University of Auckland
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Direct Hedge Portfolio Excess Return Maximisation using Deep Neural Networks

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Abstract

The publication by Gu et al. (2020) illustrates the improvement to empirical asset pricing via machine learning. Machine learning algorithms capture non-linear associations between factors not feasible by other asset pricing method. Non-linear associations may exist in constructing hedge portfolios absent when predicting excess returns from individual equities. Subsequently, we ask can neural networks configured to maximise hedge portfolios outperform standard loss minimisation configurations, when predicting one month lead excess returns using a long-short zero cost investment strategy? The data used is factor portfolio dataset from Hou et al. (2020), developed by Jensen et al. (2021) with training, testing, and validation sets of 532218, 294581, and 531461 global equity firm-year observations across 160 features, chronological divided between 1961-1989, 1990-1999, and 2000-2020, respectively. The maximisation function is a non-convex function seeking to maximise hedge portfolio returns, with hedge portfolio weights determined by a monotonic ranking function mapping. The selected mapping weights individual equities by the proportion of their contributions to aggregate returns of all equities in a given month, considering all equities in the portfolio. After model training and evaluation, the trained models are accruate, but do not outperform models trained using conventional loss minimisation functions. However, limitations render the research question inconclusive at this time.

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1 Introduction

Factor-based models feature prominently in finance literature, in forms of cross-sectional analysis on expected returns as a function of stock level characters. Another form is the surveillance of return time-series. However, limitations exist for both traditional methods in consideration a large set of characteristics or periods. Proliferating data, advancement in computing, and accessibility to technology led to a wide adoption of artificial intelligence and machine learning. The pivotal publication by Gu et al. (2020) illustrates the improvement to empirical asset pricing via machine learning. However, interpretability issues persist given the nature, opacity, and complexity of underlying algorithms and associations. Fortunately, acceptance continues to improve. Data science in finance continues to evolve in academic and industry-related uses. Most machine learning applications in equity return predictions, and finance in general, use a traditional loss function. A handful of researchers explore custom loss minimisation functions in machine learning applications, but none from the perspective of maximising hedge portfolio excess returns as far as can be told.

Our main motivation roots itself in economic significance. Investors' interests lie in maximising the hedge portfolio excess returns from their hedging strategies. Machine learning algorithms capture non-linear associations between factors not feasible by other asset pricing method. Non-linear associations may exist in constructing hedge portfolios absent when predicting excess returns from individual equities. Subsequently, we ask can neural networks configured to maximise hedge portfolios outperform standard loss minimisation configurations, when predicting one month lead excess returns using a long-short zero cost investment strategy?

Hou et al. (2020) use an extensive data library to assess 452 anomalies across anomalies literature. Jensen et al., 2021 use the above dataset to explore hierarchical bayesian models of alphas emphasising the joint behaviours of factors, and provide an alternative multiple testing adjustment, more powerful than common methods. The complete global dataset has 406 characteristics, a superset of the original 153 in Jensen et al., with

2,739,928 firm-year observations, from January 1st 1961 to December 31st 2020. One month lead excess returns is the target variable for prediction, informing hedge portfolios construction to assess the relative performance between loss functions. The exhaustive nature and accessibility of the global dataset makes it well-suited for exploring maximising monthly hedge portfolio excess returns in deep neural-networks. Neural networks demand the partitioning of the dataset into training, validation, and testing subsets. The initial training, testing, and validation sets consist of **1031516**, **706908**, and **1001504** global equity firm-year observations across 406 features, respectively. The division of subsets is chronological with firm-year observations [1961-1990), [1990-2000), [2000-2020] for training, validation, and testing, respectively. The training, testing, and validation sets are reduced to consist of **532218**, **294581**, and **531461** global equity firm-year observations across 160 features after revisions, respectively.

Cloud-centric computational infrastructure performs data processing and analysis. Deep neural networks require tensors as inputs for fitting, training, and evaluating data. Normalisation and encoding processes transform the aforementioned dataset into a tensor format. Artificial Neural Nets (ANN) frequently outperform other machine learning algorithms on large and complex problems. The architecture of the network is derivative of intended use. The neural network configuration for analysis has three hidden dense layers with ReLU activation functions, an output layer with a linear activation function, a dropour layer to prevent overfitting, and a stochastic gradient descent optimiser. This network has the optimal layer density as per Gu et al. (2020). Loss functions map an event or variable set, onto a real number, intuitively representing some loss, associated with the event e.g., difference between predicted and realised excess returns. The relative performance between conventional minimisation loss functions, and maximisation of hedge portfolio excess returns, relies on comparing derivatives to these objectives. The analysis tests three loss functions. First, a mean squared error measure optimised for Tensorflow. Second, a custom squared error function to ensure automatic differentiation functionalities in Tensorflow. Last, a non-convex function seeking to maximise hedge portfolio returns with hedge portfolio weights determined by a monotonic ranking function mapping. The selected mapping weights individual equities by the proportion of their contributions to aggregate returns of all equities in a given month, considering all equities in the portfolio. Performance metrics inform comparisons between loss functions, calculated by:

First, the trained models predict one month lead excess returns for each instance (firm-year observation) in the testing dataset. Second, standard monthly sorts of predicted one month lead excess returns form standard tercile hedge portfolios, using a long-short zero cost investment, per month. Third, use hedge portfolios to calculate the hedge portfolio mean, sharpe ratio, and treynor ratio across all months. Last, Ordinary least squares regressions, incorporating Newey-West estimators and six month lags, calculating coefficients between realised and predicted individual stock returns, and alpha on from the Capital Asset Pricing Model, and Fama-French Factors.

Both the $MSE(\hat{y}$,y) and $MSE_{Custom}(\hat{y}$,y) final training losses are near identical at 0.011 and 0.010, respectively. The pattern for validation losses is similar at 0.017 and 0.014 for $MSE(\hat{y}$,y) and $MSE_{Custom}(\hat{y}$,y), respectively. The Hedge Portfolio loss function has a minimum training and validation loss of 0.01 and 0.001 before running for a further three epochs before early termination, respectively. The learning curves fit well. The F Statistic on all tests in regressing actual individual excess returns on prediction is highly statistically significant at the one percent level, verifying realised returns are derivative of predictions. The training losses, validation losses, learning curves, and regressed realised returns on predictions show evidence of appropriate fitting. This confirms the first hypothesis in our motivations that maximising hedge portfolio returns is feasible as an optimisation function in a neural network.

The hedge portfolio means for $MSE(\hat{y}$,y), $MSE_{Custom}(\hat{y}$,y), and Hedge Portfolio ($\hat{y}$) loss functions are 0.0424, 0.0764 and, -0.0168 per month, respectively. These raise concern given they exceed observations from prior literature. However, these may be caused by data reductions further described in the main text. The sharpe ratios for both MSE variants are feasible at 1.15 to 1.45 for $MSE(\hat{y}$,y), and $MSE_{Custom}(\hat{y}$,y). Ultimately,

-0.016803 and -0.714680 for hedge portfolio mean and sharpe ratio shows the hedge portfolio maximisation strategy does not outperform traditional loss minimisation regardless of accuracy. $MSE(\hat{y}$,y) (table 5), $MSE_{Custom}(\hat{y}$,y) (6), and Hedge Portfolio ($\hat{y}$) (7) neural networks generate portfolios which align with their hedge portfolio means, across all factor models, statistical significant at the 1% level. The MSE variants only have highly statistical significant negative market premia factors, and the Hedge portfolio have statistical significant negative RMW and SMB in FF4 and FF5 (5% level). The sample period, incomplete dataset, shorting positions in the hedge portfolios, and capped weighting methodology may be driving these results. Regardless, the results are inconclusive in assessing relative performance. However, if they were, the hedge portfolio maximisation strategy would not outperform traditional loss minimisation techniques.

The analysis and outcome show maximisation strategies are feasible from a technical perspective. This is a partial, novel contribution to the literature. Another minor contribution is the validation of using of factor portfolio dataset for this form of analysis. However, the limitation relating to resources, data revisions, optimisation functions, neural network architecture, and simulations render the research question inconclusive at this stage. Further analysis will continue to work towards exploring and resolving these issues in the next chapter. The subsequent sections appear as follows: Literature (2), Motivation (3), Methodology (4), Results (5), Research Implications (7), Conclusion (8), and Appendix (9).[1]

[1] The appendix include documentation on the programming necessary to complete analysis (50+ custom functions and classes), accessible on Github

2 Literature

2.1 Asset Pricing

Literature on stock return predictability typically takes on of two forms. First, cross-sectional analysis on expected returns as a function of stock level characters (Fama and French, 2008). Second, surveillance of return time-series (Koijen and Van Nieuwerburgh, 2011,D. Rapach and Zhou, 2013). Factor-based models feature prominently in finance literature. Most models are derivative of the Capital Asset Pricing Model (CAPM), assessing exposure to systematic risk. Use persists, regardless of the invalidation from identifiable shortcomings in market proxies and empirical failings (Fama and French, 2004). E. Fama and K. French (1992) validate the substantial explanatory power of size and value (book-to-market) factors in their ability to capture the cross-sectional variation in average stock returns, in association with market risk, size, leverage, book-to-market, and earnings-price ratios. Size and value factors continue feature in factor models. E. Fama and K. French further their analysis on the common characteristics between stocks and bonds (Fama and French, 2021)[2], and add two additional factors to consider profitability and investment. E. Fama and K. French consider a momentum factor on international stock returns in subsequent years (Fama and French, 2012). The omission of momentum from models stand. E. Fama, with J. MacBeth, developed the Fama-MacBeth regression (Fama and MacBeth, 1973) to estimate factor loadings and prices. The methodology is a two-stage estimation process, similar for estimating factor loadings, and prices, for a given portfolio. The first step requires determining each asset's β exposures by regressing each of n asset returns against m proposed 35. The second step determines the risk premium (factor pricing) for each asset by regressing all asset returns for each of T periods against previously estimated βs (36). This methodology enables the estimation of unconventional factors e.g. seasonalities in mood (Hirshleifer et al., 2020), carbon risk (Bolton and Kacperczyk, 2021) etc. However, limitations exist for both traditional methods in consideration a large set of characteristics or periods.

[2]Reprinted. Originally published in 1993

2.2 Machine Learning in Finance

Proliferating data, advancement in computing, and accessibility to technology led to a wide adoption of artificial intelligence and machine learning. The pivotal publication by Gu et al (2020) illustrates the improvement to empirical asset pricing via machine learning. In summary,

1. Machine learning shows great promise for empirical asset pricing,
2. Vast predictor sets are viable for linear prediction when using either penalisation or dimension reduction.
3. Allowing for non-linearities substantially improves predictions.
4. Shallow learning outperforms deeper learning. In particular, neural network performance peaks at three layers.
5. The distance between non-linear methods and the benchmark widens when predicting portfolio returns.
6. The economic gains from machine learning are large.
7. The most successful predictors are price trends, volatility, and liquidity.
8. Simulations improve machine learning findings.

Researchers sporadically investigated utilising machine learning in financial contexts. Rapach et al. (2013) predict global equity market returns using lagged returns, of all countries, with a lasso algorithm. Multiple academics explore forecasting derivative prices using neural networks (Fleck et al., 1994, Cai et al., 2000). Regression trees predict consumer credit card delinquencies and defaults (Khandani et al., 2010, Butaru et al., 2016). Predicting mortgage risk with neural networks (Sirignano et al., 2016). Revise the multiple comparisons problem using bootstrap procedures (Harvey et al., 2016). Factor pricing estimations using dimensionality reduction (Feng et al., 2020). Application of tree-based models to portfolio sorts (Moritz and Zimmermann, 2016). Measuring corporate culture using natural language processing (Li et al., 2020). However, interpretability issues persist given the nature, opacity, and complexity of underlying algorithms and associations. Fortunately, acceptance continues to improve, with highly reputable journals e.g., The Journal of Finance, The Review of Financial Studies etc. are publishing intersections between finance and machine learning with increasing frequency. Data science in finance continues to evolve in academic and industry-related uses.

2.3 Loss Functions

Most machine learning applications in equity return predictions, and finance in general, use a traditional loss function. A subset of related literature considers customised loss functions. Gu et al. (2020) test various functions including mean squared error (MSE) (weighted and unweighted), and huber loss functions mixing MSE and mean absolute error (MAE). Lim et al. (2019) investigate enhancing time-series momentum strategies using neural networks with MSE loss functions enriched with a Sharpe ratio-based regulation. Zhou et al. (2018) assess a combination of forecasting error loss and MSE when predicting stock market prices on high-frequency data. However, the subset of custom loss functions for predicting stock returns is small. There is an investigation into the minimisation of hedging loss in options trading strategies (Ruf and Wang, 2021) Reinforcement learning methods attempt to optimise financial portfolios after dimensionality reduction but do not apply maximisation in consideration of an aggregate hedge portfolio (Soleymani and Paquet, 2020).

3 Motivation

3.1 Research Question

Our main motivation roots itself in economic significance. Machine learning algorithms rely on the minimisation of a loss function, making predictions on target variables in relation to their realisations on known, in-sample, factors. The model learns factor contributions to the targets during the training process, fine-tunes model parameters in the validation phase, and evaluate out-of-sample instances. Subsequently, the model makes predictions on unlabelled instances to estimate labels. In financial contexts, asset pricing factors and excess returns are factors and targets, respectively. Trading strategies rely on hedge portfolios to diversify idiosyncratic risk and maximise returns. Hedge portfolio excess returns are derivative of the individual equity excess returns. Subsequently, investors' interests lie in maximising the hedge portfolio excess returns from their hedging strategies. Machine learning algorithms capture non-linear associations between factors not feasible by other asset pricing method. Non-linear associations may exist in constructing hedge portfolios absent when predicting excess returns from individual equities. The inclusion of a hedge portfolio maximisation strategy to directly maximise hedge portfolio excess returns is novel at time of writing. Subsequently, we ask:

Can neural networks configured to maximise hedge portfolios outperform standard loss minimisation configurations, when predicting one month lead excess returns using a long-short zero cost investment strategy?

3.2 Hypotheses

1. It is feasible to implement maximisation strategies in machine learning algorithms given $\arg\max f(x) = \arg\min -f(x)$
2. A hedge portfolio maximisation strategy will not outperform loss minimisation strategies given model architecture.

Both relate to the research question. Hypothesis one is elementary. Neural networks are optimised for loss minimisation objective. A maximisation criteria, with no reference to a realisation, may create complications in hypothesis two. Subsequently, our analysis aims to prove and disprove hypothesis one and two, respectively.

4 Methodology

A comprehensive outline of the methodology follows.

4.1 Data

4.1.1 Global Factors Dataset

Hou et al., (2020) use an extensive data library to assess 452 anomalies across anomalies literature. Their analysis informs which anomalies drive the cross-section of expected returns. Most abnormalities fail under current standards of empirical finance when using a single hurdle test of absolute t-stat greater or equal to 1.96. Firstly, the paper finds economic fundamentals take precedence over trading frictions in explanatory power, statistical and economic significance. Secondly, micro-caps account for anomalies disproportionately, leading to NYSE breakpoints, value-weighted returns in both portfolio sorts and cross-sectional regressions with weighted least squares. Lastly, arguments in improving anomalies literature credibility follow a closer alignment to economic theory as the field persists to be statistical in nature. Overall, capital market efficiency is higher than expected. Jensen et al. 2021 use the above dataset to explore hierarchical bayesian models of alphas emphasising the joint behaviours of factors, and provide an alternative multiple testing adjustment, more powerful than common methods. Jensen et al., adapt the global dataset to focus only on one-month holding periods for all factors, only include most recent accounting data (quarterly or annually) and add 15 new factors. Section 9.9 describes factor composition, resources for data acquisition, and summary statistics. The complete global dataset has 406 characteristics, a superset of the original 153 in Jensen et al., with 2,739,928 firm-year observations, from January 1st 1961 to December 31st 2020. Subsequently, the complete dataset has 1.112 billion data points. **One month lead excess returns**[3] is the target variable for prediction, informing hedge portfolios construction to assess the relative performance between loss functions. Factors in month

[3]O ret_exc_lead1m = RET-T30RET)/21 from CRSP, extracted using WRDS. T30 is the treasury yield rate. If T30RET is unavailable, is used instead RF. If the return is a daily return rather than a monthly return, (RET - T30RET) is divided by 1 rather than 21.

t predict the excess returns in month t + 1 (e.g., one month lead excess return). The exhaustive nature and accessibility of the global dataset makes it well-suited for exploring maximising monthly hedge portfolio excess returns in deep neural-networks.

4.1.2 Processing

Neural networks demand the partitioning of the dataset into training, validation, and testing subsets. The initial training, testing, and validation sets consist of **1031516**, **706908**, and **1001504** global equity firm-year observations across 406 features, respectively. The division of subsets is chronological with firm-year observations [1961-1990), [1990-2000), [2000-2020] for training, validation, and testing, respectively. Two reasons rationalise the reduction in the number of factors from 406 in the Jensen et al., (2021) superset to 153, and the removal of firm-year observations with Micro or Nano size grouping [4] designations. Firstly, the retention of equities between 20th to 100th percentiles appeals to economic significance. The composition of aggregate market capitalisation is mostly from their contribution. Additionally, their higher liquidity increases the likelihood of analyst coverage and portfolio inclusion. Secondly, factor reduction appeals to parsimony in aligning explanatory variables to prior studies. The training, testing, and validation sets consist of **532218**, **294581**, and **531461** global equity firm-year observations across 160 features after above revisions, respectively. Subsequently, the revised dataset has 217,321,600 data points. Tables 9, 11, and 10 in section 9.9.4 describe summary statistics and factor retention after subset revision.

4.1.3 Cloud Infrastructure

Cloud-centric computational infrastructure performs data processing and analysis. Google Cloud Platform Cloud Storage buckets and Compute Engine virtual machine (VM) instances manage large datasets and build, train, and evaluate deep neural networks, respectively. Cryptographic network protocols, mostly secure shells, establish remote connec-

[4] Mega, Large, and Small remain, reflecting equities with market capitalisations greater than the 80th, 50th, and 20th percentile of all NYSE stocks, respectively. Micro equities reside between the 1st and 20th percentiles, with Nano between below the 1st percentile. The percentiles are non-overlapping and value weighted by market capitalisation on the New York Stock Exchange (NYSE).

tivity between local and remote infrastructure to communicate and execute commands. However, use of cloud computing does not resolve all resource constraints. [5] Section 9.7 elaborates on cloud infrastructure and further technologies.

