Empirical Methods in Finance

Homework 2

**Question 1 (40%) Estimation of Term Structure Models**

You will find in the data section of the Blackboard course site (Homework, Assignment 2 2016) the CRSP data set about US zero-coupon Treasury and bond yields and real US GNP growth. In this assignment I ask you to estimate a term structure model with the set of bond yields provided in this data set.

You are asked to use the Gaussian discrete-time yield curve model presented in Ang, Piazzesi and Wei (2006, Journal of Econometrics).

1. First, use the two-step estimation method described in the core of the text and detailed in the Appendix (A1). In this method the vector of state variables is entirely observable since two yields are supposed to be observed without error for the first two factors and the third one is the real GNP growth series.

Utilizing the two-step estimation method as described in text core and detailed in the Appending (A1) provides us with ….

See slide 97 lecture 6 (Estimation of the Affine Model)

Imposing cross-equation restrictions implied by no-arbitrage, in a term structure model, while allowing yields to be non-normal, for this “affine model”, we assume arbitrage-free process, with affine bond yields are constant plus linear functions (affine) of some state vector. We follow a consistent “two-step” process in accordance to Ang, Piazzesi, and Wei (2006) in order to estimate the parameters of the model.

In the first step, by least squares, we estimate the VAR parameters (using standard seemingly unrelated regression, SUR. Based on the VAR parameters, and by minimizing the sum of squared fitting errors of the model, we estimate in the second step, the parameters (

For constant risk premia Ang, Piazzesi and Wei (2006) see that it only affects the constant yield coefficient which impacts the average term spreads and average expected bond returns, meanwhile, the parameter affects the factor loading as it controls the time variation in both, term spreads and expected returns.

Then for a given value of the state victor at time *t*, we compute the model-implied yields

which determines the market prices that is achieved by solving the following non-linear least-squares equations:

For market yield at *n*-period bond at time *t*, the corresponding model-implied yield is

Under the “local” expectations hypothesis, the two-step procedure is similarly used for estimating the parameters of the equilibrium-based model estimation, which takes into consideration the least-squares estimate (only) of μ and as given, as we expect to find insignificant values, while locating insignificant values when considering the equilibrium-based model to the yields data. Considering the CRRA= 1 - α, the , for , and the persistence matrix , in the second step, we solve the non-linear least-squares equation, where by constraints on the coefficients of the VARs the arbitrage absence is imposed.

From Ang, Pizzesi Wei Research

From predictability of GDP in non-arbitrage frame work perspective, Ang, Piazzesi and Wei (2006), addressed two key issues; a) the OLS approaches and the forecasts implied by their model yielding different predictions, and b) using term structure information, they investigated the preciseness of out-of-sample GDP growth predictions. Improving on the OLS GDP predictive regression, they developed what they consider a fast, dynamic and consistent two-step procedure with term structure factors as observables for their key assumption with observable yield-curve factors for consistent two-step estimation process that describes the endogenous evolution of yields and GDP. Utilizing two factors expressed at a quarterly frequency from the yield curve, the short rate, and the 5-year term spread to proxy for the “level” and “slope” of the yield curve – consecutively. Including a factor of quarterly real GDP growth with the vector of state-variables. Hence, entirely observable. They found that GDP growth is mean reverting and compared to unrestricted OLS, their model is a better out-of-sample GDP predictor. Although various contributors have run regressions spanning very long spreads (5 or 10 years), Ang, Piazzesi and Wei (2006) study 4-quarter GDP growth with the 5-year term spread lagged by 4-quarters. They find, in particular, that 16- and 20-quarter spreads predicts GDP growth, significantly, 4-quarters ahead. In closed form, their model also allows for computing of each regression specification.

They use a flexible and parsimonious factor model without the need to specify a full general equilibrium for imposing no-arbitrage restrictions. In discrete time, they set their yield-curve model with each period representing quarterly data and augmented yield-curve factors that include quarterly real GDP growth. With Gaussian vector auto-regression for the vector of sate variables where Risk premia on bonds are linear particularly the pricing kernel being conditionally log-normal. They find that parameterizing prices of risk into time-varying enables their model to match various stylized facts associated with yield-curve dynamics. They also find that incorporating macro factors, which is GDP growth in their model, allow for better out-of-sample forecasts than relying on yield-curve factors only. Notably, they did not include inflation in their basic model as they intend to make their results directly comparable to a wide range of literature using term-structure hence imposing the structure from no-arbitrage model. Lastly, they find that including inflation in the factor VAR does not provide significant out-of-sample GDP forecasts.

