HW: Intermarket Prediction

February 16, 2025

In this HW we construct a 2-stage regression for predicting hedged CDS spread "returns" using boxcar and discounted least squares for the predictive phase, and compare the two.

1 Data

The class website contains 5 year CDS rates for debt from several companies over a multi-year range in `Liq5YCDS.delim`. Read this data, and load the corresponding adjusted close prices for the corresponding equity[1].

CDS spreads are not directly investable in the way equities are, but we can still learn a lot from treating them in ways similar to how we treat asset prices. In particular, just like equity prices, spreads are bounded below by zero and have no functional upper bound. Compute weekly Wednesday to Wednesday returns r^{Equity} on the adjusted equity close prices, and similar "returns" r^{CDS} on the CDS spreads. In addition, obtain "market equity returns" m as the weekly returns on adjusted prices of the SPY ETF.

2 Models

A *predictive* regression is aimed at predicting future behavior in some convenient way. For quantitative investment strategies, such a regression would typically be aimed at predicting asset returns or, as in this assignment, hedged asset returns. In this HW, we examine models based on the idea that idiosyncratic equity returns c are leading indicators of idiosyncratic CDS spread "returns" ρ. Our hedging to go from pure equity returns r to idiosyncratic equity returns c involves a 1-factor (CAPM) model, while the hedging of CDS spread "returns" will use a 2-factor model, against the same-company equity as well as an overall CDS market index that we construct.

We will use zero-intercept regressions, which in the case of OLS means our estimator of a regression coefficient β on independent A to predict B eschews

[1] Not all debt issuers *have* publicly traded equity. I have selected CDS rates from issuers that do.

the subtractions of the mean in our regression formula. That is,

$$\beta = (A * A)^{-1} A * B. \tag{1}$$

and we leave any constant terms out of the matrix A.

For predictive segments of the following analysis you will compare boxcar OLS window size G against exponentially decaying regression weights with half life H. Contemporaneous regressions should be boxcar OLS with window size $G \approx 10 - 30$ or exponentially decaying with similar half lives.

Begin by forming a CDS "index return" r^{Index} as the arithmetic average of the r^{CDS}.

For each ticker $E = E_1, \ldots, E_N$, you will be working with both contemporaneous and predictive models for its "spread returns". The contemporaneous model is of the form

$$r_E^{\text{CDS}} \sim r_E^{\text{Equity}} + r^{\text{Index}} + \epsilon. \tag{2}$$

Starting from the $K+1$st week of available returns, define weekly calibration data for contemporaneous returns as the returns from the K previous weeks, where in our case we tend to use $K \approx G$.

Create one contemporaneous model of the (CAPM) form

$$r_E^{\text{Equity}} \sim m + \epsilon \tag{3}$$

using G week boxcar OLS against a market indicator[2] m, and denote its weekly regression coefficients for the n-th data row as $\gamma_{E,n}$.

Also create a contemporaneous model of the form

$$r_E^{\text{CDS}} \sim r_E^{\text{Equity}} + r^{\text{Index}} + \epsilon. \tag{4}$$

using G week boxcar OLS.

For the upcoming n-th data row, we attempt to predict its change in CDS spread *hedged by the contemporaneous predictors*. Define the *hedge portfolio return* as the returns on predictors in the contemporaneous model[3]

$$f_{E,n} = \beta_{E,\text{Equity}}^{(n)} r_{E,n}^{\text{Equity}} + \beta_{E,\text{Index}}^{(n)} r_n^{\text{Index}}. \tag{5}$$

As you see $f_{E,n}$ is just a prediction from our contemporaneous model for a single data row, so it is easy to obtain.

Now we will define the *residual return*[4] as the residual error in this prediction

$$\rho_{E,n} = r_{E,n}^{\text{CDS}} - f_{E,n}. \tag{6}$$

We also define residual equity return as

$$c_{E,n} = r_{E,n}^{\text{Equity}} - \gamma_{E,n} m_n \tag{7}$$

[2]For our purposes, returns on the SPY ticker are a good choice of m.

[3]Remember that the β values depend on both the ticker and which data row n we are working with.

[4]Confusing fact: residual return is often also called "hedged return" which is dangerously similar-sounding to "hedge return".

Once we have our data series of residual returns ρ for all equities and weeks, we will form predictive regression models in exponentially decaying and boxcar forms. Create new models of the form

$$\rho_{E,n} \sim c_{E,n-1} + \epsilon \tag{8}$$

that use the past week's equity return residual to predict novel changes (i.e. residuals) to CDS spread and call the regression coefficients $\mu_{E,n}$. The residuals of the predictive model itself are

$$q_{E,n} = \rho_{E,n} - \mu_{E,n} c_{E,n-1}. \tag{9}$$

3 Opportunity

Choosing a threshold j for predicted return size, or (your choice) a quantile trading percentage p, analyze the performance of a strategy that hedges CDS spread with equity and (somehow) the CDS index. Since we are assuming hedges get done, and are ignoring costs, as position of size N will have simulated return $N \cdot \rho$.

For purposes of this exercise, you may assume CDS PL is linear in spreads, i.e. that the spreads represent some kind of total return series.

4 Analysis

Compare opportunities for a small variety of parameters decay H, boxcar G, j, and p.