4.2 Tensor Processing

4.2.1 Normalisation & Feature Encoding

Deep neural networks require tensors as inputs for fitting, training, and evaluating data. A tensor is a mathematical object describing the physical properties of an object with multilinear relationships between sets of algebraic objects related in vector space. Furthermore, transformation laws govern tensors. Therefore, a tensor is considered an n dimensional array in conjunction with associated transformation laws. The dataset, also known as the feature matrix ($\mathbf{X}$), must take the form of a tensor. The enumeration of a tensor conversion process for each data subset follows:

1. Identify target variable(s) for fitting, validation, and prediction.
2. Configure dataset into a series of tensor slices.
3. Shuffle instances in convert dataset to promotes better training as accommodates randomness.
4. Instantiate an input tensor layer and use to extract required normalisation or encoding layer per feature .
5. Normalise each numerical feature to zero mean/unit variance, and encode [6] each categorical feature, using encoding layers to form encoded features.
6. Combine instantiated input tensors (4) into one set, serving as the inputs for a configured neural network.
7. Concatenate all encoded features into an aggregate input tensor for an unconfigured neural network. The concatenation serves as the input layer when configuring a neural network.

The revised datasets consist of eight categorical features [7] and 152 numerical features.

[5] Resource constraints inhibit exploration of the entire dataset within reasonable timeframes at reasonable costs. The most material inhibitions are the inability to explore all 406 factors for all size groupings, the reduction in level of precision for numerical features, and the ability to shuffle training sets at lengths greater than or equal to the input sets when training neural networks. However, the reasons necessitating factor reduction and size grouping exclusion stated in section 9.9.3 superseed resource constraints.

[6] Encoding transforms categorical features instances into a series of binary variables. These may be one-hot encoded, and/or stored in sparse tensors, depending on input and desired application.

[7] Descriptions of the eight categorical features follow. **size_group**, the aforementioned size grouping in section . **permno**, permanent unique firm identifier from CRSP. **permco**, permanent unique issue identifier from CRSP. **crsp_shrcd**, CRSP share code. **crsp_exchcd**,Compustat stock exchange code. **sic**,Firm SIC industry. **ff49**, Classification of stocks in 49 industry groups, based on SIC codes and the

4.3 Neural Networks

4.3.1 Activation Functions, Linear Threshold Units, & Perceptrons

Artificial Neural Nets (ANN) frequently outperform other machine learning algorithms on large and complex problems. Linear threshold units (LTU) compose neural networks, feeding the weighted sum of input values (1) into an activation (step) function (2). A perceptron is a single layer of LTUs connected to every input, suitable for both regression and classification tasks. Perceptrons utilise a training algorithm to assess the strength of connections between perceptrons in consideration of errors. A perceptron feeds one training instance sequentially, making predictions for each instance. For every output LTU that produced a wrong prediction, it re-enforces the connection weights using the perception learning rule (3) from the inputs that would have contributed to the right prediction. One input perceptron, multiple hidden perceptrons, and an output perceptron create a Multi Layer Perceptron (MLP). A non-linear activation function [8] (i.e.,Logistic (4), Rectified Linear Unit (ReLU) (5)) replaces the step functions for an LTU, in each perceptron, in an MLP. A shared activation function replaces the individual activation functions in the output layer to enable exclusive classification or regression.

$$\mathbf{z} = \mathbf{w}^T \cdot \mathbf{x} \qquad (1) \qquad h_w(\mathbf{x}) = step(\mathbf{z}) \qquad (2) \qquad w_{i,j}^{\text{next step}} = w_{i,j} + \eta(\hat{y}_j - y_j)x_i \qquad (3)$$

$$\sigma(\mathbf{z}) = \frac{1}{1 + exp(-\mathbf{z})} \qquad (4) \qquad ReLU(\mathbf{z}) = max(0, \mathbf{z}) \qquad (5) \qquad Linear(\mathbf{z}) = \mathbf{z} \qquad (6)$$

- $w_{i,j}$: Connection weights between the ith input neuron and the jth output neuron.
- x_i: Ith input value of the current training instance.
- $\hat{y}_j$: Output of the jth output neuron for the current training instance.
- y_j: Output of the jth output neuron for the current training instance.
- η: Learning rate.

methodology in F.Fama & K.French 1997, with the addition of the software industry. **adjfct**, Share Adjustment Factor

[8] There are several activation functions, each with different strengths and weaknesses

4.3.2 Model Configuration

Figure 1 visualises a standard neural network topography

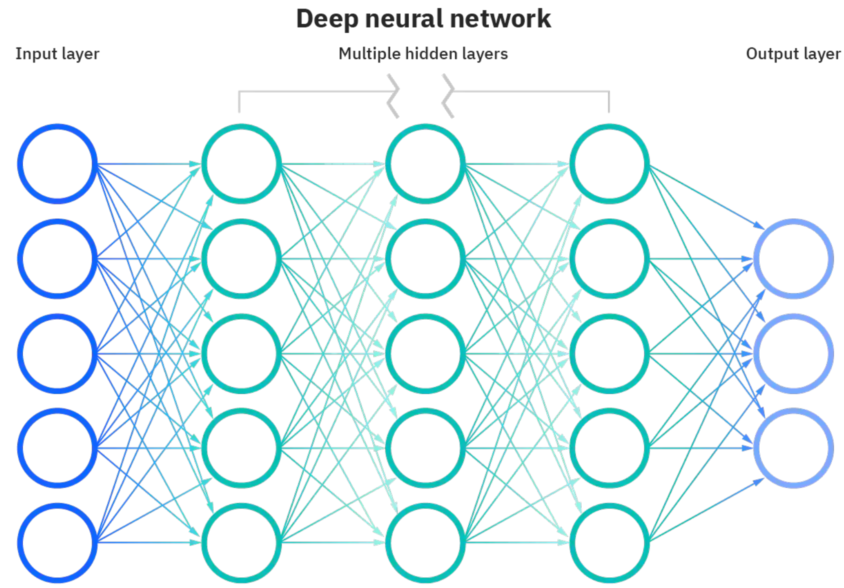


Figure 1: Standard Neural Network Topography (Source: IBM)

The dots and lines represent nodes and connections between nodes, respectively. The architecture of the network is derivative of intended use. Figure 2 illustrates the designated neural network configuration.[9] $N(x, y)$ represents the yth node in xth layer. $\mathbf{z} = \sum_{a=1}^{189} w_{(n,a,b)} x_{(n,a,b)} (= \mathbf{w}^T \cdot \mathbf{x})$ is the dot product between all outputs (x) and connection weights (w) from the nth layer, between all nodes a and b connecting layers n and n+1, respectively. The use of dense layers deeply connects two layers where each node receives an input from the previous layer. The single dropout layer randomly sets input units to 0 with a frequency of rate = 50% at each step during training time. Inputs not set to 0 are scaled up by 2 ($\frac{1}{(1-(rate=0.5))}$ to leave the sum over all inputs unchanged. The inclusion of a dropout layer helps prevent overfitting. Hidden layers and output later use ReLU 5 and linear 6 activation functions, respectively. An ouput linear activation (6) is the most suitable for regression, predicting values ($Prediction_k$) between $(-\infty, \infty)$ directly.

[9] Optimal layer density as per Gu et al. (Gu et al., 2020) with three hidden layers (The dropout is a processing layer to prevent overfitting).

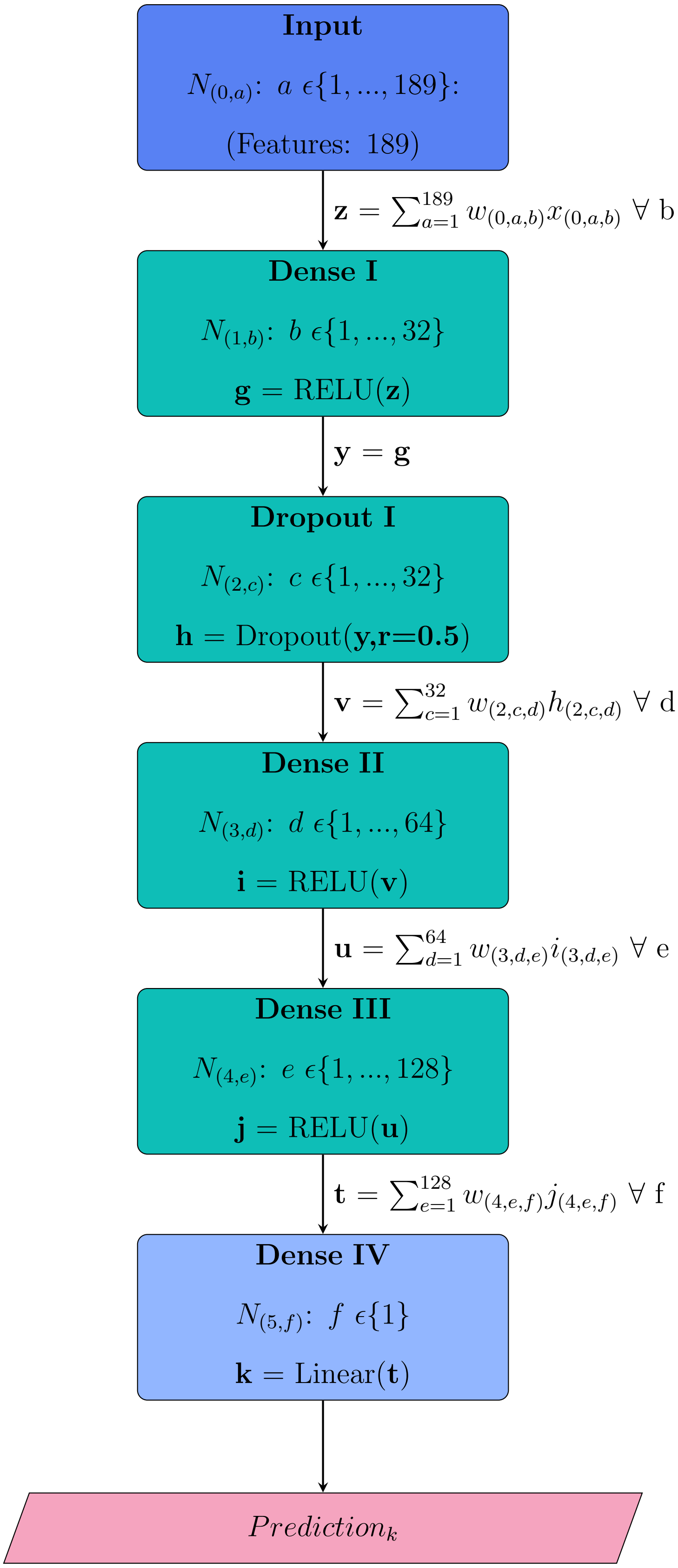


Figure 2: Neural Network Configuration

4.4 Loss Functions

Loss functions map an event or variable set, onto a real number, intuitively representing some loss, associated with the event e.g., difference between predicted and realised excess returns. Optimisation algorithms seek to minimise loss functions by finding an exact analytical solution, or applying numerical methods to find an approximate solution, terminating after meeting exit criteria, when an analytical solution is not possible. The training and evaluation of accurate neural networks use this method.[10] The configured neural network (figure 2) uses a stochastic gradient descent (SGD) algorithm (9.2).

The relative performance between conventional minimisation loss functions, and maximisation of hedge portfolio excess returns, relies on the derivatives to these objectives. The mathematical rigor and suitability of the OLS estimator (9.3) informs the widespread use of OLS regressions, and minimisation of sum of least squares, in prior asset pricing literature. The proposition of three loss functions follow:

1. **In-Built Mean Square Error**: Optimized for neural networks in Tensorflow. [11]
2. **Custom Mean Square Error**: Ensure automatic differentiation functionalities in Tensorflow. [12]
3. **Custom Hedge Portfolio**: A non-convex function seeking to maximise hedge portfolio returns with hedge portfolio weights determined by a monotonic ranking function mapping. The selected mapping weights individual equities by the proportion of their contributions to aggregate returns of all equities in a given month, considering all equities in the portfolio. Section 9.1.2 elaborates on hedge portfolio theory and formulation.

Section 9.1.3 describes both mean squared error and hedge portfolio loss functions mathematically. Best practice training, validation, and testing practice succeed configuration with one iteration per loss function. The deployment of thirty epochs, shuffling of instances prior to every epoch run, and use of early stopping procedures in validation, help prevent over and under fitting.

4.5 Performance Metrics

Performance metrics inform comparisons between loss functions, to assess relative performance, after successfully training and validating a deep neural network for each loss

[10] The optimisation algorithm is synonymous with the training algorithm in section (4.3.1).

[11] activation-functionPython library for neural network modelling from Google

[12] A set of techniques to evaluate the derivative of a function specified by a computer programme, exploiting the sequential nature of elementary arithmetic operation and functions, repeatedly applying the chain rule in both forward and backward accumulations to compute gradients. Automatic differentiation solves code inefficiencies and round off error issues associated with symbolic and numerical differentiation methods, while easily calculating higher order derivatives, and partial derivatives with many inputs.

function. Methods for performance metrics inception and formulation follow:

1. The trained models predict one month lead excess returns for each instance (firm-year observation) in the testing dataset.

2. Standard monthly sorts of predicted one month lead excess returns form standard tercile hedge portfolios, using a long-short zero cost investment, per month.[13]

3. Use hedge portfolios to calculate the hedge portfolio mean, sharpe ratio, and treynor ratio across all months [14].

4. Learning curves validate model representation.

5. Ordinary least squares regression, incorporating Newey-West[15] estimators and six month lags (Newey and West, 1987), regress:

    - Realised one month lead excess return on predicted one month lead excess return

    - Realised hedge portfolio excess return on predicted one month lead excess return

    - Hedge portfolio returns on monthly Fama-French factors, [16] to find alpha in CAPM, FF3, FF4, and FF5 models (9.5). [17]

[13] Aligns with methodology in constructing one month holding period returns

[14] Uses the estimation for systematic risk from the CAPM OLS estimator

[15] The estimator aims to ensure autocorrelation and heteroskedasticity consistency for the regressions of time-series panel data.

[16] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[17] Standard Fama-MacBeth regressions only correct standard error for cross-sectional variation, omitting time-series autocorrelation. Standard forms suffice when using daily or weekly returns (and by extension, prices) as time-series correlation is weak. Stronger time-series autocorrelations may exist during longer period. Therefore, one month lead excess returns necessitate time-series correction. Newey-West suceeds Fama-MacBeth adjusted for clustered covariance with entity and time fixed effects.

5 Results

5.1 Main Findings

Table 1 summarises main findings across model training, validation, individual return predictability, performance measures, and hedge portfolio comparisons. Gu et al. (2020) benchmarks analysis [18].

Result	$MSE(\hat{y}$,y)	$MSE_{Custom}(\hat{y}$,y)	Hedge Portfolio ($\hat{y}$)
$\theta_{(Final)}$	0.011	0.010	0.010
$\lambda_{(Final)}$	0.017	0.014	0.001
OMLER	0.129***	0.238***	−1.319***
Adjusted R^2	0.012	0.042	0.001
F Statistic	1188.583***	2037.581***	39.655***
$\mu_{(HP)}$	0.042428	0.076401	-0.016803
$Sharpe_{HP}$	1.150458	1.450415	-0.714680
$Treynor_{HP}$	-0.300111	-0.309781	-0.283188
β_{HP}	−0.141***	−0.309781***	−0.283188***
$\alpha_{(HP,CAPM)}$	0.043***	0.078***	−0.017***
$\alpha_{(HP,FF3)}$	0.043***	0.077***	−0.017***
$\alpha_{(HP,FF4)}$	0.044***	0.078***	−0.016***
$\alpha_{(HP,FF5)}$	0.042***	0.076***	−0.016***

Table 1: Summary of Main Findings

1. $\theta_{(Final)}$ is the final training loss after training.
2. $\lambda_{(Final)}$ is the final validation loss after validation.
3. OMLER is the coefficient when regressing actual lead one month returns on predicted.
4. $\mu_{(HP)}$ is the hedge portfolio mean across all months.
5. $Sharpe_{HP}$ is the sharpe ratio for the hedge portfolio

[18] Discrepancies in data and methodologies exist, raised appropriately

6. $Treynor_{HP}$ is the treynor ratio for the hedge portfolio
7. β_{HP} is systematic market risk for the hedge portolio
8. $\alpha_{(HP,CAPM)}$, $\alpha_{(HP,FF3)}$, $\alpha_{(HP,FF4)}$, and $\alpha_{(HP,FF5)}$ are the hedge portfolio alphas generated in their respective asset pricing models.
9. Adjusted R^2 is explained variation when regressing actual one month lead excess returns on predicted returns.
10. $MSE(\hat{y}$,y) is the traditional mean squared error loss function.
11. $MSE_{Custom}(\hat{y}$,y) is the customised mean squared error loss function.
12. Hedge Portfolio ($\hat{y}$) is the hedge portfolio optimisation function.

5.2 Revision of Hypotheses

Our restated hypothesis in our motivations follows:

1. It is feasible to implement maximisation strategies in machine learning algorithms given $\arg\max f(x) = \arg\min -f(x)$
2. A hedge portfolio maximisation strategy will not outperform loss minimisation strategies given model architecture.

The confirmation, or rejection, of these hypotheses is relatively simple, and intuitive. Comparisons between training/validation losses, return predictability measures, and hedge portfolios alphas are telling. The results from Gu et al., (2020) serve as a benchmark to gauge feasibility. The complexity in this article lies in the mathematics (9.1.3) and implementation of neural network architecture (9.8).

6 Training & Validation Losses

Table 2 outlines the training and validation losses from neural network using the specified loss functions.

1. $\theta_{(Final)}$ is the final validation loss after training.
2. $\lambda_{(Final)}$ is the final validation loss after validation.
3. $MSE(\hat{y}$,y) is the traditional mean squared error loss function.
4. $MSE_{Custom}(\hat{y}$,y) is the customised mean squared error loss function.
5. Hedge Portfolio ($\hat{y}$) is the hedge portfolio optimisation function.

Result	$MSE(\hat{y}$,y)	$MSE_{Custom}(\hat{y}$,y)	Hedge Portfolio ($\hat{y}$)
$\theta_{(Final)}$	0.011	0.010	0.010
$\lambda_{(Final)}$	0.017	0.014	0.001

Table 2: Training and validation losses

Both the $MSE(\hat{y}$,y) and $MSE_{Custom}(\hat{y}$,y) final training losses are near identical at 0.011 and 0.010, respectively. The pattern for validation losses is similar at 0.017 and 0.014 for $MSE(\hat{y}$,y) and $MSE_{Custom}(\hat{y}$,y), respectively. The similarity confirms automatic differentiation is working[19] The Hedge Portfolio loss function has a minimum training and validation loss of 0.01 and 0.001 before running for a further three epochs before early termination, respectively. The latter shows promising signs a loss function maximising is feasible. Subsequently, it is important to test fit through the observation of learning curves. Figure 3 and 4 visualise learning curves for hedge portfolio loss functions, and both mean squared error variants, respectively.

