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Dynamic prediction of hedge fund survival in crisis-prone financial markets

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ABSTRACT

This study focuses on dynamic changes in survival probabilities over the lifetimes of hedge funds. To model such probabilities, a mixed Cox proportional hazards (CPH) model-specifically, a survival/hazard model with time-varying covariates and fixed covariates- is employed. Resulting dynamic survival probabilities show that the mixed CPH model provides significantly higher accuracy in predicting hedge fund failure than other models in the literature, including fixed covariate CPH models and discrete logit models. Our results are useful to investors and regulators of hedge funds in crisis-prone financial markets.

1. Introduction

Since the onset of the global financial crisis (GFC), periodic local financial crises have continued to occur worldwide. Against the backdrop of crisis-prone financial markets, possible causes of the GFC have been suggested, with varying weights assigned by experts to different hypotheses. Posited causes include the collapse of high-profile hedge funds, such as Amaranth and Bear Sterns; the bankruptcy of large financial institutions, such as Lehman Brothers and Merrill Lynch; the bailout of banks by national governments; and downturns in global stock markets. As shown by Boyson et al. (2010), hedge fund failures not only create large losses for their own investors but have detrimental effects on the entire industry and on other asset classes. Thus, the international investment community is increasingly concerned about hedge fund failures and, accordingly, increasingly desires the ability to predict financial distress of hedge funds in real-time. This need motivates the present paper to investigation into a dynamic assessment mechanism of hedge fund failure.

The present paper proposes a model that can be used to predict dynamic changes in the survival probabilities of hedge funds in crisis-prone financial markets. Dynamic prediction is especially necessary in crisis-prone financial markets because well-understood relationships that exist in stable markets are observed not to hold in crisis-prone markets. Several academic efforts to predict hedge fund failure have adopted survival analysis or qualitative response models. For example, Brown et al. (2001, 2009), Bares et al. (2001), Boyson (2002), Gregoriou (2002), Rouah (2005), Grecu et al. (2007), Chapman et al. (2008), Ng (2008), Baba and Goko (2009), and Liang and Park (2010) use the Cox proportional hazards (CPH) model to examine factors affecting hedge fund failure, while Chan et al. (2006), Baquero et al. (2005), and Malkiel and Saha (2005) use logit or probit models to investigate hedge fund survival. Since the study of Rouah (2005), several studies have used a CPH model that incorporates time-varying covariates to examine hedge fund survival (Chapman et al., 2008; Grecu et al., 2007; Ng, 2008; Baba and Goko, 2009; Liang and Park, 2010). In these studies, however, survival probabilities are not calculated over a fund's lifetime; rather, such studies examine only the relationships between covariates and hazard rates. By contrast, the present study uses a mixed CPH model that incorporates both time-varying and fixed covariates to generate dynamic changes in hedge fund survival probabilities over a fund's lifetime. Note that the effects of the time-varying covariates

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of the mixed CPH model typically occur contemporaneously and are thus difficult to capture in a CPH model that incorporates only fixed covariates.

Using two datasets, the "live funds[2]" and the "dead funds[3]" datasets provided by Hedge Fund Research, Inc. (HFR), the current study establishes a mixed survival/hazards model with covariates that are both fixed and time-varying. The sample of failed hedge funds is drawn from the "dead funds" dataset by applying filter criteria based on returns and assets under management. After estimating the model, dynamic changes in survival probabilities are predicted, and the predictive power of the model is evaluated using the relative operating characteristic (ROC) curve as a prediction accuracy metric. The dynamic survival probabilities derived from the model indicate that non-failed funds have higher survival probabilities than failed funds across a given time horizon. Furthermore, the survival probabilities of failed funds decrease much more rapidly than those of non-failed funds along the timeline. In addition, the ROC curve shows that the mixed CPH model is far superior in predicting survival probabilities than the fixed CPH model, which only incorporates fixed covariates and a discrete-time hazard logit model of Shumway (2001) that also incorporates mixed covariates. Therefore, the mixed model developed in this study provides an effective tool for real-time predictions of survival probabilities of hedge funds. Importantly, our study shows how crisis-prone financial markets distort well-known effects of covariates on hedge fund failure in non-crisis-prone markets and demonstrates how the mixed CPH model with time-varying covariates successfully adapts to dynamic market conditions. These results are useful for investors and regulators monitoring potential fund failures in real-time.

