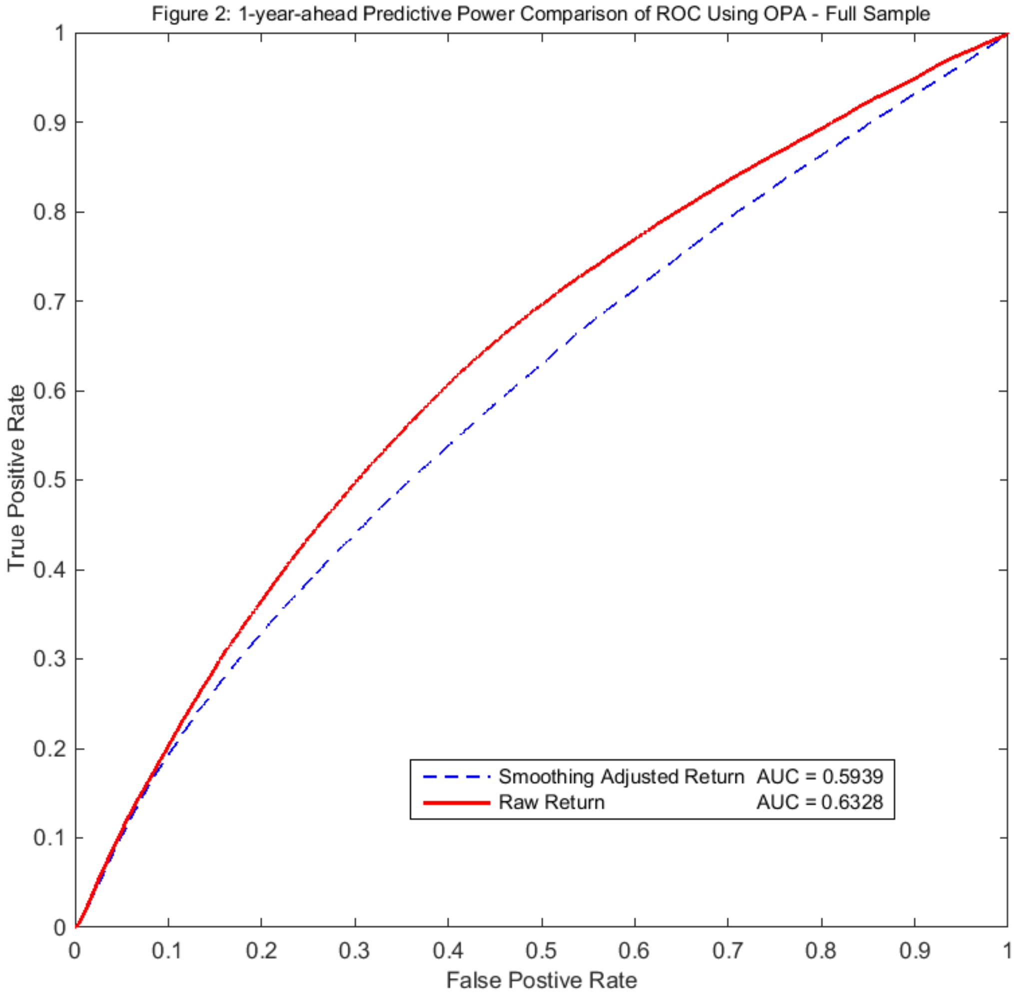
Figure 2: 1-year-ahead Predictive Power Comparison of ROC Using OPA - Full Sample
True Positive Rate
False Postive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Smoothing Adjusted Return AUC = 0.5939
Raw Return AUC = 0.6328