[19]Tensorflow's Automatic Differentiation functionality using Keras Backend

6.1 Learning Curves

Learning curves [20] serve as diagnostic tools for underfitting, or overfitting.[21] Both MSE loss functions (fig 4a and fig 4b) show evidence of a good fit. Both sets of losses display convexity, continuing to decrease until beginning to plateau. Early stopping does not initiate as the minimum allowed loss is zero in this instance. Hedge Portfolio loss function (fig **??**) shows an interesting trend, displaying signs of non-convexity. This is not a surprising as the loss function is non-trivial, and the permutation of nodes within the hidden layers, in combination with weights in subsequent connections, could have multiple solutions, resulting in the same loss. The validation loss does follow the training loss closely, and early stopping is initiated at the eleventh epoch, and terminated at epoch fourteen. The rapid change in gradient may be a combination in the complexity of the loss function in conjunction with an unsatisfactory learning rate of $\eta = 0.001$[22] Section 9.4 aggregates learning curves, and conventional performance metrics, evaluating model training and validation.

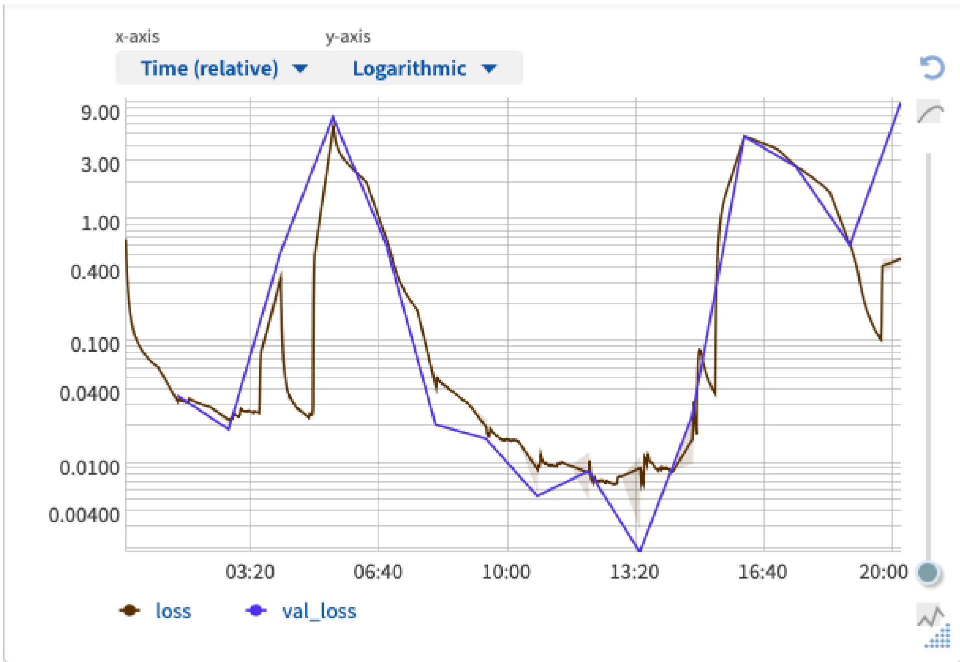
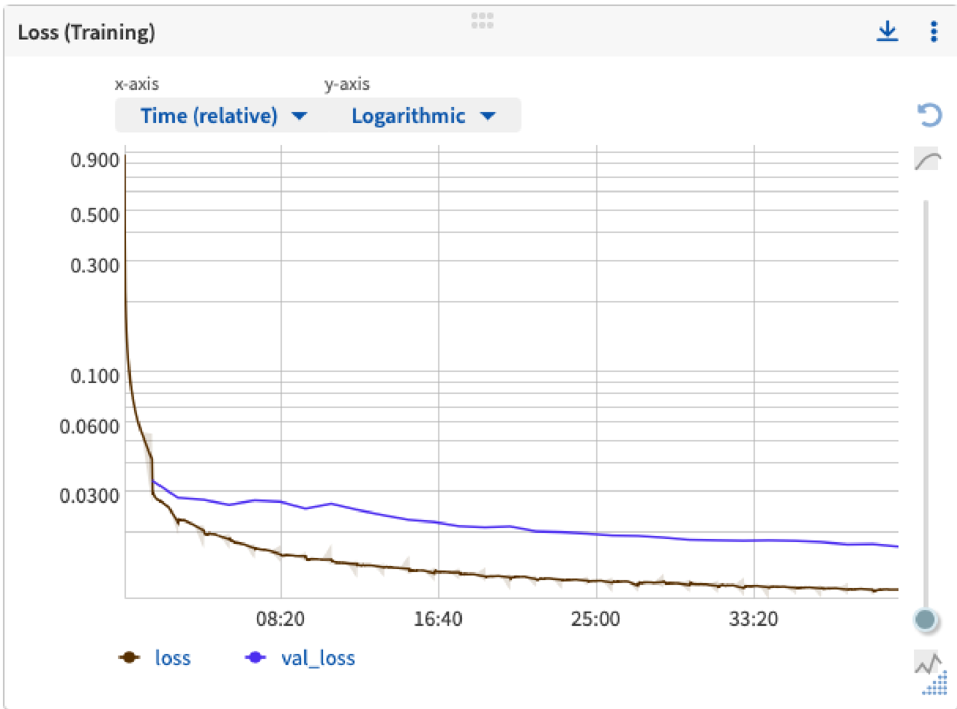
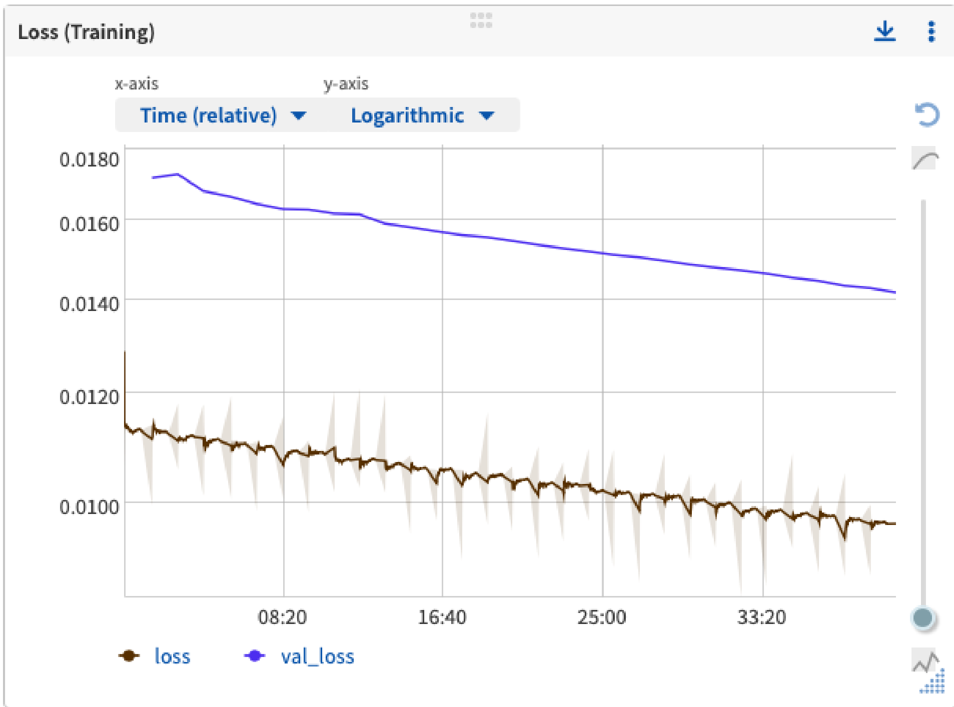


Figure 3: Hedge Portfolio Learning Curves

[20] Generated using a Custom Neptune.ai callback during model fitting.
[21] Overfitting: Overlearns training data, generalises new data poorly. Underfitting: Inadequate training leading to poor predictions.
[22] The appropriate range is between 0.1 and $1e^{-6}$



(a) In-Built Mean Square Error Learning curve



(b) Custom MSE

Figure 4: Learning Curves

6.2 Return Predictability

Table 3 regresses realised one month lead excess returns, on the predicted returns, for every loss function. The F Statistic on all tests is highly statistically significant at the one percent level, verifying realised returns are derivative of predictions. The out-of-sample adjusted R^2 values are 0.012, 0.042, and 0.001 for $MSE(\hat{y}$,y), $MSE_{Custom}(\hat{y}$,y), and $HedgePortfolio(\hat{y})$ respectively. Gu et al. (2020) has a range of out-of-sample from 0.33% (0.0033) to 0.40% (0.004) for non-linear predictions. Our are higher, but may be from using a more powerful algorithm (neural networks) and one-sixth the number of factors. The coefficients of $MSE(\hat{y}$,y), $MSE_{Custom}(\hat{y}$,y), and $HedgePortfolio(\hat{y})$ highly statistical significant at the one percent level, 0.129, 0.238, and -1.319, respectively. The negative coefficient is not unexpected given the objective function seeks to maximise predicted hedge portfolio returns opposed minimising the loss between actual and realised. Subsequently, it is feasible to use maximisation strategies in neural networks, confirming our first hypothesis. Ultimately, the adoption of maximisation strategies lies in their economic significance.

	Dependent variable: POMLER		
	$MSE(\hat{y}$,y)	$MSE_{Custom}(\hat{y}$,y)	$HedgePortfolio(\hat{y})$
OMLER	0.129***	0.238***	-1.319***
	(0.004)	(0.005)	(0.210)
Observations	531,461	531,461	531,461
R^2	0.012	0.042	0.001
Adjusted R^2	0.012	0.042	0.001
Residual Std. Error	0.137	0.135	0.137
	(df = 531460)	(df = 531460)	(df = 531460)
F Statistic	1188.583***	2037.581***	39.655***
	(df = 1.0; 531460.0)	(df = 1.0; 531460.0)	(df = 1.0; 531460.0)

Note: *p<0.1; **p<0.05; ***p<0.01

1. POMLER is the Predicted One Month Lead Excess Returns by the Neural Networks for respective loss functions.

2. OMLER is the Realised One Month Lead Excess Returns

Table 3: Realised One Month Lead Excess Returns regressed on Predicted One Month Lead Excess Returns

6.3 Hedge Portfolio Performance

Figure 4 displays the mean, sharpe ratio, and treynor ratio from the predicted hedge portfolios per loss function. The hedge portfolio means for $MSE(\hat{y}$,y), $MSE_{Custom}(\hat{y}$,y), and Hedge Portfolio ($\hat{y}$) loss functions are 0.0424, 0.0764 and, -0.0168 per month, respectively. These raise concern given they exceed observations from prior literature. However, there are some hypotheses. Section 9.9.2 describe the method Jensen et al.

(2021) in constructing factor portfolios. In summary, they sort stocks into terciles in the 20th percentile on market capitalisation or higher first, then evenly distribute all the stock below the 20th percentile on market capitalisation evenly into the three terciles using similar sorting characteristics. Following, each tercile has it's capped value weight return calculated, ensuring tiny stocks have tiny weight, and large stocks don't dominate the portfolio. The predicting of construction of hedge portfolios should reflect this methodology. However, equities below the 20th percentile were omitted, as mentioned in section 4.1.[23] Therefore, large stocks dominate the portfolio, raising the hedge portfolio mean. Preliminary analysis used deciles, recording 0.05 and 0.1 for $MSE(\hat{y}$,y), and $MSE_{Custom}(\hat{y}$,y), respectively. The change to deciles reduced the hedge portfolio means to the aforementioned figures. For context, the mean excess return on realised one month lead excess returns is 0.0007 (0.7%). The treynor ratio indicates the excess return on systematic risk is consistent across the three strategies (-0.30). The sharpe ratios for both MSE variants are feasible at 1.15 to 1.45 for $MSE(\hat{y}$,y), and $MSE_{Custom}(\hat{y}$,y). Ultimately, -0.016803 and -0.714680 for hedge portfolio mean and sharpe ratio shows the hedge portfolio maximisation strategy does not outperform traditional loss minimisation regardless of accuracy.

6.3.1 Hedge Portfolio Mean, Sharpe, and Treynor

Loss Function	$\mu_{(HP)}$	$Sharpe_{HP}$	$Treynor_{HP}$
$MSE(\hat{y}$,y)	0.042428	1.150458	-0.300111
$MSE_{Custom}(\hat{y}$,y)	0.076401	1.450415	-0.309781
Hedge Portfolio ($\hat{y}$)	-0.016803	-0.714680	-0.283188

Table 4: Performance Measures

[23]Discovered very late in analysis, well after datapipeline were finalised infrastructure

6.3.2 Asset Pricing Models

Tables 5, 6, and 7 show estimations for hedge portfolio alpha per month, for each standard factor pricing model, using an optimisation strategy, for $MSE(\hat{y}$,y), $MSE_{Custom}(\hat{y}$,y), and Hedge Portfolio ($\hat{y}$), respectively.

1. SMB_t: Size Premium (small minus big) is the difference in average return between nine small stock and nine large value-weighted portfolios.

2. HML_t: Value Premium (high minus low) is the difference in average return between two value and two growth value-weighted portfolios.

3. RMW_t: Profitability Premium (robust minus weak) is the difference in average return between two robust operating profitability and two weak operating profitability value-weighted portfolios.

4. CMA_t: Investment Premium minus aggressive is the difference in average return on the two conservative and two aggressive investment portfolios

5. $(R_{M,t} - R_{f,t})$: Market Risk Premium

6. $\alpha_{(HP,CAPM)}$, $\alpha_{(HP,FF3)}$, $\alpha_{(HP,FF4)}$, and $\alpha_{(HP,FF5)}$ are the hedge portfolio alphas generated in their respective asset pricing models.

7. CAPM is the capital asset pricing model

8. FF3 is the Fama-French Three Factor Model

9. FF4 is the Fama-French Four Factor Model

10. FF5 is the Fama-French Five Factor Model

$MSE(\hat{y}$,y) (table 5), $MSE_{Custom}(\hat{y}$,y) (6), and Hedge Portfolio ($\hat{y}$) (7) neural networks generate portfolios which align with their hedge portfolio means, across all factor models, statistical significant at the 1% level. The MSE variants only have highly statistical significant negative market premia factors, and the Hedge portfolio have statistical significant negative RMW and SMB in FF4 and FF5 (5% level). The market risk premia is statistical insignificant in CAPM, FF4, and FF5 for the maximising hedge portfolio returns. The market risk premia factor is negative in all models across loss functions. The out-of-sample period includes both the Dotcom crash and Financial Crisis. The sample period, incomplete dataset, shorting positions in the hedge portfolios, and capped weighting methodology may be driving these results. Regardless, the results are inconclusive in assessing relative performance. However, if they were, the hedge portfolio maximisation strategy would not outperform traditional loss minimisation techniques.

	Dependant: One Month Lead Excess Hedge Portfolio			
	CAPM	FF3	FF4	FF5
CMA				0.435**
				(0.218)
HML		0.080	0.130	-0.030
		(0.105)	(0.120)	(0.101)
Mkt-RF	-0.141***	-0.178***	-0.202**	-0.147**
	(0.054)	(0.068)	(0.096)	(0.067)
RMW			-0.134	-0.115
			(0.208)	(0.186)
SMB		0.180	0.128	0.105
		(0.120)	(0.081)	(0.077)
α	0.043***	0.043***	0.044***	0.042***
	(0.004)	(0.004)	(0.005)	(0.004)
Observations	252	252	252	252
R^2	0.031	0.057	0.063	0.096
Adjusted R^2	0.027	0.046	0.048	0.078
Residual Std.	0.036	0.036	0.036	0.035
Error	(df = 250)	(df = 248)	(df = 247)	(df = 246)
F Statistic	6.741***	2.751**	2.294*	2.581**
	(df = 1.0; 250.0)	(df = 3.0; 248.0)	(df = 4.0; 247.0)	(df = 5.0; 246.0)

Note: *p<0.1; **p<0.05; ***p<0.01 *Insert Variable Explanations*

Table 5: Mean Square Error Loss Function: Asset Pricing Models

	Dependant: One Month Lead Excess Hedge Portfolio			
	CAPM	FF3	FF4	FF5
CMA				0.547*
				(0.283)
HML		0.180	0.214	0.014
		(0.151)	(0.162)	(0.144)
Mkt-RF	-0.247***	-0.300***	-0.316***	-0.247***
	(0.080)	(0.090)	(0.121)	(0.087)
RMW			-0.090	-0.066
			(0.276)	(0.247)
SMB		0.261*	0.226*	0.197
		(0.154)	(0.126)	(0.121)
α	0.078***	0.077***	0.078***	0.076***
	(0.007)	(0.006)	(0.007)	(0.007)
Observations	252	252	252	252
R^2	0.046	0.081	0.082	0.108
Adjusted R^2	0.042	0.070	0.067	0.090
Residual Std.	0.052	0.051	0.051	0.050
Error	(df = 250)	(df = 248)	(df = 247)	(df = 246)
F Statistic	9.463***	4.398***	3.332**	3.647***
	(df = 1.0; 250.0)	(df = 3.0; 248.0)	(df = 4.0; 247.0)	(df = 5.0; 246.0)
Note:		*p<0.1; **p<0.05; ***p<0.01 *Insert Variable Explanations*		

Table 6: MSE (Custom) Loss Function: Asset Pricing Models

	Dependant: One Month Lead Excess Hedge Portfolio			
	CAPM	FF3	FF4	FF5
CMA				-0.006
				(0.111)
HML		-0.108**	-0.054	-0.052
		(0.046)	(0.046)	(0.064)
Mkt-RF	0.059	0.074*	0.047	0.046
	(0.037)	(0.038)	(0.034)	(0.035)
RMW			-0.146**	-0.146**
			(0.067)	(0.068)
SMB		-0.070	-0.127**	-0.126**
		(0.052)	(0.057)	(0.057)
α	-0.017***	-0.017***	-0.016***	-0.016***
	(0.002)	(0.002)	(0.002)	(0.001)
Observations	252	252	252	252
R^2	0.013	0.044	0.062	0.062
Adjusted R^2	0.014	0.040	0.049	0.045
Residual Std.	0.029(df = 250)	0.028	0.028	0.028
Error	(df = 250)	(df = 248)	(df = 247)	(df = 246)
F Statistic	5.117**	4.666***	3.830***	3.145***
	(df = 1.0; 250.0)	(df = 3.0; 248.0)	(df = 4.0; 247.0)	(df = 5.0; 246.0)

Note: *p<0.1; **p<0.05; ***p<0.01 *Insert Variable Explanations*

Table 7: Hedge Portfolio Loss Function: Asset Pricing Models

7 Research Implications

7.1 Contributions

7.1.1 Maximisation Strategies

Maximisation strategies are feasible from a technical perspective. Neural net architecture, and automatic differentiation in Keras Backend, enable the construction of custom optimisation functions in consideration of objectives outside standard loss minimisation. You can consider the maximisation of hedge portfolios, However, the extent to their economic significance remains unanswered. This is a partial, novel contribution to the literature.