Opposite to OLS, in the model-implied coefficients by Ang, Piazzesi and Wei (2006) they assign more predictive power to the short rate than to term spread. Additionally, for long forecasting horizons and in univariate regressions, the point estimate of the model implied short rate coefficients are significant in univariate regressions. Their 3-factor basic framework (short rate, spread and GDP) makes it easy to accommodate more/additional factors. Since including additional factors augments the VAR in the factor structure.

Since two yields (of …. and ….. ) are supposed to be observed without error for the first two factors (of … and ) and with the third factor being the GNP growth series, the vector of state variables is entirely observable in this case

1. Second, use the estimation method by maximum likelihood proposed by Joslin et al. (2011) and for which he provides the code (available in Blackboard).

The estimation likelihood proposed by Joslin et al. (2011) suggests that (…….)…. .

Joslin et al (2011) developed a GDTSM, Gaussian Dynamic Term Structure Model, where the conditional forecasts of pricing factors are maintained. This invariance to the imposition of no-arbitrage restrictions is maintained despite the existence of a variety of restrictions on the factor structure of bond yields. They show that the GDTSM-implied forecasts of underlying factors are identical to the unrestricted vector-auto-regressive, VAR, model for *P* by developing an all-encompassing canonical model. The pricing factors *P* in the model are linear combinations of collections of yields , where they follow un-restricted VAR yield factors. Enforcing no-arbitrage has no effect on the out-of-sample forecasts as long as *P* is measured without error with the unconstrained OLS, ordinary least squares, provides the ML, maximum likelihood, . The GDTSM’s feature of no-arbitrage has no effect on the ML estimates of implying that future forecasts of *P* are identical to forecasts from an unconstrained VAR(1) model.

The authors developed what they called it their own JSZ canonical representation of GDTSMs starting with a generic representation of a GDTSM with the discrete-time of the state vector (risk factors) is governed by equations (1,2 and 3 in their paper) under one period spot interest rate and the conditional co-variance matrix of . Subject to normalizations ensuring econometric identifications, the canonical GTSM is maximally flexible in Q and P parameterization distributions of . With pricing observable factors, the underlying parameter space of P’s Q distribution fully characterized by Joslin et al (2011) also refers to linear combinations of yields as portfolios of yields.

For a zero-coupon bond with *m* maturity, the model implied yield is an affine function of the state (equation 4). Joslin et al (2011) start with “Case *P”* where for N portfolio of bond yields P in accordance with *W* weights perfectly priced by the GDTSM , hence a unique GDTSM with pricing factors for portfolios of yields is observationally equivalent to any canonical GDTSM. From the main results for Case P, theorem 1, supposing that it holds and their canonical form is parametrized by .

The goal is to prove that any GDTM is observationally equivalent to a model where the states are the observed bond portfolios. They establish the first step for any *GDTSM* with latent state, satisfying (eq. 5), apply the change of variables, then under both P and Q compute the dynamics of P*t*  while expressing *rt* as an affine function of P*t* . Noting that after change of variables, the parameters give an observationally equivalent model with the states being the portfolios of yields. In other words, in the first step, the authors establish that any model can be rotated to one with the observed states, P*t.* In the second step, the authors establish uniqueness through proving that no two *GDTSM*s in are observationally equivalent. They formalize the intuition that when two *GDTSM*s are observationally equivalent with the same factors, it must be that are the same, meaning that if the parameters ρ0ρ1) are not the same, the price of some bonds would depend differently on the factors (i.e. a contradiction). Consistent with no arbitrage and the states being the portfolios of yields , the authors additionally show that, for given, there exists a unique ρ0ρ1).Their third and final step is reparametrizing in terms of the free parameters

From the perspective of P Dynamics and Maximum Likelihood Estimation, and consistent with no-arbitrage, the JSZ normalization prescribes observable yield portfolios P and parametrized their Q distribution in a maximally flexible approach - rather than defining latent states indirectly through normalization on parameters governing the dynamics of latent states (under P or Q). Under their estimation normalization, there is an inherent separation between the parameters of the P and Q distributions of P*t*. On the other hand, and by contrast, when the risk factors are latent, estimates of the parameters governing the P distribution must depend on Q distribution estimates of the state. Since the pricing model is required to; a) either filter for the unobserved states when all bonds are measured with errors, or b) for the fitted states, invert the model when *N* bonds are priced perfectly. Hence the convenience of separating parameters in likelihood function. Hence the canonical form allows for overcoming empirical estimation challenges arising from filtering cases of GDTSMs

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**Question 2 (60%) Evaluation of Performance**

The goal of the assignment is to assess the performance of a set of funds by using the methodology developed by Barras, Scaillet and Wermers (Journal of Finance, 2010) and its extension by Ferson and Chen (2015). First read the BSW paper and the corresponding Appendix as well as the FC paper (provided on Blackboard), and spell out the steps needed to produce the final results in both papers.