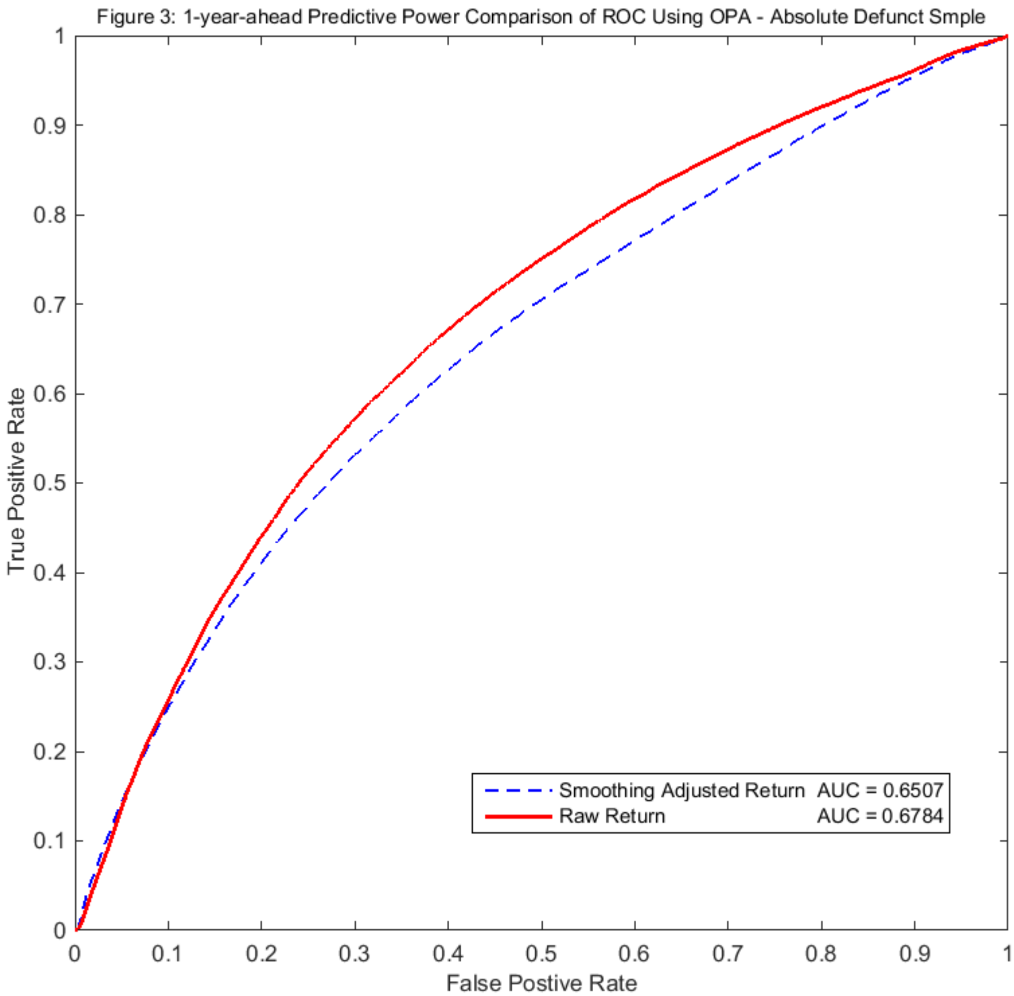

Figure 3: 1-year-ahead Predictive Power Comparison of ROC Using OPA - Absolute Defunct Smple
True Positive Rate
False Postive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Smoothing Adjusted Return AUC = 0.6507
Raw Return AUC = 0.6784

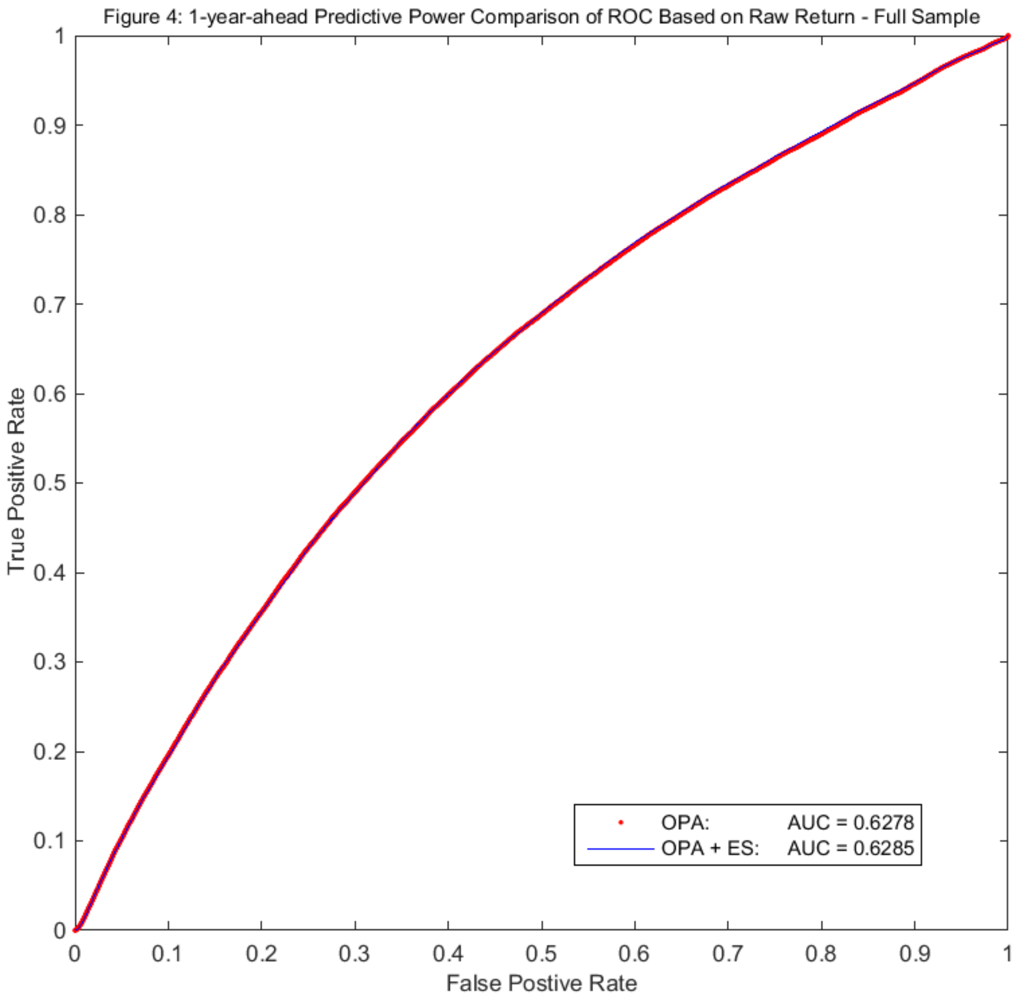
Figure 4: 1-year-ahead Predictive Power Comparison of ROC Based on Raw Return - Full Sample
True Positive Rate
False Postive Rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
OPA: AUC = 0.6278
OPA + ES: AUC = 0.6285

Figure 5: 1-year-ahead Predictive Power Comparison of ROC Based on Raw Return - Absolute Defunct Smple