7.1.2 Use of Factor Portfolio Dataset

A minor contribution is validating the use of factor portfolio dataset by Jensen et al. (2021) for empirical asset pricing analysis with machine learning techniques. The dataset is of sufficient size, quality, and granularity for this form of analysis.

7.2 Limitations

Material limitations persist, evident from the economically (or lack there of) significant outcomes.

7.2.1 Resources

Resource constraints in exploring the entire dataset within reasonable timeframes, and at reasonable costs, within the scope of an 30pt honours dissertation. Google's Cloud Platform Free Trial gave an allocation of $300 in free credit. Analysis consumed all free credit on the lowest cost infrastructure. The most material inhibitions are the inability to explore all 400 factors for all size groupings, the reduction in level of precision for numerical features, and the ability to shuffle training sets at lengths greater than or equal to the input sets. Training includes two hours of numerical encoding, a further hour per model to train and evaluate across 30 epochs with early stopping activated.

7.2.2 Data revisions

The condensed dataset omits entities in the 20th percentile of market capitalisation, and halves the number of instances from approximately 2.7 million to 1.35 million. The omission was material given the methodology in constructing factors, discovered towards

7.2.3 Optimisation Functions

The maximisation strategy mapping a monotonic ranking function by weighting by contributions of individual predicted excess returns to aggregate predicted excess returns is one form of hedge portfolio. There are many permutations. This objective function does not reference realisations. Permutations of objective function exist. It is possible to include factors originating from the input feature in loss calculations This opens the possibility of exploring a whole range of decisions

7.2.4 Neural Network Architecture

The analysis is highly dependent of neural net architecture. Our research only consider one configuration in this instance. Greater attention to model architecture and hyper-parameter fine tuning would be most beneficial.

Simulations

Our analysis only considers one combination of model architecture and minimisation/-maximisation functions. Distributions, gathered through simulation, improve evaluating outcomes and answering to motivations. This is a key finding in Gu et al. (2020).

7.2.5 Use in Conjunction with Optimisation Technologies

Other optimisation techniques exist which may add value e.g., reinforcement learning, dynamic programming etc. They may be considered in parallel, out in pipelines, to neural networks in maximising

7.3 Assessment of Motivations

Our motivations asked:

Can neural networks configured to maximise hedge portfolios outperform standard loss minimisation configurations, when predicting one month lead excess returns using a long-short zero cost investment strategy?

The answer is inconclusive in this instance given the combined poor performance measure outcomes and limitations. However, if outcomes and limitation were acceptable, the answer would be no. Furthermore, both hypotheses would be true.

1. It is feasible to implement maximisation strategies in machine learning algorithms given $\arg\max f(x) = \arg\min -f(x)$: **Yes**

2. A hedge portfolio maximisation strategy will not outperform loss minimisation strategies given model architecture: **Yes**

8 Conclusion

In this paper, I document the outcomes from assessing the accuracy and relative performance in predicting hedge portfolio excess returns between deep neural networks using a maximisation of a hedge portfolio excess return optimisation function, and conventional mean squared error loss minimisation functions. I document the mathematical derivations for a non-convex optimisation function incorporating a monotonic ranking function to weight stocks proportionally by their contributions to aggregate excess returns, supported by mathematical theory surrounding ordinary least squares (OLS) regressions. I document the infrastructure and extensive programming to conduct analysis. Next, I record the maximisation function makes well generalised out-of-sample predictions given the in-sample training processes, but all models performed inconsistently when evaluating and interpreting performance measures from the lens of economic significance.

Gu et al. (2020)'s pivotal paper frames the feasibility of machine learning for empirical asset pricing via machine learning in attempts to advance the field. Data science in finance continues to evolve in academic and industry-related uses. Most machine learning applications in equity return predictions, and finance in general, use a traditional loss functions. A handful of researchers explore custom loss minimisation functions in machine learning applications, but none from the perspective of maximising hedge portfolio excess returns as far as can be told.

Furthermore, I hypothesised it was feasible to train a neural network using a hedge portfolio excess return optimisation strategy, but would not outperform traditional loss minimisation functions given neural network architecture and the mathematics surrounding loss functions. Both hypotheses prove to be true with the given dataset.

The analysis and outcome show maximisation strategies are feasible from a technical perspective. This is a partial, novel contribution to the literature. Another minor contribution is the validation of using of factor portfolio dataset for this form of analysis. However, the limitations relating to resources, data revisions, optimisation functions, neural network architecture, and simulations, render the research question inconclusive at this stage. Further analysis will continue to work towards exploring and resolving these issues in the next chapter.

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9 Appendix

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9.1 Mathematics

9.1.1 Equations & Derivations

9.1.2 Hedge Portfolio

Hedge portfolios rely on monotonic ranking functions for optimisation as their monotonic nature preserves or reverses a given ordered set. The analysis cross-section of one-month lead portfolio excess returns using monotonic functions

$$R(y_{i,t}) \tag{7}$$

The ranking function (R($y_{i,t}$)) and thresholds (u,v) form subsets of long and short portfolios. Long (L) or Short (S) sets include excess returns conditioned on the associated monotonic ranking given a threshold, bound by the cardinality of the excess return vector ($|y|$). The subsequent truth sets mathematically express aforementioned time-series hedge portfolios.

$$
\begin{aligned}
&L = \{y_{i,t} | R(y_{i,t}) \leq u\} \\
&S = \{y_{i,t} | R(y_{i,t}) \geq v\} \\
&0 < u \leq |y| \\
&0 < v \leq |y| \\
&u < v
\end{aligned}
$$

Equation 8 describes hedge portfolio lead excess returns (H_t) at a given time (t).

$$H_t = \frac{1}{|L|} \sum_{i \epsilon L} y_{i,t} - \frac{1}{|S|} \sum_{i \epsilon S} y_{i,t} \tag{8}$$

Figure 5) illustrates an approximate linear monotonic ranking function with a sample of 100 uniformly distributed excess returns between -10% and 10%. Boundary conditions u and v are set to 20 and 80, respectively. Subsequently, excess returns above (below) the green (blue) dotted line belong to the long (L) (short (S)) set.

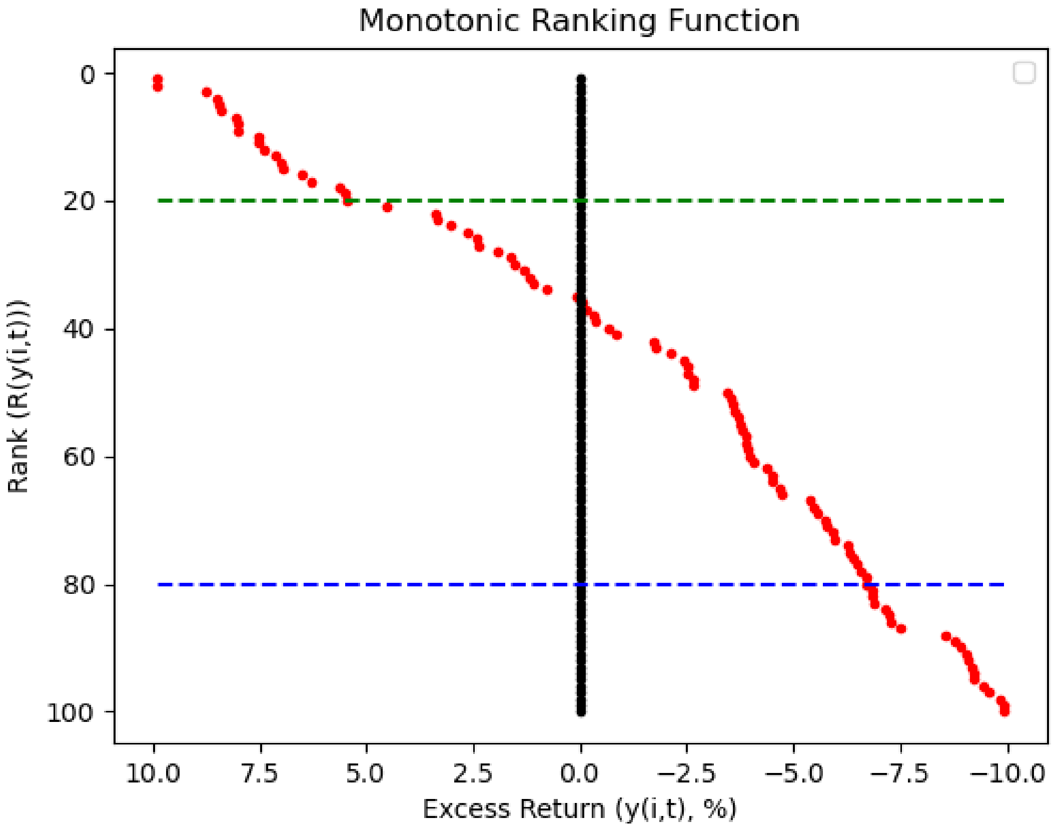

Figure 5: Approximate Linear Monotonic Ranking Function

The permutations in monotonic ranking functions, and subsequent hedge portfolios, are endless. This research essay develops a monotonic ranking function proportionally weighting one month lead excess returns (9). Therefore, equation 10 defines the loss function.

$$R(\hat{y}) = W \tag{9}$$

$$W := \frac{\hat{y}}{\vec{\mathbf{1}}\hat{y}}$$

$$\hat{y} = X^T\hat{\theta}$$

$$f_{\hat{\theta}}(X) = (\frac{X^T\hat{\theta}}{\vec{\mathbf{1}}X^T\hat{\theta}})^\top X^T\hat{\theta} \tag{10}$$

The above loss function is differentiable using symbolic mathematic as shown in equation 11.

$$\frac{\partial f_{\hat{\theta}}(X)}{\partial\hat{\theta}} = \frac{\partial((\frac{X^T\hat{\theta}}{\vec{\mathbf{1}}X^T\hat{\theta}})^\top X^T\hat{\theta})}{\partial\hat{\theta}}$$

$$\frac{\partial(f_{\hat{\theta}}(X))}{\partial\hat{\theta}} = \frac{1}{(\hat{\theta}^\top X\vec{1})}XX^\top\hat{\theta} + \frac{1}{\vec{1}X^\top\hat{\theta}}XX^\top\hat{\theta} - \frac{1}{(\hat{\theta}^\top X\vec{1})^2}\hat{\theta}^\top XX^\top\hat{\theta}X\vec{1} \tag{11}$$

Subsection **??** explains the theory supporting loss minimisation. Applying gradient descent methods to the product of the loss function and scaler of -1 transforms the minimisation to maximisation. This transformation leads to finding the argmax of maximisation function with respect to $\hat{\theta}$ (12). The aforementioned transformation is simply and suitable for exploration in the context of the research intent. More sophisticated methods exist for maximisation such as reinforcement learning (**??**).

$$\arg\max_{\hat{\theta}} : \left(\frac{X^T\hat{\theta}}{\vec{\mathbf{1}}X^T\hat{\theta}}\right)^\top X^T\hat{\theta} \tag{12}$$

9.1.3 Loss Functions

Equations 13 and 14 show the loss functions calculating mean squared errors and aforementioned hedge portfolios, respectively. Equations 15 and 16 illustrate optimisation objectives for mean squared error and hedge portfolio loss functions, respectively. [24] Equations 17 and 18 describe the partial derivative functions for both mean squared error and hedge portfolio loss functions, respectively. The global optimum for both functions is the combination of parameters ($\hat{\theta}$) setting the partial derivative to zero. The first is trivial in an analytical form. The second is non-trivial, requiring symbolic, numerical, or automatic methods. The immediate code listings show the translation of loss functions mathematical expressions (13 and 14) into tensor compatible formats for analysis.

$$f_{\hat{\theta}}(y, X) = \frac{\vec{1}}{\vec{1}^T\vec{1}}(\mathbf{y} - X^T\hat{\theta})^{\circ 2} \tag{13}$$

$$f_{\hat{\theta}}(X) = \left(\frac{X^T\hat{\theta}}{\vec{\mathbf{1}}X^T\hat{\theta}}\right)^\top X^T\hat{\theta} \tag{14}$$

$$\arg\min_{\hat{\theta}} : (f_{\hat{\theta}}(y, X)) \tag{15}$$

$$\arg\max_{\hat{\theta}} : (f_{\hat{\theta}}(X)) \tag{16}$$

$$\frac{\partial f_{\hat{\theta}}(y, X)}{\partial \hat{\theta}} = \frac{\vec{1}}{\vec{1}^T\vec{1}}(-2(\mathbf{y} - X^T\hat{\theta})^{\circ 1}) \tag{17}$$

$$\frac{\partial(f_{\hat{\theta}}(X))}{\partial \hat{\theta}} = \frac{1}{(\hat{\theta}^\top X\vec{1})}XX^\top\hat{\theta} + \frac{1}{\vec{1}X^\top\hat{\theta}}XX^\top\hat{\theta} - \frac{1}{(\hat{\theta}^\top X\vec{1})^2}\hat{\theta}^\top XX^\top\hat{\theta}X\vec{1} \tag{18}$$

```
class custom_mse(tf.keras.losses.Loss):
  def __init__(self, extra_tensor=None, reduction=tf.keras.losses.
 Reduction.AUTO, name='custom_mse'):
    super().__init__(reduction=reduction, name=name)
    self.extra_tensor = extra_tensor

  def call(self, y_true, y_pred):
    extra_tensor = self.extra_tensor
    loss = K.mean(K.square(y_pred - y_true))
    return loss
```

Listing 1: Custom Mean Squared Error Implementation

```
class custom_hp(tf.keras.losses.Loss):
  def __init__(self, extra_tensor=None, reduction=tf.keras.losses.
 Reduction.AUTO, name='custom_hp'):
    super().__init__(reduction=reduction, name=name)
```

[24] $\arg\max_{\hat{\theta}} : (f_{\hat{\theta}}(X)) \equiv \arg\min_{\hat{\theta}} : (-f_{\hat{\theta}}(X))$

```
      self.extra_tensor = extra_tensor

    def call(self, y_true, y_pred):
      extra_tensor = self.extra_tensor
      # Calculates sum over vector tensors
      y_true_sum = K.sum(y_true)
      y_pred_sum = K.sum(y_pred)
      #
      y_true_weights = (y_true/y_true_sum)
      y_pred_weights = (y_pred/y_pred_sum)
      # Transpose the weights
      y_true_transposed = K.transpose(y_true_weights)
      y_pred_transposed = K.transpose(y_pred_weights)
      # Multiply by the weights
      y_true_loss = K.dot(y_true_transposed, y_true)
      y_pred_loss = K.dot(y_pred_transposed, y_pred)
      loss = -1*(y_pred_loss)
      return loss
```

Listing 2: Custom Hedge Portfolio Implementation

9.2 Stochastic Gradient Descent

Firstly, SGD finds loss function partial derivatives, with the respect to the parameter in a predictive model. Secondly, the exploration of epochs update parameters using a learning rate, moving away from the partial derivatives, until settling in a minimum as a potential solution. Several methods aid escape from local minima to continue searching for global minimum solutions, depending on the algorithm. The below illustrates the use of mean squared error as a loss function, on a linear model, where SGD would adjust both intercept and co-efficient parameters, in order to find the argmax of the loss function. Equations for linear model (19) and mean squared error ().

$$\hat{y} = mx_i + b \tag{19}$$

$$f(y, (mx_i + b)) = \frac{1}{n}\sum_{i=1}^{n}(y_i - (mx_i + b))^2 \tag{20}$$

Partial derivatives of parameters m (21) and b (22), respectively.

$$\frac{\partial f(y, (mx_i + b)}{\partial m} = \frac{1}{n}\sum_{i=1}^{n} -2x_i(y_i - (mx_i + b))^2 \tag{21}$$

$$\frac{\partial f(y, (mx_i + b)}{\partial b} = \frac{1}{n}\sum_{i=1}^{n} -2(y_i - (mx_i + b))^2 \tag{22}$$

9.3 Ordinary Least Squares (OLS)

The OLS regression is the most prominent statistical model in asset pricing theory. Rosenfeld (2021) summarises OLS. The composition of the true OLS (23) model includes four components. Firstly, **X**, an n x k matrix of k independent variables for n observations. Secondly, **y**, an n x 1 vector of observation on the dependent variable. Thirdly, ϵ, an n x 1 vector of unexplained error. Lastly, θ, a k x 1 vector of parameters to be estimated.

$$y = X\theta + \epsilon \tag{23}$$

9.3.1 Estimation Criteria

The criteria to obtain the parameter estimate ($\hat{\theta}$) relies on the minimisation of the sum of squared residuals (24). We highlight the observed residuals (e) are distinct from unexplained disturbances (ϵ). Equation 25 derives residuals by taking the difference between observations based on parameter estimates.

$$\sum e_i^2 \tag{24}$$

$$e = y - X\hat{\theta} \tag{25}$$

Expanding the quadratic $e^T e$ after substituting in equation 25 leads to the alternative expression of the sum of squared residuals in equation 26. Minimizing the sum of square residuals requires taking the partial derivative of equation 26 with respect to the estimated parameters (equation) using matrix differentiation (27). It is imperative X has full rank where all vectors in the matrix are linearly independent, validating both the presence of a positive definite matrix and minimum.

$$e^T e = y^T y - 2\hat{\theta}^T X^T y + \hat{\theta}^T X^T \hat{\theta} X \tag{26}$$

$$\frac{\partial e^T e}{\partial \hat{\theta}} = -2X^T y + 2X^T X\hat{\theta} = 0 \tag{27}$$

We find the expression for the Ordinary Least Squares (OLS) estimator (28) after rearranging equation 27 to normal form, utilizing inverse matrices to form identity matrices, and simplifying.

$$\begin{aligned} 2X^T X\hat{\theta} &= 2X^T y \\ (X^T X)^{-1}(X^T X)\hat{\theta} &= (X^T X)^{-1} X^T y \\ I\hat{\theta} &= (X^T X)^{-1} X^T y \\ \hat{\theta} &= (X^T X)^{-1}(X^T y) \end{aligned} \tag{28}$$

Therefore, we can use the OLS estimator to make predictions with OLS (29).

$$\hat{y} = X^T \hat{\theta} \tag{29}$$

9.3.2 Properties of OLS Estimators

There are six key properties in addition to the satisfaction in minimizing the summation of squared residuals.