2. HFR data and covariate selection

This paper employs two HFR databases commonly used by both academics and practitioners. As their names suggest, the "live funds" database includes information regarding all hedge funds that currently report to HFR, while the "dead funds" database includes information regarding hedge funds that have stopped reporting to HFR. The live funds and dead funds databases used in this study cover the period from January 1990 to December 2009. The live funds database includes 2003 funds, while the dead funds database includes 2303 funds. In this study, we consider only funds that have a minimum of 36 months of data to guarantee a sufficient number of observations for the estimation process.[4] To avoid data heterogeneity, funds that do not report returns net of fees to HFR on a monthly basis or have missing data are deleted. As a result, our HFR data consist of 1484 live funds and 1329 dead funds.[5] The HFR database provides three information tables: the administrative table, the performance table, and the assets under management (AUM) table. The administrative table discloses a wide range of time-invariant data on each fund, while the other two tables present monthly time series information regarding the funds.

Several hedge fund characteristics that may be considered covariates to be used in CPH models are included in the three information tables. In particular, the administrative table contains information that can be used to categorize funds into four categories according to investment strategy: equity hedge, event-driven, macro, and relative value arbitrage. Additional information in the administrative table includes inception date, minimum investment requirements, redemption policies, fee structures, leverage, and domicile. These fund characteristics can be directly or indirectly incorporated into CPH models as fixed or time-varying covariates. The fixed covariates include minimum investment, leverage, high-water mark, hurdle rate, redemption period, notice period, lockup period, domicile,[6] and strategy, while incentive fee is used as a time-varying covariate in the model. Returns and fund size variables that would be incorporated into the mixed CPH model as time-varying covariates are provided in the performance and asset tables, respectively. Note that classifying covariates as fixed or time-varying depends on how HFR reports them but that classifications are adjusted whenever necessary and possible. For example, the incentive fee reported as a fixed percentage of profit in the HFR database is potentially time-varying because it is directly related to monthly profit; hence, it is incorporated as a time-varying covariate by recalculating it in terms of monthly dollar value. See Panel A of Table 1 below for more details.

Table 1 presents summary statistics of these fund characteristics (or covariates) based on the live, dead and combined fund datasets, together with test results pertaining to differences between live and dead funds. Summary statistics for the overall covariates are given in Panel A, where each cell represents the average of the corresponding covariate values across all months and funds in the live or dead funds database, unless otherwise stated. To identify differences more precisely, monthly returns and AUM are further analyzed in terms of three fixed time horizons (1 month, 3 months and 6 months before the death of a fund) in Panel B.

The covariate statistics in Panel A of Table 1 allow for an analysis of the differences between live and dead hedge funds. Among covariates, duration, management fee, average monthly AUM, incentive fee, and average monthly return distinguish dead funds from live funds most significantly ($p < 0.0001$). Notice period, minimum investment, domiciled offshore, and high-water mark distinguish the dead from the live funds significantly ($0.0058 < p < 0.0132$), whereas hurdle rate, lockup period, redemption period, and leverage fail to distinguish between the two types of funds. These results are largely consistent with our intuitions and provide useful tips for the management of funds. For instance, the average duration of live funds is longer than that of dead funds, and average monthly AUM and returns of live funds are higher than for dead funds. Additionally, observe that the amount of minimum investment or the proportion of funds with high-water mark provisions is higher among live funds than among dead funds.

A number of useful findings can be obtained from Panel B. First, variances in AUM (returns) for dead funds are significantly lower (higher) for the three fixed time horizons compared with those for live funds. The low variances in AUM for dead funds are likely due to a significant decrease in the mean values of AUM over the three fixed time horizons (i.e., 222.53 is decreased to 67.93, 74.41 and 83.19 for 1 month, 3 months, and 6 months, respectively), while the increased variances in returns are likely due to the significant decreases in the returns of failed funds for the three fixed time horizons. Second, as expected, the average lifetime monthly return and AUM of live funds is significantly higher than the average values of monthly returns in the three fixed time hori-

2 The "live fund" dataset includes information on hedge funds that currently report to HFR.

3 The "dead fund" dataset includes information on hedge funds that have stopped reporting to HFR.

4 We exclude 341 live funds and 714 dead funds from the databases due to failure to meet the minimum observation requirement. Gregoriou (2002), Chapman et al.(2008), Ng (2008), Baba and Goko (2009), and Liang and Park (2010) employ similar minimum observation requirements and report no significant sample selection biases. In unreported work, we applied the same analysis used in this paper to funds with a minimum of 24 months of data and found no significant bias in our 36-month requirement.

5 The backfilled returns and AUM data, which cover the period before each fund initially joined the HFR databases, are removed from the databases to avoid backfill bias. Additionally, two index funds and funds-of-hedge funds are deleted from the databases to ensure that hedge funds are distinct from portfolios of hedge funds.

6 Domicile indicates whether a fund is offshore or based in the USA.