Appendix (A1) provides us with ….

Starting with estimation process, the first phase of the procedure begins with determining value from the data using bootstrap procedure in order to estimate the proportion of zero-alpha funds in the population as per Storey (2002). Then forming 1,000 bootstrap replications of for each possible value through replacements from the vector of funds, M x 1, p-values. The second phase of the estimation process is determining the value from the data. Using bootstrap procedures, in order to estimate the proportions of skilled versus unskilled funds in the population, by minimizing the estimated MSE of and . Starting with computing then for each possible value of , forming 1,000 bootstrap replications of In the third phase of the estimation process, and for the two-sided test with equal tail significant level, using again bootstrap procedure in order to compute the fund (alpha) p-value. Noting the number 1,000 of bootstrap iterations. Relying on the large-sample theory, the estimation process ends with determining the standard deviation of the estimators. In this last phase, all estimators are recognized as being stochastic process indexed by both, and conversing into a Gaussian process as M (the number of funds) goes to infinity.

Following estimation, the second process consists of performing Monte Carlo analysis, under cross-sectional for both independence and dependence. For the cross-sectional independence phase, the performance of all estimators is examined accordingly by generating the vector of funds monthly excess returns, M x 1, in accordance to the four-factor model (size, market, book-to-market, as well as the momentum factors). Using the same return-generating process under cross-sectional dependence phase, the fund residuals are treated as cross-correlated with the MxM residual co-variance matrix with the constraint of positive semi-definite being imposed. Under this particular phase of dependency, three cases are considered in addition to the baseline dependence scenario; firstly examining the block dependence case, secondly utilizing the residual factor specifications for capturing the role non-priced factors, and thirdly by considering the case of extreme dependency of only 898 fund population since all funds are cross-correlated.

The process continues with further methodology analysis consisting of three phases. In the first phase the proportions of zero-alpha funds and the p-value histogram are examined through modification of fund p-values histogram by considering two different fund populations with one population containing zero-alpha funds only and the other containing 75% zero-alpha with the remaining 25% from skilled funds. In the second phase, a comparison between the bootstrap and fixed-value procedures takes place where the threshold is used for estimating the proportion of zero-alpha funds for determining the number of funds (setting at 0.5 and 0.6 respectively for each procedure). Also, the significant level is determined in this phase in order to determine the proportion of skilled and unskilled funds. The second phase ends by comparing the results of the two approaches; bootstrap with fixed value. The methodology analysis ends with comparing the approach of false discovery rate, FDR, with existing methods by assessing sensitivity to changes in through measuring the proportions of extreme left/right tails (unlucky/lucky and unskilled/skilled) of the cross-sectional by plotting the different relations and utilizing a significance level equaling 0.10.

The empirical results based on the above three processes include; robustness test by performing sensitivity analysis and measuring the impact of luck on long-term performance using a sample of funds having at least 60 monthly return observations, then repeating the analysis while reducing the monthly return observations to 36 months. Another robustness test is performed by using the conditional four-factor model. Following robustness, long-term performance analysis across investment categories are conducted for individual investment objective categories consisting of; Growth, Aggressive Growth, Growth & Income sub-groups with the later category containing the highest proportion of unskilled funds with the lowest performance among categories. Additionally, the evolution of skilled and unskilled mutual fund over time performance is examined pre-expense (by adding the monthly expense of each fund to its return). This examination revealed a reduction in the net-expense skills that is mostly driven by a decline is stock-picking skills overtime. In place of controlling false discovery rate, FDR, following a Bayesian perspective, the last phase consists of minimizing the loss function of the investor. In this approach, a Bayesian investor becomes subject to two kinds of misclassifications in the portfolio; wrong inclusion of a zero-alpha fund (reject while it is true), or failure to include a skilled fund (accept while it is wrong). The analysis conclude with choosing a very high significant level (i.e. including the vast majority of the skilled funds in the portfolio) which means that the behavior of a Bayesian investor is consistent with high FDR target.

In their extension, Ferson and Chen (2015).