1. The residuals are uncorrelated with the observed values of X i.e., $X^T e = 0$.
2. The sum of the residuals is zero i.e., $\sum e_i = 0$.

3. The sample mean of the residuals is zero i.e., $\bar{e} = \frac{\sum e_i}{n} = 0$.

4. The regression hyperplane passes through the means of observed values i.e., $\frac{e}{=}\frac{y-X\theta}{n} = 0$. Since $\bar{e} = 0$ assumed, it is implied $\bar{y} = \bar{x}\bar{\theta}$.

5. The residuals are uncorrelated with the predicted y i.e., $\hat{y} = X\hat{\theta}$, $\hat{y}^T e = (X\hat{\beta})^T e = b^T X^T e = 0$

6. The mean of $\hat{y}$ for the sample will equal the mean of the y.

9.3.3 The Gauss-Markov Theorem

However, OLS makes Gauss-Markov assumptions about the true model to make inferences regarding β from $\hat{\beta}$. The intention of the Gauss-Markov Theorem, conditional on the below assumptions, states the OLS estimator is the best linear, unbiased, and efficient estimator:

$$
\begin{aligned}
y &= x\beta + \epsilon \\
E[\epsilon|X] &= 0 && (30) \\
E(\epsilon\epsilon^T|X) &= \Omega = \sigma^2 I && (31) \\
\epsilon|X\ & N[0, \sigma^T I] \text{ (hypothesis testing)}
\end{aligned}
$$

- X is an n x k matrix of full rank
- X must be generated randomly, or fixed, by a mechanism uncorrelated to disturbances.

Equation 30 implies $E(y) = X\beta$ as no observations of the independent variables convey any information about the expected values of the disturbances. Equation 31 captures homoskedasticity and no autocorrelation assumptions.

9.4 Model Training & Validation Performance

Figure 6: Performance: In-Built Mean Square Error

Figure 7: Performance: Custom Mean Square Error

Figure 8: Performance: Custom Hedge Portfolio

9.5 Asset Pricing Models

9.5.1 Capital Asset Pricing Model

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta^1_{i,t}(R_{M,t} - R_{f,t}) \tag{32}$$

9.5.2 Fama-French Factor Models

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,t}(R_{M,t} - R_{f,t}) \tag{33}$$
$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,t}(R_{M,t} - R_{f,t}) \tag{34}$$

where

- $R_{i,t} - R_{f,t}$: Portfolio Excess Return on the market for a given portfolio and time, value-weighted using all incorporated US CRSP firms incorporated in the US, listed on the NYSE, AMEX, or NASDAQ.
- $\alpha_{i,t}$: Jensen's alpha indicating mispricing in the asset.
- β^1_t: Market Risk Factor (co-efficient)
- β^1_t: Size Factor (co-efficient)
- β^2_t: Value Factor (co-efficient)
- β^2_t: Value Factor (co-efficient)
- β^3_t: Profitability Factor (co-efficient)
- β^4_t: Investment Factor (co-efficient)
- $(R_{M,t} - R_{f,t})$: Market Risk Premium
- SMB_t: Size Premium (small minus big) is the difference in average return between nine small stock and nine large value-weighted portfolios.
- HML_t: Value Premium (high minus low) is the difference in average return between two value and two growth value-weighted portfolios.
- RMW_t: Profitability Premium (robust minus weak) is the difference in average return between two robust operating profitability and two weak operating profitability value-weighted portfolios.
- CMA_t: Investment Premium minus aggressive is the difference in average return on the two conservative and two aggressive investment portfolios

9.5.3 Fama-MacBeth Regressions

$$R_{n,t} = \alpha_n + \sum_{f=1}^{F} \beta_{n,F_f} F_{f,t} + \epsilon_{n,t} \tag{35}$$
$$\forall\ n\epsilon\{1, ..., N\}$$
$$R_{i,t} = \gamma_{t,0} + \sum_{f=1}^{F} \gamma_{t,f} \hat{\beta_{i,F_f}} + \epsilon_{i,t} \tag{36}$$
$$t\epsilon\{1, ..., N\}$$

Where

- $R_{n,t}$: Return for an asset (n) at a time (t).
- α_n: Jensen's alpha for an asset (n) implying mispricing.
- β_{n,F_f}: An asset's (n) exposure to a factor (f)
- $\hat{\beta_{i,F_f}}$: Estimated factor loading for a factor (f) from regression of asset (i)
- $F_{f,t}$: Risk factor (f) at a given time (t) e.g., SMB, HML etc.,
- $\epsilon_{n,t}$: Residual for an asset at a time (t)
- $\gamma_{t,f}$: Factor pricing for a factor (f)

9.6 Performance Measures

9.6.1 Sharpe Ratio

Nobel Laurette William F. Sharpe (1994) introduced the Sharpe Ratio (37) as a measure for risk-adjusted returns, where $\mathbb{E}[R_a - R_f]$ is the expectation for excess returns, and $\sigma(R_a)$ is the standard deviation of excess returns.

$$SR = \mathbb{E}\frac{[R_a - R_f]}{\sigma(R_a)} \tag{37}$$
$$\sigma = \sqrt{\sum_{i=1}^{n} \frac{(R_a) - \bar{R_a})^2}{n}}$$

9.6.2 Treynor Ratio

The Treynor ratio is another risk-return measure (38), evaluating the excess return of a portfolio per unit of systemic risk[25]. $\mathbb{E}[R_a - R_f]$ is the excess return on the market. β_M

[25]

is systematic risk

$$\text{Treynor} = \mathbb{E}\,\frac{[R_a - R_b]}{\beta_M} \tag{38}$$

9.7 Technical Details

9.7.1 Organisation

This research essay uses data science best practise (Wilson et al., 2016). Data and results saved regularly and reproducible. Data retention in all forms receives high levels of attention. Project files synchonises continuously to Google Drive (Google LLC, 2020). Git (Linus Torvalds, 2020) manages version control protocols for source code, data, documents, and results. Git stores a complete history of versions using Git hashes. These hashes are strings unique to each state of the publicly available finance-honours repository[1]. Git hashes enable discretisation of finance-honours development, enabling the accessibility and recollection of all previous states given a unique git hash. This functionality enables reproducibility, error correction, and the ability to revert to previous models.

9.7.2 Version Control

Git, hosted by GitHub, provides a comprehensive set of version control technologies and range of benefits. These technologies manage version control for the programming of approximately 40 methods, classes, and functions. Firstly, Git enables collaborative functionalities. The master version of a project is accessible for all who have access to the repository. Each contributor can create custom copies of branches through pull requests on the master branch. Contributors can commit changes to custom branches and push these changes to the master branch through push requests. Product managers can review push requests, approving valid requests for integrating changes to the master branch. Collaborative efforts are possible with commit messages describing contributions from each contributor. This research essay has only one contributor, rendering collaborative functionalities redundant in this instance. Git ensures the storage of code, work, and author histories. The descriptive nature of commit logs ensures journal accuracy.

9.7.3 Directories

This research essay follows directory structure recommendations from Wilson et al (2016). Organisation is crucial as the modelling of artificial neural networks involves integrating a range of optimisation models, data files and documents. Directory management is most efficient and comprehensive. **finance-honours** is the root directory containing the following sub directories: bin, data, doc, src, and results. The **bin** sub directory contains external scripts and compiled programmes. The **data** sub directory contains all raw data associated with the project. The **doc** sub directory stores user guides, academic resources, research reports and project deliverables. The **results** sub directory contains the outputs from project analysis. The **src** sub directory stores the source code for preparing datasets, partitioning sets of geographies with varying granularities. All files were continuously backed up using Google Drive and Git.

9.7.4 Python

Python 3.9.7 is the primary programming language for this research essay. The language is omnipresent, widespread in software development. Python's language design makes

[1]https://github.com/CMCD1996/finance-honours

the language highly productive and simple to use. Python can hand off computationally straining tasks to C/C++ using supporting first-class integration capabilities. The language also has a very active and supportive community. Python is the most popular coding language on the planet defined by the PYPL PopularitY of Programming Language Index. As at December 2021, Python has 30.21% of all language tutorial search instances on Google (PYPL, 2021). Python's dynamic, low cost, and open source nature makes programming quick.

9.7.5 Package Management

The Anaconda package management platform for Python (Anaconda, Inc., 2020) is the chosen coding environment. Anaconda is a well defined, free platform, with known versions of python packages such as matplotlib, numpy, and pip. The use of this environment ensures reproducibility and consistency across infrastructure. Pip is the default package manager for Python, included in the Anaconda package. Pip manages package installation and updates.

9.7.6 Code Style

The PEP8 style for Python Code is formatting style for development code Guido Van Rossum and Coghlan, 2001. Yapf, a formatter maintained by Google, manages formatting. Standardised formatting is important as makes supports readability, optimisation, and consistency. Docstrings and rigourous commenting are important in documentation. A docstring is a Python inline comment describing function use, inputs, and outputs. An unique docstring belongs to each Python class and function. The Google style docstring is most appropriate because of it's readability, writing ease, and consistency with Google's Style Guide. The parsing of yapf docstrings enables automated documentation generators to create docstring documents describing functions and classes.

9.7.7 Infrastructure

This research essay deploys variations in artificial neural networks of changing size and complexity. Analysis either took place locally, or remotely, depending on the computational requirements for the particular analysis. An Apple MacBook Pro 13 Inch 2019 with 8 GB 2133 MHz LPDDR3 memory and 1.4 GHz Quad-Core Intel Core i5 processor handles simple tasks locally. A Virtual Machine Instance on the Google Cloud Platform handles more complex tasks remotely. The instance is a n1-standard-8 machine, with an intel Broadwell CPU platform, outfitted with one NVIDIA Tesla K80 GPU. The boot disk stores up to 100GB. CPU and GPU capacity are 30GB and 10GB, respectively

9.7.8 Documentation

The research essay documentation keeps an accurate record of key design decisions. Commit histories (9.7.2) is the most important form of documentation. Application of auxiliary documentation methods are supplementary.

9.8 Code

All files, resources, and code is available for download from Github. The document listing function and class docstring is available for download here. Furthermore, the coding listings for this research essay follow. Try update.

9.9 Data

9.9.1 Description & Sources

The authors provide documentation and web-based resources on GitHub to reconstruct an updated dataset from Wharton Research Data Services (WRDS) using SAS Studio. Identifier variables (e.g., size group), Accounting variables (e.g., COGS), accounting characteristics (e.g., change in net working capital, solvency ratios etc.), market variables (e.g., share price, excess return), market characteristics (e.g., market equity, 60 month CAPM β), and detailed characteristics (e.g., equity duration, Altman Z-Score) and Foreign Exchange Conversion Rates feature in the dataset's composition.

9.9.2 Factor Portfolio Construction

The below enumeration describes verbatim one month holding period return within each country by Jensen et al. (Jensen et al., 2021).

1. In each country and month, we sort stocks into characteristic terciles (top, middle, and bottom with breakpoints based on non-micro stocks in that country. Specifically, we start with all non-micro stocks in a country (i.e., larger than NYSE 20th percentile) and sort them into three groups of equal numbers of stocks based on the characteristic, say book-to-market. Then we distribute the micro-cap stocks into the three groups based on the same characteristic breakpoints. This process ensures that the non-micro stocks are distributed equally among across portfolios, creating more tradable portfolios.

2. For each tercile, we compute its capped value weight" return, meaning that we weight stocks by their market equity, winsorized at the NYSE 80th percentile. This construc- tion ensures that tiny stocks have tiny weights and any one mega stock does not dominate a portfolio, seeking to create tradable, yet balanced, portfolios.

3. The factor is then defined as the high-tercile return minus the low-tercile return, corre- sponding to the excess return of a long-short zero-net-investment strategy. The factor is long (short) the tercile identified by the original paper to have the highest (lowest) expected return.

4. For a factor return to be non-missing, we require that it has at least 5 stocks in each of the long and short legs. We also require a minimum of 60 valid monthly observations for each country-specific factor for inclusion in our sample.

9.9.3 Data Processing

However, the computational complexity exceeds resources available at the time of analysis. The replacement of NaN values in a feature columns with the median value of the respective column to retain observations. Subsequently, training sets require further preprocessing in addition to reconfiguring infrastructure. Furthermore, the reduction in numerical feature precision from float64 to float32 effectively halves memory usage. Memory monitoring methods accompany the aforementioned preprocessing adjustments, monitoring CPU and GPU utilisation, reconfiguring GPU's, and configuring application programming interfaces for monitoring modelling performance.

9.9.4 Summary Statistics

The dataset is exhaustive as illustrated by the both summary statistics and Global Factor Data Documentation in the author's GitHub repository. Table 8 describes summary statistics for the entire global factor dataset. Tables 9, 10, and 11 list summary statistics for revised training, validation, and testing sets, respectively.

	count	mean	std	min	25%	50%	75%	max
permno	2739928.0	5.405281e+04	2.782267e+04	10000.0000	2.651800e+04	5.715400e+04	8.018600e+04	9.343600e+04
permco	2739928.0	1.843974e+04	1.402881e+04	3.0000	7.702000e+03	1.640850e+04	2.321000e+04	5.766700e+04
crsp_shrcd	2739928.0	1.089520e+01	4.571000e-01	10.0000	1.100000e+01	1.100000e+01	1.100000e+01	1.200000e+01
crsp_exchcd	2739928.0	2.127400e+00	9.343000e-01	1.0000	1.000000e+00	3.000000e+00	3.000000e+00	3.000000e+00
sic	2692217.0	4.605936e+03	1.921398e+03	100.0000	3.271000e+03	4.011000e+03	6.036000e+03	9.999000e+03
ff49	2674304.0	3.037380e+01	1.341740e+01	1.0000	1.800000e+01	3.400000e+01	4.300000e+01	4.900000e+01
adjfct	2739928.0	2.838700e+00	1.267170e+01	0.0000	1.000000e+00	1.000000e+00	2.000000e+00	1.215000e+03
shares	2739928.0	6.078630e+01	2.852566e+02	0.0830	4.399000e+00	1.251900e+01	3.808200e+01	2.920640e+04
me	2739928.0	2.241254e+03	1.473073e+04	1.1708	4.367020e+01	1.565628e+02	7.167608e+02	2.255969e+06
me_company	2739928.0	2.283180e+03	1.527340e+04	1.1708	4.387450e+01	1.574086e+02	7.211363e+02	2.255969e+06
prc	2739928.0	2.876220e+01	6.488772e+02	0.0078	7.875000e+00	1.612500e+01	2.912500e+01	1.416000e+05
prc_local	2739928.0	2.876220e+01	6.488772e+02	0.0078	7.875000e+00	1.612500e+01	2.912500e+01	1.416000e+05
dolvol	2580622.0	3.282292e+08	2.520900e+09	0.0000	1.070786e+06	7.165154e+06	7.076108e+07	8.441730e+11
ret	2719460.0	1.640000e-02	1.672000e-01	-1.0000	-5.880000e-02	4.100000e-03	7.410000e-02	2.400000e+01
ret_local	2719460.0	1.640000e-02	1.672000e-01	-1.0000	-5.880000e-02	4.100000e-03	7.410000e-02	2.400000e+01
ret_exc	2719460.0	1.270000e-02	1.673000e-01	-1.0068	-6.250000e-02	7.000000e-04	7.060000e-02	2.399690e+01
ret_lag_dif	2739928.0	1.000000e+00	0.000000e+00	1.0000	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
ret_exc_lead1m	2732542.0	6.400000e-03	1.559000e-01	-1.0113	-6.560000e-02	-1.800000e-03	6.710000e-02	1.988170e+01
market_equity_rank_x	2739928.0	5.982920e+01	2.380660e+01	1.0000	4.000000e+01	6.000000e+01	8.000000e+01	9.950000e+01
enterprise_value_rank_x	2480615.0	5.845440e+01	2.501660e+01	1.0000	3.800000e+01	5.900000e+01	8.000000e+01	9.950000e+01
book_equity_rank_x	2452453.0	5.800700e+01	2.593820e+01	1.0000	3.800000e+01	5.900000e+01	8.000000e+01	9.950000e+01
assets_rank_x	2522907.0	5.751850e+01	2.635510e+01	1.0000	3.700000e+01	5.900000e+01	8.000000e+01	9.950000e+01
sales_rank_x	2509790.0	5.691950e+01	2.717080e+01	1.0000	3.600000e+01	5.900000e+01	8.000000e+01	9.950000e+01
net_income_rank_x	2517298.0	5.581200e+01	2.878360e+01	1.0000	3.300000e+01	6.000000e+01	8.000000e+01	9.950000e+01
bidask_x	2739928.0	1.289000e-01	3.351000e-01	0.0000	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
prc_high_x	2355383.0	2.540480e+01	2.608370e+01	0.1790	9.250000e+00	1.850000e+01	3.300000e+01	4.617600e+02
prc_low_x	2365005.0	2.211970e+01	2.325750e+01	0.0818	7.640000e+00	1.600000e+01	2.880000e+01	4.175300e+02
tvol_x	2580622.0	8.316484e+06	2.941295e+07	0.0000	9.875000e+04	5.510000e+05	3.923700e+06	6.485186e+08
div1m_me_x	2718102.0	1.300000e-03	3.700000e-03	0.0000	0.000000e+00	0.000000e+00	0.000000e+00	9.010000e-02

	count	mean	std	min	25%	50%	75%	max
div3m_me_x	2718121.0	4.000000e-03	6.000000e-03	0.0000	0.000000e+00	0.000000e+00	6.700000e-03	1.164000e-01
div6m_me_x	2660395.0	8.100000e-03	1.170000e-02	0.0000	0.000000e+00	0.000000e+00	1.360000e-02	1.472000e-01
div12m_me_x	2548844.0	1.670000e-02	2.350000e-02	0.0000	0.000000e+00	3.800000e-03	2.780000e-02	4.015000e-01
chcsho_1m_x	2720001.0	3.200000e-03	2.550000e-02	-0.1168	0.000000e+00	0.000000e+00	0.000000e+00	1.096800e+00
chcsho_3m_x	2681179.0	1.240000e-02	6.180000e-02	-0.1424	0.000000e+00	0.000000e+00	3.300000e-03	1.686700e+00
chcsho_6m_x	2624125.0	2.810000e-02	1.189000e-01	-0.1880	0.000000e+00	9.000000e-04	1.070000e-02	3.832600e+00
chcsho_12m_x	2514147.0	6.190000e-02	2.297000e-01	-0.2696	0.000000e+00	4.700000e-03	3.390000e-02	8.477000e+00
eqnpo_1m_x	2718435.0	-1.500000e-03	2.310000e-02	-0.6801	-0.000000e+00	0.000000e+00	0.000000e+00	1.263000e-01
eqnpo_3m_x	2677912.0	-6.200000e-03	5.200000e-02	-0.9973	-1.800000e-03	0.000000e+00	8.000000e-03	1.696000e-01
eqnpo_6m_x	2618619.0	-1.350000e-02	8.900000e-02	-1.5754	-7.400000e-03	0.000000e+00	1.640000e-02	2.788000e-01
eqnpo_12m_x	2504936.0	-2.670000e-02	1.474000e-01	-2.2489	-2.450000e-02	0.000000e+00	3.340000e-02	4.743000e-01
ret_1_0_x	2541516.0	1.490000e-02	1.481000e-01	-0.7242	-6.120000e-02	7.900000e-03	7.690000e-02	2.176500e+00
ret_2_0_x	2521767.0	2.960000e-02	2.125000e-01	-0.8327	-8.110000e-02	1.480000e-02	1.176000e-01	3.342500e+00
ret_3_0_x	2503682.0	4.400000e-02	2.649000e-01	-0.8864	-9.610000e-02	2.270000e-02	1.506000e-01	5.000000e+00
ret_3_1_x	2502019.0	2.870000e-02	2.108000e-01	-0.8310	-8.140000e-02	1.440000e-02	1.167000e-01	3.342500e+00
ret_6_0_x	2447794.0	8.830000e-02	3.970000e-01	-0.9396	-1.267000e-01	4.500000e-02	2.336000e-01	8.555600e+00
ret_6_1_x	2446030.0	7.230000e-02	3.553000e-01	-0.9171	-1.184000e-01	3.700000e-02	2.059000e-01	8.411800e+00
ret_9_0_x	2393988.0	1.336000e-01	5.093000e-01	-0.9721	-1.466000e-01	6.750000e-02	3.069000e-01	9.857100e+00
ret_9_1_x	2392087.0	1.168000e-01	4.700000e-01	-0.9555	-1.414000e-01	5.930000e-02	2.812000e-01	9.273700e+00
ret_12_0_x	2341375.0	1.813000e-01	6.179000e-01	-0.9783	-1.593000e-01	9.080000e-02	3.773000e-01	1.301590e+01
ret_12_1_x	2339380.0	1.635000e-01	5.789000e-01	-0.9728	-1.558000e-01	8.200000e-02	3.514000e-01	1.223080e+01
ret_12_7_x	2337747.0	7.050000e-02	3.478000e-01	-0.9055	-1.163000e-01	3.610000e-02	2.015000e-01	8.509400e+00
ret_18_1_x	2239551.0	2.625000e-01	7.812000e-01	-0.9850	-1.710000e-01	1.321000e-01	4.926000e-01	2.048480e+01
ret_24_1_x	2145964.0	3.596000e-01	9.260000e-01	-0.9890	-1.717000e-01	1.837000e-01	6.267000e-01	1.484620e+01
ret_24_12_x	2142652.0	1.821000e-01	6.037000e-01	-0.9678	-1.493000e-01	9.260000e-02	3.714000e-01	1.345160e+01
ret_36_1_x	1976435.0	5.673000e-01	1.234400e+00	-0.9935	-1.548000e-01	2.964000e-01	8.916000e-01	1.914000e+01
ret_36_12_x	1972590.0	3.838000e-01	9.482000e-01	-0.9864	-1.546000e-01	2.006000e-01	6.490000e-01	1.702520e+01
ret_48_12_x	1821582.0	5.938000e-01	1.256400e+00	-0.9918	-1.358000e-01	3.161000e-01	9.172000e-01	1.811810e+01
ret_48_1_x	1826053.0	7.976000e-01	1.577300e+00	-0.9965	-1.285000e-01	4.175000e-01	1.176300e+00	1.772000e+01

	count	mean	std	min	25%	50%	75%	max
ret_60_1_x	1691563.0	1.064400e+00	2.014800e+00	-0.9985	-9.170000e-02	5.486000e-01	1.492300e+00	2.754720e+01
ret_60_12_x	1686573.0	8.258000e-01	1.611700e+00	-0.9960	-1.096000e-01	4.364000e-01	1.200000e+00	2.063640e+01
ret_60_36_x	1680619.0	3.857000e-01	9.340000e-01	-0.9860	-1.429000e-01	2.072000e-01	6.479000e-01	1.808570e+01
seas_1_1an_x	2426517.0	1.420000e-02	1.421000e-01	-0.6705	-6.040000e-02	7.600000e-03	7.560000e-02	1.823500e+00
seas_1_1na_x	1870192.0	1.490000e-02	4.360000e-02	-0.2355	-7.800000e-03	1.280000e-02	3.460000e-02	3.871000e-01
seas_2_5an_x	1599992.0	1.520000e-02	6.790000e-02	-0.2970	-2.260000e-02	1.180000e-02	4.810000e-02	6.337000e-01
at_gr1_x	2426455.0	2.641000e-01	9.239000e-01	-0.7398	4.800000e-03	9.050000e-02	2.391000e-01	3.163840e+01
ca_gr1_x	2184566.0	3.206000e-01	1.336600e+00	-0.8313	-3.830000e-02	9.400000e-02	2.815000e-01	4.636900e+01
nca_gr1_x	2183067.0	3.950000e-01	1.682300e+00	-0.8737	-1.530000e-02	8.250000e-02	2.844000e-01	5.781320e+01
lt_gr1_x	2408077.0	3.042000e-01	9.791000e-01	-0.8021	-2.990000e-02	8.560000e-02	2.894000e-01	1.783760e+01
cl_gr1_x	2190296.0	2.996000e-01	8.898000e-01	-0.8494	-6.490000e-02	1.114000e-01	3.701000e-01	1.634630e+01
ncl_gr1_x	2075342.0	9.926000e-01	5.509500e+00	-1.0000	-1.023000e-01	3.970000e-02	3.376000e-01	1.990000e+02
be_gr1_x	2311345.0	3.178000e-01	1.301000e+00	-0.9166	5.900000e-03	9.660000e-02	2.271000e-01	3.373330e+01
debt_gr1_x	2158693.0	7.838000e-01	4.707200e+00	-1.0000	-1.456000e-01	1.900000e-02	3.292000e-01	1.090000e+02
sale_gr1_x	2362404.0	2.228000e-01	6.711000e-01	-0.9960	5.000000e-03	1.032000e-01	2.478000e-01	1.370570e+01
cogs_gr1_x	2358805.0	2.142000e-01	6.122000e-01	-0.9619	-4.700000e-03	1.032000e-01	2.613000e-01	1.190030e+01
sga_gr1_x	1997437.0	1.844000e-01	3.963000e-01	-1.0000	1.340000e-02	1.044000e-01	2.389000e-01	6.765800e+00
opex_gr1_x	2387208.0	1.949000e-01	4.470000e-01	-0.7668	7.900000e-03	1.058000e-01	2.505000e-01	7.187400e+00
capx_gr1_x	2147147.0	6.016000e-01	2.183000e+00	-1.3370	-2.236000e-01	1.144000e-01	6.251000e-01	3.425000e+01
inv_gr1_x	1910333.0	2.595000e-01	9.931000e-01	-1.0000	-6.850000e-02	8.260000e-02	2.909000e-01	1.698080e+01
at_gr3_x	2114339.0	9.104000e-01	2.670800e+00	-0.8797	8.870000e-02	3.426000e-01	8.167000e-01	6.899070e+01
ca_gr3_x	1898998.0	9.832000e-01	3.187300e+00	-0.9099	2.890000e-02	3.230000e-01	8.289000e-01	7.748590e+01
nca_gr3_x	1897746.0	1.592100e+00	6.786800e+00	-0.9628	4.280000e-02	3.455000e-01	1.005000e+00	1.792615e+02
lt_gr3_x	2091277.0	1.135900e+00	3.376000e+00	-0.8936	3.580000e-02	3.474000e-01	9.457000e-01	5.633890e+01
cl_gr3_x	1906078.0	9.845000e-01	2.656400e+00	-0.9194	9.000000e-03	3.652000e-01	9.754000e-01	4.535460e+01
ncl_gr3_x	1803330.0	4.168200e+00	2.242620e+01	-1.0000	-1.231000e-01	2.914000e-01	1.285200e+00	8.323333e+02
be_gr3_x	1998122.0	1.009400e+00	3.275200e+00	-0.9384	7.210000e-02	3.326000e-01	7.902000e-01	6.699660e+01
debt_gr3_x	1882647.0	3.622500e+00	2.086590e+01	-1.0000	-2.165000e-01	2.251000e-01	1.145100e+00	4.310000e+02
sale_gr3_x	2063618.0	8.605000e-01	2.814400e+00	-1.0000	7.210000e-02	3.286000e-01	7.527000e-01	8.620390e+01

	count	mean	std	min	25%	50%	75%	max
cogs_gr3_x	2052669.0	7.935000e-01	2.179500e+00	-1.0000	4.870000e-02	3.267000e-01	7.894000e-01	4.537560e+01
sga_gr3_x	1713690.0	6.540000e-01	1.324200e+00	-1.0000	9.470000e-02	3.366000e-01	7.294000e-01	2.400000e+01
opex_gr3_x	2073541.0	7.171000e-01	1.625000e+00	-0.8979	7.650000e-02	3.367000e-01	7.689000e-01	2.833740e+01
capx_gr3_x	1846897.0	1.692700e+00	5.902400e+00	-1.2088	-2.368000e-01	3.214000e-01	1.355700e+00	1.128462e+02
cash_gr1a_x	2396920.0	1.480000e-02	1.380000e-01	-1.1898	-1.600000e-02	2.800000e-03	3.520000e-02	8.303000e-01
inv_gr1a_x	2351255.0	1.250000e-02	5.090000e-02	-0.3723	-7.000000e-04	7.000000e-04	2.250000e-02	2.978000e-01
rec_gr1a_x	2363716.0	2.190000e-02	6.430000e-02	-0.4405	-2.700000e-03	1.190000e-02	4.270000e-02	3.340000e-01
ppeg_gr1a_x	2178200.0	5.240000e-02	1.039000e-01	-0.8431	8.900000e-03	3.670000e-02	8.330000e-02	5.756000e-01
lti_gr1a_x	2205853.0	5.400000e-03	4.060000e-02	-0.4964	0.000000e+00	0.000000e+00	1.100000e-03	3.478000e-01
intan_gr1a_x	2110874.0	1.080000e-02	6.690000e-02	-0.9608	-7.000000e-04	0.000000e+00	1.700000e-03	5.336000e-01
debtst_gr1a_x	2395084.0	3.900000e-03	6.220000e-02	-0.5236	-5.000000e-03	0.000000e+00	1.320000e-02	4.847000e-01
ap_gr1a_x	2267822.0	1.460000e-02	4.890000e-02	-0.2766	-3.900000e-03	6.100000e-03	2.540000e-02	2.945000e-01
txp_gr1a_x	2057276.0	9.000000e-04	1.130000e-02	-0.0902	-9.000000e-04	0.000000e+00	2.200000e-03	9.250000e-02
debtlt_gr1a_x	2411829.0	1.770000e-02	9.970000e-02	-0.6085	-1.080000e-02	0.000000e+00	3.540000e-02	5.760000e-01
txditc_gr1a_x	2135161.0	2.300000e-03	1.280000e-02	-0.1302	0.000000e+00	0.000000e+00	4.800000e-03	8.330000e-02
coa_gr1a_x	2167569.0	3.450000e-02	1.005000e-01	-0.7908	-4.200000e-03	2.200000e-02	7.140000e-02	4.923000e-01
col_gr1a_x	2191221.0	1.980000e-02	6.480000e-02	-0.4855	-5.500000e-03	1.350000e-02	4.240000e-02	3.834000e-01
cowc_gr1a_x	2146736.0	1.440000e-02	8.680000e-02	-0.6052	-1.810000e-02	9.000000e-03	4.750000e-02	4.185000e-01
ncoa_gr1a_x	2185140.0	4.890000e-02	1.438000e-01	-1.8841	-5.500000e-03	2.970000e-02	9.040000e-02	7.494000e-01
ncol_gr1a_x	2174709.0	6.300000e-03	3.310000e-02	-0.3605	-1.100000e-03	1.900000e-03	1.180000e-02	3.338000e-01
nncoa_gr1a_x	2147813.0	4.270000e-02	1.424000e-01	-1.8841	-9.700000e-03	2.500000e-02	8.290000e-02	7.692000e-01
oa_gr1a_x	2167557.0	8.310000e-02	2.025000e-01	-2.5884	-3.400000e-03	6.800000e-02	1.668000e-01	8.176000e-01
ol_gr1a_x	2174709.0	2.620000e-02	8.090000e-02	-0.6433	-4.900000e-03	2.070000e-02	5.460000e-02	5.422000e-01
fna_gr1a_x	2497393.0	5.700000e-03	6.030000e-02	-0.7055	0.000000e+00	0.000000e+00	0.000000e+00	6.896000e-01
fnl_gr1a_x	2418391.0	2.150000e-02	1.353000e-01	-1.2296	-1.620000e-02	1.000000e-04	5.400000e-02	1.130300e+00
nfna_gr1a_x	2418391.0	-1.580000e-02	1.552000e-01	-1.1078	-5.900000e-02	-9.000000e-04	2.760000e-02	1.384100e+00
gp_gr1a_x	2387365.0	3.580000e-02	1.161000e-01	-0.8663	-2.200000e-03	2.080000e-02	7.290000e-02	1.372100e+00
ebitda_gr1a_x	2390711.0	9.700000e-03	9.740000e-02	-0.8685	-1.050000e-02	9.300000e-03	3.840000e-02	1.237100e+00
ebit_gr1a_x	2392217.0	5.200000e-03	9.760000e-02	-0.8536	-1.310000e-02	6.700000e-03	3.280000e-02	1.345400e+00

	count	mean	std	min	25%	50%	75%	max
ope_gr1a_x	2056758.0	9.400000e-03	1.005000e-01	-0.9869	-1.390000e-02	1.090000e-02	3.950000e-02	1.233300e+00
ni_gr1a_x	2402691.0	8.000000e-04	1.303000e-01	-1.6889	-1.340000e-02	3.900000e-03	2.430000e-02	2.739400e+00
nix_gr1a_x	2402691.0	6.000000e-04	1.422000e-01	-1.8549	-1.540000e-02	3.800000e-03	2.570000e-02	2.791300e+00
dp_gr1a_x	2309627.0	3.900000e-03	1.560000e-02	-0.3935	-0.000000e+00	2.500000e-03	7.500000e-03	1.932000e-01
fincf_gr1a_x	2053075.0	1.220000e-02	2.465000e-01	-2.0255	-5.480000e-02	2.700000e-03	7.330000e-02	1.485100e+00
ocf_gr1a_x	2334713.0	1.000000e-04	1.397000e-01	-0.9941	-4.190000e-02	2.900000e-03	4.640000e-02	1.151200e+00
fcf_gr1a_x	2181931.0	-7.300000e-03	1.637000e-01	-1.1368	-6.050000e-02	-4.000000e-04	5.020000e-02	1.202900e+00
nwc_gr1a_x	2164316.0	2.640000e-02	1.763000e-01	-1.4272	-2.650000e-02	1.650000e-02	7.240000e-02	9.090000e-01
eqnetis_gr1a_x	2052797.0	1.170000e-02	2.127000e-01	-1.9975	-1.000000e-02	0.000000e+00	1.380000e-02	1.207600e+00
dltnetis_gr1a_x	2373431.0	-3.100000e-03	1.313000e-01	-0.7874	-2.580000e-02	0.000000e+00	2.250000e-02	7.003000e-01
dstnetis_gr1a_x	2290818.0	7.000000e-04	8.970000e-02	-0.8063	-1.090000e-02	0.000000e+00	1.870000e-02	7.197000e-01
dbnetis_gr1a_x	2374474.0	-2.600000e-03	1.670000e-01	-1.0269	-4.130000e-02	0.000000e+00	4.330000e-02	1.017900e+00
netis_gr1a_x	2052412.0	8.700000e-03	2.717000e-01	-2.0764	-6.040000e-02	1.700000e-03	7.550000e-02	1.539900e+00
eqnpo_gr1a_x	2047069.0	-1.040000e-02	2.148000e-01	-1.1821	-1.480000e-02	0.000000e+00	1.310000e-02	1.940900e+00
tax_gr1a_x	2398103.0	3.100000e-03	2.840000e-02	-0.2157	-3.800000e-03	1.000000e-03	1.140000e-02	2.047000e-01
eqbb_gr1a_x	1893504.0	1.700000e-03	3.370000e-02	-0.3806	0.000000e+00	0.000000e+00	3.000000e-04	2.809000e-01
eqis_gr1a_x	2000469.0	1.360000e-02	2.117000e-01	-2.0255	-2.500000e-03	0.000000e+00	5.700000e-03	1.226200e+00
div_gr1a_x	2382722.0	1.100000e-03	1.270000e-02	-0.2183	0.000000e+00	0.000000e+00	1.200000e-03	2.439000e-01
eqpo_gr1a_x	1891334.0	2.900000e-03	4.380000e-02	-0.4620	-1.000000e-04	0.000000e+00	4.100000e-03	3.915000e-01
capx_gr1a_x	2184434.0	7.400000e-03	5.440000e-02	-0.4868	-7.300000e-03	2.300000e-03	1.940000e-02	4.471000e-01
be_gr1a_x	2311289.0	4.620000e-02	1.699000e-01	-2.0718	1.600000e-03	3.510000e-02	8.970000e-02	8.561000e-01
cash_gr3a_x	2081646.0	2.960000e-02	1.755000e-01	-2.5781	-1.260000e-02	9.500000e-03	6.320000e-02	9.052000e-01
inv_gr3a_x	2033267.0	2.900000e-02	8.700000e-02	-0.6971	0.000000e+00	6.800000e-03	5.550000e-02	4.115000e-01
rec_gr3a_x	2047864.0	4.970000e-02	1.082000e-01	-0.7795	1.400000e-03	3.280000e-02	8.960000e-02	4.887000e-01
ppeg_gr3a_x	1890568.0	1.277000e-01	2.118000e-01	-2.1282	3.190000e-02	1.080000e-01	2.163000e-01	9.231000e-01
lti_gr3a_x	1864897.0	1.290000e-02	7.040000e-02	-0.6566	0.000000e+00	0.000000e+00	8.800000e-03	4.683000e-01
intan_gr3a_x	1784074.0	2.520000e-02	1.171000e-01	-1.7938	-0.000000e+00	0.000000e+00	2.360000e-02	6.632000e-01
debtst_gr3a_x	2078323.0	8.500000e-03	7.970000e-02	-0.8315	-6.500000e-03	3.000000e-04	2.440000e-02	5.514000e-01
ap_gr3a_x	1936459.0	3.440000e-02	8.510000e-02	-0.4973	-3.000000e-04	1.600000e-02	4.880000e-02	4.801000e-01