To find the proportion of positive and negative alpha mutual funds, Ferson and Chen, FC, (2015) extend the model of BSW (2010) as they take into account various hypothesis tests for a population of funds consisting of three sub-populations in terms of alphas; zero-alpha, positive-alpha for good funds and negative-alpha for bad funds. These test, which is not considered in BSW (2010) model, could classify –falsely- bad funds as good and good funds as bad. FC estimate the alpha location of the fund group simultaneously with the fractions of the funds within each group. With the difficulties associated with accommodating the differential information of investors and managers correctly, as well as non-linear payoffs biases, market incompleteness, and time-varying model parameters, the standard benchmark might not capture co-variances of return of investor funds, their paper uses standard alphas as they develop their methodology for classification of funds.

Since the estimation of fund groups’ alpha locations are crucial in evaluating the attractiveness of fund selection, expected alphas of the fund groups and the probability of selecting a particular fund are of a particular significance. Building on more of BSW probability structure, FC show that estimating alpha locations of the fund groups as well as the fractions the funds in each group while accounting for multiple comparisons simultaneously lead to improved decision making. For mutual funds, and consistent with Berk and Green, BG, (2004) equilibrium, they find that the best fund’s alphas are centered near zero, with zero alpha for expected fund selection and small incentive for searching for good funds. On the other hand, it might be worthwhile to actively engage in fund selection if alphas of the good funds are centered around large values economically. According to BG (2002), “In equilibrium, investors who choose to invest with active managers cannot expect to receive positive excess returns on a risk-adjusted basis. If they did, there would be an excess supply of capital to those managers”.

In BSW (2010), the standard alphas are measured after fund costs, while not net of investor’s costs which include information costs necessary to select and monitor fund(s) in addition to their pre-tax costs. Which becomes a separation problem of association with true performance from luck when some of these costs are fixed. While applying their approach to US equity mutual funds during 1984-2011, the main attempt of FC (2015) model is to refine the separation of skill and luck by detecting positive-alpha funds in simulations with known fractions of zero and positive alpha funds while showing that the BSW estimator is a special case of their approach. Under the assumption of 100% test power, alpha>0 for good funds and alpha<0 for bad funds with no confusion. As they estimate the model on rolling 60 months windows for over-time parameters trends with the assumption that funds are drawn from one of three distributions centered at different alphas with the rolling window reflecting performance worsening overtime.

The key steps of FC (2015) model consist of; hypothetical densities with the three sub-populations of funds, parameters estimation in three stages using three simulations for parameters estimation, then cross-sectional estimation of mutual funds’ alphas while imposing the null hypothesis that all alphas are zero which producing two-critical values of t-statistics. Following the first estimation is imposing the alternative hypothesis that alphas are centered at >0 for good funds while including an additional variable for the confusion parameter. The alternative hypothesis that the funds are bad is utilized in the third simulation that alphas are centered values <0 for finding bad funds. In FC’s approach bad, or good, funds has a single value of alphas with robust capability to model random bad and good alphas centered around bad and good alphas.

Secondly, in the actual data, they combine the simulation estimates with cross-sectional fund results assuming with enough simulation trials they can determine the parameters with zero errors. Lastly, locating the best-fitting alpha values in their research. Noting that at these parameter values, a mixture of distributions is implied by the model for fund return’s cross section. Searching for the alpha value choices until the simulated mixture distribution generates a cross-section of alpha fund estimates that best matches cross-sectional t-ratios of estimated in actual data.

FC’s estimators provide full structure of probability model as it generalizes BSW estimator which is obtained as a special case of BSW when taking two assumptions; first test has 100% power which biases the estimates in favor of locating too many zero alpha funds meaning low test power, and second test is arriving at BSW as a special case with zero confusion of close location of good and bad alphas. In their study, they picked funds reporting net-of-fee US dollar returns, mitigating backfill bias by removing the first 24 moths of returns as well as returns before funds entered the database.

Is FC good extension of not necessary?

In their well described and data analyzed research, among their findings, FC claim that with the improved power of their CF model, it is rather “costly” due to more false discoveries than that that of the FDR model, or the classical t-ratio model while indicating the possibility for assigning utility costs to various cases of potential misclassification which will intrinsically affect their methodology through a trade-off between correct and false discoveries. Although their model offered an important key improvement, their conclusion is concerning particularly as it comes from the creators of the FC model themselves which warrants careful consideration of the application of their model.

Need to elaborate more on their approach and the risks as per identified above weakness.

* Make a link on how to assess the performance of a set of funds by using the methodology developed by BSW. Why it is unique and important.
* What are the steps needed to produce the final results in both papers.