	count	mean	std	min	25%	50%	75%	max
txp_gr3a_x	1751204.0	1.900000e-03	1.400000e-02	-0.0976	-1.200000e-03	0.000000e+00	4.400000e-03	1.079000e-01
debtlt_gr3a_x	2098723.0	4.090000e-02	1.579000e-01	-1.1700	-1.120000e-02	1.060000e-02	1.011000e-01	7.496000e-01
txditc_gr3a_x	1843283.0	6.200000e-03	2.480000e-02	-0.2172	0.000000e+00	0.000000e+00	1.330000e-02	1.273000e-01
coa_gr3a_x	1880953.0	7.660000e-02	1.701000e-01	-1.4412	6.100000e-03	6.190000e-02	1.549000e-01	6.791000e-01
col_gr3a_x	1907173.0	4.420000e-02	9.650000e-02	-0.9653	4.300000e-03	3.750000e-02	8.380000e-02	4.559000e-01
cowc_gr3a_x	1861920.0	3.210000e-02	1.338000e-01	-1.0405	-2.130000e-02	2.260000e-02	9.140000e-02	5.604000e-01
ncoa_gr3a_x	1899708.0	1.091000e-01	2.575000e-01	-4.5815	1.230000e-02	1.026000e-01	2.250000e-01	8.112000e-01
ncol_gr3a_x	1887939.0	1.640000e-02	5.970000e-02	-0.5782	-0.000000e+00	9.000000e-03	3.080000e-02	4.104000e-01
nncoa_gr3a_x	1861492.0	9.300000e-02	2.474000e-01	-3.9391	1.200000e-03	8.690000e-02	2.030000e-01	8.094000e-01
oa_gr3a_x	1880920.0	1.840000e-01	3.641000e-01	-5.1474	4.560000e-02	2.082000e-01	3.829000e-01	9.247000e-01
ol_gr3a_x	1887939.0	6.020000e-02	1.295000e-01	-1.1795	1.270000e-02	5.900000e-02	1.138000e-01	6.233000e-01
fna_gr3a_x	2302373.0	1.560000e-02	8.920000e-02	-1.1421	0.000000e+00	0.000000e+00	0.000000e+00	7.162000e-01
fnl_gr3a_x	2105333.0	4.560000e-02	2.040000e-01	-1.8999	-1.910000e-02	2.600000e-02	1.304000e-01	8.753000e-01
nfna_gr3a_x	2105333.0	-3.150000e-02	2.282000e-01	-1.3255	-1.318000e-01	-2.310000e-02	4.440000e-02	2.048000e+00
gp_gr3a_x	2074121.0	7.850000e-02	1.870000e-01	-1.2858	4.200000e-03	5.550000e-02	1.554000e-01	1.274100e+00
ebitda_gr3a_x	2079592.0	2.410000e-02	1.330000e-01	-1.0362	-8.600000e-03	2.410000e-02	7.360000e-02	1.478800e+00
ebit_gr3a_x	2081034.0	1.490000e-02	1.346000e-01	-1.1637	-1.460000e-02	1.620000e-02	6.010000e-02	1.985300e+00
ope_gr3a_x	1772515.0	2.290000e-02	1.350000e-01	-1.1140	-1.410000e-02	2.540000e-02	7.260000e-02	1.382600e+00
ni_gr3a_x	2095331.0	5.500000e-03	1.607000e-01	-2.0040	-1.480000e-02	8.900000e-03	4.110000e-02	3.365400e+00
nix_gr3a_x	2095331.0	5.200000e-03	1.722000e-01	-2.2144	-1.670000e-02	8.800000e-03	4.270000e-02	3.330500e+00
dp_gr3a_x	1998657.0	9.200000e-03	2.780000e-02	-0.6566	5.000000e-04	7.400000e-03	1.760000e-02	3.627000e-01
ocf_gr3a_x	2026157.0	1.030000e-02	1.536000e-01	-0.9623	-3.950000e-02	1.100000e-02	6.680000e-02	1.459300e+00
fcf_gr3a_x	1875380.0	-2.300000e-03	1.806000e-01	-0.9594	-6.520000e-02	3.500000e-03	6.430000e-02	1.668700e+00
nwc_gr3a_x	1880705.0	5.470000e-02	2.333000e-01	-3.1433	-2.400000e-02	4.470000e-02	1.438000e-01	9.475000e-01
dltnetis_gr3a_x	2057295.0	-7.000000e-03	1.381000e-01	-0.9437	-3.150000e-02	0.000000e+00	2.360000e-02	8.602000e-01
dstnetis_gr3a_x	1975805.0	-1.000000e-04	7.960000e-02	-0.7776	-1.420000e-02	0.000000e+00	1.680000e-02	6.541000e-01
dbnetis_gr3a_x	2058325.0	-7.400000e-03	1.681000e-01	-1.2437	-4.610000e-02	0.000000e+00	4.140000e-02	1.075700e+00
tax_gr3a_x	2090131.0	6.500000e-03	3.600000e-02	-0.2190	-4.800000e-03	2.700000e-03	1.970000e-02	2.106000e-01
div_gr3a_x	2069485.0	2.200000e-03	1.420000e-02	-0.2110	0.000000e+00	0.000000e+00	4.200000e-03	2.609000e-01

	count	mean	std	min	25%	50%	75%	max
capx_gr3a_x	1877910.0	1.340000e-02	6.720000e-02	-0.6838	-6.700000e-03	6.500000e-03	3.240000e-02	3.679000e-01
capx_at_x	2305667.0	6.630000e-02	7.300000e-02	-0.0305	1.920000e-02	4.470000e-02	8.570000e-02	6.092000e-01
spi_at_x	2376699.0	-1.010000e-02	4.960000e-02	-1.3123	-2.700000e-03	0.000000e+00	0.000000e+00	1.961000e-01
xido_at_x	2513016.0	-5.000000e-04	1.800000e-02	-0.4152	0.000000e+00	0.000000e+00	0.000000e+00	1.762000e-01
nri_at_x	2375825.0	-1.080000e-02	6.070000e-02	-1.5759	-4.600000e-03	0.000000e+00	0.000000e+00	2.675000e-01
gp_sale_x	2468341.0	8.440000e-02	3.062100e+00	-124.7476	2.080000e-01	3.345000e-01	5.045000e-01	9.763000e-01
ebitda_sale_x	2470375.0	-3.073000e-01	4.409900e+00	-171.6176	5.970000e-02	1.272000e-01	2.277000e-01	7.373000e-01
ebit_sale_x	2470818.0	-3.840000e-01	4.578500e+00	-185.0447	3.170000e-02	8.990000e-02	1.721000e-01	6.154000e-01
pi_sale_x	2473639.0	-4.469000e-01	4.876400e+00	-184.2990	1.190000e-02	7.260000e-02	1.445000e-01	7.101000e-01
ni_sale_x	2474362.0	-4.693000e-01	4.796100e+00	-184.2990	7.200000e-03	4.550000e-02	9.440000e-02	5.566000e-01
nix_sale_x	2472905.0	-4.745000e-01	4.848700e+00	-184.2990	6.200000e-03	4.620000e-02	9.640000e-02	6.508000e-01
ocf_sale_x	2414346.0	-3.439000e-01	3.755000e+00	-140.2577	-1.520000e-02	5.800000e-02	1.448000e-01	1.412300e+00
fcf_sale_x	2267091.0	-5.418000e-01	4.134400e+00	-125.9694	-1.053000e-01	-1.100000e-03	6.670000e-02	1.210500e+00
gp_at_x	2503159.0	3.011000e-01	2.895000e-01	-1.2660	1.023000e-01	2.659000e-01	4.563000e-01	1.412300e+00
ebitda_at_x	2505194.0	7.710000e-02	1.992000e-01	-2.1076	2.950000e-02	1.080000e-01	1.699000e-01	5.122000e-01
ebit_at_x	2506116.0	4.100000e-02	1.986000e-01	-2.1142	1.820000e-02	7.130000e-02	1.269000e-01	4.730000e-01
fi_at_x	2185678.0	1.660000e-02	2.114000e-01	-2.6041	2.010000e-02	6.410000e-02	9.800000e-02	3.716000e-01
cop_at_x	2259456.0	1.333000e-01	1.925000e-01	-1.1882	3.940000e-02	1.365000e-01	2.302000e-01	1.940400e+00
ni_at_x	2514966.0	-5.000000e-03	2.045000e-01	-2.8828	3.400000e-03	3.510000e-02	7.410000e-02	3.332000e-01
ope_be_x	2108352.0	1.569000e-01	5.427000e-01	-8.8149	9.490000e-02	2.136000e-01	3.261000e-01	3.725100e+00
ni_be_x	2444347.0	-1.990000e-02	5.962000e-01	-10.7541	1.720000e-02	9.500000e-02	1.504000e-01	1.450500e+00
nix_be_x	2444347.0	-2.270000e-02	6.187000e-01	-11.9515	1.490000e-02	9.590000e-02	1.526000e-01	1.558300e+00
ocf_be_x	2375509.0	4.150000e-02	5.350000e-01	-7.2459	-3.990000e-02	1.089000e-01	2.199000e-01	4.068700e+00
fcf_be_x	2219533.0	-1.352000e-01	6.520000e-01	-9.8959	-2.117000e-01	-4.000000e-03	1.206000e-01	2.895100e+00
gp_bev_x	2404319.0	6.940000e-01	1.236500e+00	-11.0645	2.172000e-01	4.625000e-01	8.366000e-01	1.753110e+01
ebitda_bev_x	2406313.0	5.730000e-02	1.310800e+00	-38.6063	9.750000e-02	1.837000e-01	2.972000e-01	3.290900e+00
ebit_bev_x	2406990.0	-2.510000e-02	1.386000e+00	-41.0563	5.220000e-02	1.282000e-01	2.282000e-01	2.800000e+00
fi_bev_x	2116451.0	-8.600000e-02	1.345800e+00	-38.5103	4.190000e-02	9.910000e-02	1.608000e-01	2.274200e+00
cop_bev_x	2188818.0	3.139000e-01	8.344000e-01	-8.9448	8.920000e-02	2.259000e-01	4.111000e-01	1.607970e+01

	count	mean	std	min	25%	50%	75%	max
gp_ppen_x	2466653.0	2.766900e+00	6.510900e+00	-130.5385	4.559000e-01	1.518900e+00	3.353000e+00	1.035052e+02
ebitda_ppen_x	2468488.0	-1.134000e-01	1.280070e+01	-558.0000	1.689000e-01	4.726000e-01	1.116300e+00	3.389320e+01
fcf_ppen_x	2270795.0	-8.658000e-01	1.104610e+01	-423.4211	-3.778000e-01	-1.180000e-02	3.338000e-01	3.272670e+01
fincf_at_x	2181057.0	6.050000e-02	2.270000e-01	-0.9085	-4.100000e-02	1.800000e-03	8.120000e-02	1.643700e+00
netis_at_x	2180970.0	2.900000e-02	2.576000e-01	-1.3681	-4.860000e-02	0.000000e+00	5.940000e-02	1.592800e+00
eqnetis_at_x	2181226.0	5.680000e-02	1.918000e-01	-0.3507	-8.000000e-04	6.000000e-04	1.520000e-02	1.488800e+00
eqis_at_x	2142004.0	7.050000e-02	1.912000e-01	-0.1034	0.000000e+00	3.200000e-03	2.280000e-02	1.535600e+00
dbnetis_at_x	2487875.0	-2.120000e-02	1.573000e-01	-1.3624	-3.980000e-02	-8.000000e-04	2.270000e-02	6.456000e-01
dltnetis_at_x	2487184.0	-2.430000e-02	1.364000e-01	-1.2268	-3.180000e-02	-2.200000e-03	1.200000e-03	5.184000e-01
dstnetis_at_x	2428021.0	3.500000e-03	6.050000e-02	-0.4789	-5.100000e-03	0.000000e+00	1.130000e-02	4.836000e-01
eqnpo_at_x	2177364.0	-4.470000e-02	1.949000e-01	-1.4673	-1.110000e-02	8.000000e-04	2.020000e-02	4.462000e-01
eqbb_at_x	2059717.0	1.250000e-02	3.500000e-02	-0.0026	0.000000e+00	0.000000e+00	5.300000e-03	4.018000e-01
div_at_x	2500964.0	1.160000e-02	2.170000e-02	0.0000	0.000000e+00	1.900000e-03	1.660000e-02	3.183000e-01
oaccruals_at_x	2261617.0	-1.580000e-02	1.522000e-01	-2.2637	-7.200000e-02	-1.830000e-02	4.760000e-02	6.719000e-01
oaccruals_ni_x	2260635.0	-5.853000e-01	6.180500e+00	-71.4418	-1.208700e+00	-2.712000e-01	6.967000e-01	8.515790e+01
taccruals_at_x	2240180.0	-3.100000e-02	2.045000e-01	-2.4802	-9.100000e-02	-1.180000e-02	4.930000e-02	1.294200e+00
taccruals_ni_x	2238904.0	-1.448100e+00	8.683400e+00	-131.5096	-1.516600e+00	-1.946000e-01	7.622000e-01	6.728570e+01
noa_at_x	2142866.0	6.816000e-01	4.649000e-01	-1.1515	4.896000e-01	6.884000e-01	8.418000e-01	1.038840e+01
be_bev_x	2368048.0	1.343100e+00	2.666700e+00	0.0326	5.543000e-01	8.086000e-01	1.190400e+00	6.053070e+01
debt_bev_x	2416506.0	4.732000e-01	6.162000e-01	0.0000	1.399000e-01	3.804000e-01	6.012000e-01	1.276120e+01
cash_bev_x	2397575.0	8.357000e-01	3.110100e+00	0.0000	3.800000e-02	1.245000e-01	4.276000e-01	8.007360e+01
pstk_bev_x	2418755.0	2.720000e-02	1.704000e-01	0.0000	0.000000e+00	0.000000e+00	0.000000e+00	7.089400e+00
debtlt_bev_x	2412477.0	3.446000e-01	4.482000e-01	0.0000	5.390000e-02	2.671000e-01	4.815000e-01	9.026500e+00
debtst_bev_x	2403343.0	1.233000e-01	2.903000e-01	0.0000	3.200000e-03	3.390000e-02	1.172000e-01	5.633000e+00
int_debt_x	1959042.0	1.258000e-01	3.153000e-01	0.0000	5.310000e-02	7.610000e-02	1.063000e-01	7.750000e+00
int_debtlt_x	1874541.0	3.393000e-01	1.552500e+00	0.0000	6.360000e-02	9.400000e-02	1.485000e-01	4.145000e+01
ebitda_debt_x	2242375.0	2.161600e+00	2.312980e+01	-362.2105	1.666000e-01	3.959000e-01	9.501000e-01	5.562212e+02
profit_cl_x	2270271.0	4.298000e-01	1.566600e+00	-11.9038	2.114000e-01	5.648000e-01	1.016300e+00	6.155300e+00
ocf_cl_x	2269486.0	5.390000e-02	1.456200e+00	-14.9568	-1.363000e-01	2.183000e-01	5.993000e-01	5.976400e+00

	count	mean	std	min	25%	50%	75%	max
ocf_debt_x	2189764.0	1.253200e+00	1.968000e+01	-264.1167	-7.590000e-02	1.564000e-01	5.185000e-01	4.307215e+02
cash_lt_x	2487462.0	7.781000e-01	2.113200e+00	0.0000	4.150000e-02	1.312000e-01	5.084000e-01	2.990910e+01
inv_act_x	2124755.0	2.719000e-01	2.276000e-01	0.0000	4.860000e-02	2.538000e-01	4.448000e-01	9.113000e-01
rec_act_x	2130411.0	3.499000e-01	2.071000e-01	0.0000	1.990000e-01	3.479000e-01	4.754000e-01	9.455000e-01
debtst_debt_x	2235158.0	2.916000e-01	3.181000e-01	0.0000	3.900000e-02	1.578000e-01	4.582000e-01	1.000000e+00
cl_lt_x	2271050.0	5.408000e-01	2.822000e-01	0.0172	3.033000e-01	5.188000e-01	7.861000e-01	1.000000e+00
debtlt_debt_x	2251637.0	7.215000e-01	3.158000e-01	0.0000	5.637000e-01	8.571000e-01	9.724000e-01	1.000000e+00
lt_ppen_x	2467297.0	1.413180e+01	4.095230e+01	0.0809	1.032300e+00	2.019600e+00	5.768200e+00	7.630447e+02
debtlt_be_x	2439883.0	7.140000e-01	1.464700e+00	0.0000	3.360000e-02	3.025000e-01	7.618000e-01	2.225160e+01
opex_at_x	2503218.0	9.413000e-01	8.196000e-01	0.0029	3.295000e-01	7.872000e-01	1.304500e+00	7.158500e+00
nwc_at_x	2253296.0	2.724000e-01	2.457000e-01	-0.7924	8.520000e-02	2.536000e-01	4.349000e-01	9.547000e-01
debt_at_x	2514980.0	2.331000e-01	2.095000e-01	0.0000	5.090000e-02	1.957000e-01	3.591000e-01	1.428700e+00
debt_be_x	2444508.0	9.825000e-01	1.972300e+00	0.0000	9.520000e-02	4.426000e-01	1.023800e+00	3.440000e+01
ebit_int_x	2038745.0	1.266250e+01	1.784445e+02	-3702.0000	1.253300e+00	4.003000e+00	1.124330e+01	3.302250e+03
inv_days_x	2394275.0	8.869850e+01	1.683021e+02	0.0000	9.009300e+00	5.392190e+01	1.091676e+02	3.574195e+03
rec_days_x	2403668.0	3.602296e+02	9.967740e+02	0.0000	3.863530e+01	5.827670e+01	8.822010e+01	7.354934e+03
ap_days_x	2314657.0	1.459695e+03	7.489965e+03	0.7812	2.587680e+01	4.209780e+01	7.865320e+01	1.412089e+05
cash_conversion_x	1836443.0	1.256743e+02	2.122532e+02	0.0000	4.172550e+01	8.193360e+01	1.398610e+02	3.521431e+03
cash_cl_x	2262167.0	1.419800e+00	3.231200e+00	0.0000	1.124000e-01	3.726000e-01	1.177400e+00	3.650000e+01
caliq_cl_x	2241081.0	2.487700e+00	3.827100e+00	0.0581	9.004000e-01	1.378900e+00	2.376600e+00	4.066670e+01
ca_cl_x	2252774.0	3.162200e+00	3.912700e+00	0.0824	1.372500e+00	2.102000e+00	3.307100e+00	4.119530e+01
inv_turnover_x	1990611.0	1.861590e+01	4.951140e+01	0.0438	2.956600e+00	5.130900e+00	1.205000e+01	7.307939e+02
at_turnover_x	2482416.0	1.084900e+00	9.318000e-01	0.0000	3.768000e-01	9.269000e-01	1.525100e+00	9.298300e+00
rec_turnover_x	2400338.0	1.234110e+01	2.636800e+01	0.0000	4.039600e+00	6.187900e+00	9.236800e+00	2.787135e+02
ap_turnover_x	2229997.0	1.163840e+01	1.238900e+01	-0.1258	4.826800e+00	8.918500e+00	1.434510e+01	1.336129e+02
sale_bev_x	2408388.0	2.269200e+00	2.923100e+00	0.0000	7.623000e-01	1.580300e+00	2.598800e+00	3.887110e+01
sale_be_x	2437063.0	2.732600e+00	3.718300e+00	0.0000	9.001000e-01	1.758000e+00	3.096000e+00	5.438940e+01
div_ni_x	1963756.0	3.126000e-01	5.775000e-01	0.0000	0.000000e+00	1.650000e-01	4.135000e-01	1.293670e+01
sale_nwc_x	2017664.0	9.746900e+00	2.267620e+01	0.0000	2.066900e+00	3.971600e+00	7.750900e+00	3.110241e+02