Program the methodologies and apply them to the alphas and t-statistics of the provided set of returns of funds on Blackboard in DataHF (File FoF.xlsx).

List the methodologies

Program them and state how they are programmed

Apply them to the alphas and t-stats

State how do you apply them to the alphas and t-stats

To compute fund performance, ***use the benchmark model of Fung and Hsieh*** (Review of Financial Studies, 2001) as follows:

where denotes the excess returns of the hedge fund or index to be explained, *SNPexc* is the monthly return on the S&P 500 minus the 1-month T-bill, *SML* is the Russell 2000 index total monthly return minus the S&P 500 total monthly return, *MSCIem* is the monthly total return on the MSCI Emerging Markets index, *RBD10* is the change in constant maturity yield 10-year Treasury bond, *BAAMBD10* is the change in the spread between Moody's BAA and the 10-year Treasury, and finally the returns on three Primitive trend following strategies (PTFS) for bonds (BD), currency (FX), and commodities (COM). These factors are there to capture nonlinear exposures to bonds, currencies and commodities.

What is the benchmark model of Fung and Hsieh (2004)

In an Asset-Based-Style, ABS, factor model distinguishing between returns derived from alternative alphas (hedge fund alphas) and alternative betas (systematic risks), Fung and Hsieh (2004) start by extracting common sources of risk factors in hedge funds, then link them to observable market prices. In their model, where the common source of return is the systematic part, betas are permitted to vary over time and equity risk factors modeled using CAPM (Capital Asset Pricing Model), or APT (Arbitrage Pricing Theory).

With conventional models relying on the assumption that assets are homogenous with “hold-on” as the dominating investing strategy, the authors argue that hedge funds performance characteristics are of diverse nature with dynamic investment nature. In their approach, FH (2004) start their process with extracting common resources of return risk in hedge funds, then link them to observable market prices calling them identifiable ABS risk factors and using them to construct an APT-like model for hedge fund risk-factor with betas permitted to vary over time. With the possibility of a significant payoff in accordance to these models, equity factors can be modeled using CAMP, or APT. Since the systematic part is the common source of return, it is the market portfolio in CAPM, while it is the same for APT in addition to other risk factors as interest rate spread.

As investors are concerned with the common sources of equity risk in portfolios, the authors find their hedge fund risk-factor model helps investors identify commons sources of risk in a familiar setting utilizing conventional asset prices like ABS factors. The seven risk factors identified by FH are; two equity risk factors for long/short hedge funds, two interest rate related risk factors for which fixed income hedge funds are exposed to, and three risk factors stemming from portfolios of options for trend-following funds.

Additionally, the authors draw to attention the key element of hedge funds selection bias which, unlike mutual funds, are not required to publically disclose their activities, and that their data are largely collected by date vendors in addition to the possibility of selection bias for date sample being not representative of the universe. From survival bias perspective, the majority of hedge funds datasets are provided for live/operating funds only, with performance of disappearing funds worsening overtime than surviving funds. Another form of bias is that of instant history that arises when a fund enters a data base with its history immediately appended to the database for past performance with the possibility of backfilling funds and upward biases.

In order to reduce the above biases, FH suggested using the returns of funds-of-hedge funds since the performance of a particular fund will still be reflected as part of the fund of hedge funds’ performance. Additionally, the historical return will ensure reducing survivorship bias and eliminate the instant history bias. Other drawbacks associated with hedge funds are that of its short history since its data starts in the 1990s with lack of transparency due to disclosure absence. Skewness of distribution of assets among hedge funds is another challenging aspect of hedge funds as managers are skewed towards the top funds. Additionally, the absence of explicit objectives makes it difficult to reach an optimal solution to combine hedge fund managers to form an index suitable for all investors.

Rather than hedge fund returns, FH construct their benchmarks based on asset returns linking hedge funds common components of returns to observable market risk factors. Using a statistical procedures named principle components for extracting common components of hedge fund returns while calling them “return-based” style factor while using “asset-based” as an identifier for models involving observable market risk factors only. Finding five most important common components accounting for about 50% of covariations among funds while grouping funds with correlated returns, when traded similar assets in similar manner, the common return component is the correlated part. Also, they show that option portfolios have return characteristic that are very similar as they constructed five portfolios of lookback options from exchange-traded options.

FH found the seven risk factor is 57% TASS hedge funds and 37% in HFR with the portfolios of lookback options on bonds, currencies and commodities as significant drivers in trend-following funds which tend to benefit during equity market conditions that are stressing. Using HFR funds-of-funds and regressing from 1994 until 2002 on the seven hedge fund factors; two equity (SP500 and SC-LC), two interest rate risk factors (change in yield of 10 year treasury and change in credit spread), and three trend-following factors (portfolio returns on options on currencies, long term bonds an commodities). Noting the stressful market events for the period of 1994 to 2002, causing betas of their risk factor model to shift over time. Testing the stability of their ABS factors betas, they ran regression backwards starting in December 2002 while adding observations one month at a time as they looked for sample breakpoint and as the information is likely to decline with the age of the return observations. Noting the unbiased way of sample identification breakpoint due to exogenous market events to regression equations. Their model provided insightful clues with respect to hedge-fund bets place as they varied over time and if any added value beyond systematic bets on the ABS factors.

In order to gain insight on time varying bets and weather they are a derivative of systematic shifts, or a consequence of management strategy, the authors applied the same analysis to standard hedge fund indices using the established risk factors. First, to explore the criteria of existing hedge funds indices, they applied the ABS factors. The results revealed that risk factor models, can identify database differences from standard provides of hedge fund data with the ability to differentiate which database is dominated by hedge funds with equity-related bets, and other database with better balance between funds that have interest-related bets and the others with equity-related bets.

Additionally, on a reserved time scale, they applied cumulative recursive residual technique in order to detect regime changes in the risk factor model. Finding that for the two equity ABS factors, all three indices reflected statistically significant betas and declining ABS betas equity for the second sub-period.

They conclude with the behavior of alpha, the intercept terms where all three indices showing significant alphas for both sub-periods with small alpha decline in the second sub-period. Concluding that among hedge funds, after adjusting for systematic risk factors, there is a statistically reliable alpha loss from the industry’s average to the average fund-of-funds. Consequently, and analyzing the possibility of unrealistic index construction rules creating alphas, or possibility of structural costs in managing very large hedge fund portfolio, or poor performing funds-of-hedge funds. Noting the unrealistic cost advantage in portfolio rebalancing created by artificial rebalancing rules with possibilities of too many inefficient funds-of-hedge funds with significantly large number in the database (>500 in HFR). Appling the model to data not used in the model’s structure, out-of-sample, and finding that the equity exposures is the major difference among indices with the accuracy of the model dependent on the index’ structure.

Although the seven hedge risk factors, using conventional securities prices, can explain a considerable part of systematic risk for typical hedge fund portfolio, FH discuss the limitations of the model in terms of assessing the exposure of a diversified hedge fund portfolio claiming the lack of uniqueness in their model with respect to the risk factors and that another set of highly correlated variables to the seven risk factors can produce similar results. Another limitation is lack of explanation of performance niche styles by the model. In other words, similar to equity models, the necessary need to construct another set of additional risk factors specific to certain styles. At the end, FH recommend having individual fund exposures to a set of common market risk factors in order to assist the investor to better design hedge fund portfolios as they set suitable and relevant performance benchmarks and manage risk. It also helps hedge fund managers to communicate the strategy’s inherit systematic risk to investors. It will be good for regulators also in terms of collecting exposure of risk factors from the different market participants, particularly for highly-levered institutions in terms of risk exposure.

what are the key elements of this model

How is it used for homework model(s)

Data for these factors are provided on Blackboard in DataHF (File factors.xlsx). **To construct excess returns use the one-month T-bill in the CRSP file for Part 1 of the assignment.**

To run these regressions, choose and justify the minimum number of return months you will require to compute the alpha of the fund.

What is the minimum number of return months?

Why did you choose this number of months?

Why does it make sense that this minimum number?

What type of results do you anticipate by your choice?

Why it is reliable?

Report and discuss the results of your analysis.

State results

Analyze results

Are the results in agreement with what was expected?

Why do you believe that the results are reliable?

Most importantly, position yourself on the extension of the SBW methodology proposed by FC.

What does the extension of the SBW methodology proposed by FC suggests?

How will it impact your results?

Is it statistically sound?

Are the results of the regression based on FC procedures sound?

Do they pass the parameters, or predictability measures and expectations suggested as covered in core class?

Do they pass the steps covered by SBW?

Do you trust the results?

If not, why?

How about errors..etc.?

Do you see a major problem with it or do you feel it is a needed improvement to the original methodology of SBW?

Compare results of FC to results of SBW

Are there any problems with it?

What is its biggest problem/issue?

Was there any added value of FC to the SBW?

Is the added value worth it?

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