	count	mean	std	min	25%	50%	75%	max
tax_pi_x	1999061.0	3.279000e-01	3.117000e-01	-7.2981	2.705000e-01	3.654000e-01	4.329000e-01	5.548900e+00
cash_at_x	2496082.0	1.581000e-01	2.035000e-01	0.0000	2.580000e-02	7.260000e-02	2.026000e-01	9.799000e-01
ni_emp_x	2332173.0	-1.044570e+01	1.898294e+02	-3810.3810	4.055000e-01	4.200600e+00	1.703640e+01	1.438498e+03
sale_emp_x	2328826.0	2.691786e+02	5.003031e+02	0.0000	6.301400e+01	1.411000e+02	2.763478e+02	7.782523e+03
sale_emp_gr1_x	2120715.0	1.123000e-01	4.553000e-01	-0.9563	-3.330000e-02	5.300000e-02	1.513000e-01	7.027000e+00
emp_gr1_x	2048454.0	7.670000e-02	2.504000e-01	-1.3333	-3.060000e-02	4.520000e-02	1.538000e-01	1.483100e+00
ni_inc8q_x	1837805.0	3.116800e+00	3.262400e+00	0.0000	0.000000e+00	2.000000e+00	7.000000e+00	8.000000e+00
noa_gr1a_x	2130139.0	1.277000e-01	4.002000e-01	-0.7366	-1.750000e-02	4.940000e-02	1.574000e-01	1.075230e+01
ppeinv_gr1a_x	2130674.0	1.104000e-01	2.282000e-01	-0.5663	9.400000e-03	5.870000e-02	1.436000e-01	3.078700e+00
lnoa_gr1a_x	2042945.0	3.180000e-02	9.170000e-02	-0.5778	-3.800000e-03	1.370000e-02	4.740000e-02	7.544000e-01
capx_gr2_x	1996106.0	1.219100e+00	4.305300e+00	-1.4277	-2.477000e-01	2.272000e-01	1.043000e+00	7.697220e+01
saleq_gr1_x	2256822.0	2.428000e-01	8.315000e-01	-1.0000	-1.270000e-02	9.890000e-02	2.606000e-01	1.574840e+01
niq_be_x	2153966.0	5.000000e-04	1.393000e-01	-2.0216	1.600000e-03	2.420000e-02	4.290000e-02	6.993000e-01
niq_at_x	2218680.0	-2.200000e-03	6.080000e-02	-0.6672	0.000000e+00	8.200000e-03	2.060000e-02	1.818000e-01
niq_be_chg1_x	1961181.0	-7.700000e-03	1.339000e-01	-2.0038	-1.650000e-02	-6.000000e-04	1.090000e-02	1.227600e+00
niq_at_chg1_x	2044996.0	3.000000e-04	5.400000e-02	-0.4547	-7.100000e-03	-0.000000e+00	5.600000e-03	8.413000e-01
dsale_dinv_x	1796036.0	-4.380000e-02	8.780000e-01	-19.4778	-1.460000e-01	2.150000e-02	1.949000e-01	5.598300e+00
dsale_drec_x	2136436.0	-3.080000e-02	6.202000e-01	-7.3996	-1.418000e-01	1.500000e-03	1.418000e-01	7.637700e+00
dgp_dsale_x	2120443.0	2.720000e-02	5.405000e-01	-5.9700	-7.530000e-02	2.300000e-03	8.380000e-02	1.201120e+01
dsale_dsga_x	1827645.0	2.310000e-02	3.643000e-01	-2.2251	-8.920000e-02	-1.000000e-04	9.360000e-02	6.963700e+00
saleq_su_x	1944544.0	1.618000e-01	1.699500e+00	-16.0960	-8.666000e-01	1.532000e-01	1.125000e+00	3.358810e+01
niq_su_x	1972831.0	-1.123000e-01	1.940400e+00	-50.8463	-7.565000e-01	5.100000e-03	7.529000e-01	2.019490e+01
capex_abn_x	1806456.0	1.173000e-01	9.626000e-01	-1.1469	-3.685000e-01	-6.920000e-02	2.932000e-01	1.196350e+01
op_atl1_x	2415570.0	1.320000e-01	2.472000e-01	-6.9463	4.860000e-02	1.355000e-01	2.227000e-01	1.125400e+00
gp_atl1_x	2413733.0	3.639000e-01	3.763000e-01	-1.9036	1.162000e-01	3.032000e-01	5.356000e-01	2.788000e+00
ope_bel1_x	2010286.0	2.202000e-01	6.575000e-01	-13.6285	1.063000e-01	2.425000e-01	3.880000e-01	4.617600e+00
cop_atl1_x	2237311.0	1.409000e-01	2.863000e-01	-3.8344	4.500000e-02	1.505000e-01	2.563000e-01	1.923400e+00
pi_nix_x	1959639.0	1.615000e+00	6.861000e-01	0.1059	1.340700e+00	1.572900e+00	1.777900e+00	1.989360e+01
ocf_at_x	2449158.0	1.150000e-02	1.872000e-01	-1.8184	-2.140000e-02	4.090000e-02	1.033000e-01	5.979000e-01

	count	mean	std	min	25%	50%	75%	max
op_at_x	2505194.0	1.113000e-01	1.575000e-01	-1.2330	4.200000e-02	1.205000e-01	1.892000e-01	5.662000e-01
ocf_at_chg1_x	2333855.0	2.300000e-03	1.627000e-01	-1.0782	-4.770000e-02	-1.000000e-04	4.630000e-02	1.390100e+00
at_be_x	2452393.0	3.714900e+00	4.779700e+00	1.0000	1.469000e+00	2.029600e+00	3.240900e+00	5.963100e+01
niq_saleq_std_x	1902197.0	1.360600e+00	1.149800e+01	0.0008	1.930000e-02	4.260000e-02	1.236000e-01	3.177766e+02
roe_be_std_x	1799259.0	1.611000e-01	4.732000e-01	0.0021	2.230000e-02	4.760000e-02	1.133000e-01	9.225400e+00
tangibility_x	2201788.0	6.502000e-01	1.916000e-01	0.0025	5.540000e-01	6.638000e-01	7.614000e-01	1.684700e+00
earnings_variability_x	1752776.0	8.639000e-01	1.037400e+00	0.0243	2.577000e-01	5.765000e-01	1.052900e+00	1.145280e+01
aliq_at_x	2174808.0	8.263000e-01	8.005000e-01	0.1044	5.792000e-01	6.946000e-01	8.423000e-01	2.803980e+01
f_score_x	1978727.0	4.911500e+00	1.728500e+00	0.0000	4.000000e+00	5.000000e+00	6.000000e+00	9.000000e+00
o_score_x	2127585.0	-1.902100e+00	3.035200e+00	-9.3872	-3.598500e+00	-2.309000e+00	-8.857000e-01	2.287030e+01
z_score_x	2126989.0	5.526800e+00	9.357000e+00	-37.3359	1.992200e+00	3.446700e+00	5.637300e+00	1.744239e+02
intrinsic_value_x	1899809.0	1.317903e+03	5.258077e+03	0.0982	3.489040e+01	1.295681e+02	5.706605e+02	1.130984e+05
kz_index_x	2167838.0	-1.126290e+01	5.190800e+01	-1723.5716	-6.936600e+00	-1.467200e+00	5.962000e-01	8.903350e+01
gpoa_ch5_x	1799428.0	-5.000000e-03	1.939000e-01	-1.1201	-7.080000e-02	-2.900000e-03	5.560000e-02	1.669700e+00
roe_ch5_x	1718355.0	-1.400000e-02	5.543000e-01	-7.5143	-7.570000e-02	-6.100000e-03	5.400000e-02	7.791500e+00
roa_ch5_x	1824336.0	4.900000e-03	1.917000e-01	-1.6595	-3.640000e-02	-1.800000e-03	2.650000e-02	3.283900e+00
cfoa_ch5_x	1759171.0	1.520000e-02	1.825000e-01	-0.9610	-5.570000e-02	2.500000e-03	7.100000e-02	2.175100e+00
gmar_ch5_x	1777826.0	4.200000e-02	9.593000e-01	-24.3597	-4.330000e-02	2.700000e-03	5.140000e-02	3.059480e+01
ni_ar1_x	1798398.0	2.127000e-01	6.110000e-01	-3.9640	-1.463000e-01	1.674000e-01	5.078000e-01	9.144200e+00
ni_ivol_x	1798398.0	5.090000e-02	1.054000e-01	0.0003	7.900000e-03	1.910000e-02	4.640000e-02	1.756800e+00
at_me_x	2522907.0	2.710400e+00	4.953100e+00	0.0086	5.788000e-01	1.230200e+00	2.687400e+00	1.923122e+02
be_me_x	2452453.0	7.411000e-01	7.141000e-01	0.0050	3.072000e-01	5.729000e-01	9.557000e-01	2.516310e+01
debt_me_x	2515141.0	7.136000e-01	1.647800e+00	0.0000	3.610000e-02	2.333000e-01	7.145000e-01	6.550580e+01
netdebt_me_x	2515141.0	4.707000e-01	1.480500e+00	-3.4965	-6.240000e-02	1.146000e-01	5.472000e-01	5.866260e+01
cash_me_x	2496218.0	2.459000e-01	5.843000e-01	0.0000	3.340000e-02	9.500000e-02	2.301000e-01	1.478940e+01
sale_me_x	2509790.0	1.848400e+00	3.088100e+00	0.0000	3.854000e-01	9.080000e-01	2.049100e+00	7.507530e+01
gp_me_x	2504145.0	4.729000e-01	6.845000e-01	-5.3506	1.503000e-01	2.955000e-01	5.587000e-01	1.896990e+01
ebitda_me_x	2506237.0	1.594000e-01	2.707000e-01	-5.8474	5.650000e-02	1.331000e-01	2.363000e-01	5.597900e+00
ebit_me_x	2507305.0	9.600000e-02	2.455000e-01	-7.4186	3.000000e-02	9.500000e-02	1.716000e-01	3.506600e+00

	count	mean	std	min	25%	50%	75%	max
ope_me_x	2183835.0	1.085000e-01	2.516000e-01	-8.0248	3.920000e-02	1.084000e-01	1.911000e-01	3.793500e+00
ni_me_x	2517298.0	1.200000e-03	3.459000e-01	-18.9294	5.500000e-03	4.900000e-02	8.530000e-02	9.917000e-01
nix_me_x	2517298.0	-1.200000e-03	3.693000e-01	-20.3694	4.100000e-03	4.920000e-02	8.650000e-02	1.036200e+00
cop_me_x	2259562.0	2.183000e-01	5.014000e-01	-3.5452	4.550000e-02	1.406000e-01	2.768000e-01	2.124680e+01
ocf_me_x	2450553.0	4.280000e-02	2.747000e-01	-5.6691	-1.830000e-02	5.360000e-02	1.205000e-01	5.711200e+00
fcf_me_x	2303306.0	-7.030000e-02	3.536000e-01	-8.5448	-1.065000e-01	-2.600000e-03	5.530000e-02	4.202300e+00
div_me_x	2501593.0	1.780000e-02	2.950000e-02	0.0000	0.000000e+00	3.900000e-03	2.660000e-02	1.049700e+00
eqbb_me_x	2059868.0	1.380000e-02	3.780000e-02	-0.0037	0.000000e+00	0.000000e+00	7.800000e-03	8.704000e-01
eqis_me_x	2142182.0	4.550000e-02	1.388000e-01	-0.1339	1.000000e-04	3.500000e-03	1.830000e-02	5.839400e+00
eqpo_me_x	2058263.0	3.150000e-02	5.660000e-02	-0.0013	0.000000e+00	1.120000e-02	4.150000e-02	1.725500e+00
eqnpo_me_x	2177501.0	-1.430000e-02	1.450000e-01	-6.1142	-8.100000e-03	1.200000e-03	3.130000e-02	1.442900e+00
eqnetis_me_x	2181408.0	3.130000e-02	1.401000e-01	-0.6866	-1.400000e-03	7.000000e-04	1.260000e-02	5.679700e+00
at_mev_x	2480516.0	1.759600e+00	3.280300e+00	0.0085	5.638000e-01	1.008000e+00	1.587100e+00	6.916660e+01
bev_mev_x	2404633.0	6.919000e-01	5.487000e-01	0.0009	3.194000e-01	6.308000e-01	9.482000e-01	1.692550e+01
ppen_mev_x	2459710.0	3.322000e-01	3.872000e-01	0.0000	5.950000e-02	1.893000e-01	4.753000e-01	6.654400e+00
be_mev_x	2410201.0	6.153000e-01	8.336000e-01	0.0050	2.513000e-01	4.357000e-01	7.057000e-01	2.914710e+01
cash_mev_x	2460357.0	2.333000e-01	6.611000e-01	0.0000	2.350000e-02	6.940000e-02	1.825000e-01	1.486960e+01
sale_mev_x	2472091.0	1.265200e+00	1.765600e+00	0.0000	3.146000e-01	7.343000e-01	1.550900e+00	3.775600e+01
gp_mev_x	2467238.0	3.453000e-01	4.647000e-01	-2.4081	1.209000e-01	2.305000e-01	4.284000e-01	1.314000e+01
ebitda_mev_x	2469299.0	1.012000e-01	2.101000e-01	-5.5869	5.090000e-02	1.060000e-01	1.669000e-01	2.711700e+00
ebit_mev_x	2470075.0	6.010000e-02	2.226000e-01	-6.8743	2.670000e-02	7.470000e-02	1.222000e-01	2.601300e+00
cop_mev_x	2243652.0	1.516000e-01	2.798000e-01	-2.3844	4.200000e-02	1.203000e-01	2.126000e-01	8.747500e+00
ocf_mev_x	2431339.0	3.150000e-02	1.968000e-01	-4.7377	-1.650000e-02	4.340000e-02	9.350000e-02	2.334400e+00
fcf_mev_x	2286863.0	-3.800000e-02	2.261000e-01	-6.0410	-8.630000e-02	-2.300000e-03	4.670000e-02	1.728000e+00
debt_mev_x	2480615.0	3.008000e-01	3.502000e-01	0.0000	4.020000e-02	2.106000e-01	4.607000e-01	7.224300e+00
pstk_mev_x	2479267.0	1.480000e-02	5.860000e-02	0.0000	0.000000e+00	0.000000e+00	0.000000e+00	1.220500e+00
debtlt_mev_x	2476104.0	2.224000e-01	2.443000e-01	0.0000	1.400000e-02	1.446000e-01	3.542000e-01	2.411300e+00
debtst_mev_x	2461067.0	8.090000e-02	2.125000e-01	0.0000	9.000000e-04	1.690000e-02	7.010000e-02	5.292900e+00
dltnetis_mev_x	2453443.0	-3.150000e-02	1.853000e-01	-3.5613	-3.440000e-02	-1.900000e-03	1.200000e-03	6.324000e-01

	count	mean	std	min	25%	50%	75%	max
dstnetis_mev_x	2393968.0	4.100000e-03	9.390000e-02	-1.0163	-4.800000e-03	0.000000e+00	1.110000e-02	1.122900e+00
dbnetis_mev_x	2454176.0	-2.880000e-02	2.223000e-01	-4.4848	-4.210000e-02	-6.000000e-04	2.280000e-02	1.188800e+00
netis_mev_x	2164671.0	-8.300000e-03	2.729000e-01	-4.6395	-5.040000e-02	0.000000e+00	5.030000e-02	5.358400e+00
fincf_mev_x	2164802.0	3.700000e-02	2.405000e-01	-2.3006	-4.040000e-02	1.300000e-03	7.090000e-02	6.822000e+00
aliq_mat_x	2036506.0	5.016000e-01	2.661000e-01	0.0270	3.052000e-01	4.793000e-01	6.504000e-01	3.973200e+00
eq_dur_x	2193667.0	1.598720e+01	5.630900e+00	0.2861	1.413720e+01	1.612420e+01	1.764670e+01	3.430355e+02
beta_60m_x	2090801.0	1.153800e+00	6.856000e-01	-1.7467	6.897000e-01	1.081600e+00	1.528500e+00	4.912400e+00
ivol_capm_60m_x	2090801.0	1.172000e-01	6.560000e-02	0.0288	7.050000e-02	1.002000e-01	1.454000e-01	5.392000e-01
resff3_12_1_x	2274040.0	-2.210000e-02	2.736000e-01	-1.1550	-1.908000e-01	-8.900000e-03	1.610000e-01	7.899000e-01
resff3_6_1_x	2273172.0	-5.420000e-02	5.396000e-01	-2.9537	-3.435000e-01	-2.040000e-02	2.734000e-01	1.925800e+00
mispricing_mgmt_x	2414716.0	4.896000e-01	1.856000e-01	0.0147	3.610000e-01	5.047000e-01	6.284000e-01	9.427000e-01
mispricing_perf_x	2649116.0	5.208000e-01	2.065000e-01	0.0099	3.773000e-01	5.270000e-01	6.749000e-01	9.881000e-01
zero_trades_21d_x	2568596.0	9.102000e-01	2.670500e+00	0.0000	1.800000e-03	3.700000e-03	7.200000e-03	2.100980e+01
dolvol_126d_x	2527407.0	1.272436e+07	5.041472e+07	36.1000	6.023594e+04	3.756701e+05	3.493927e+06	1.038495e+09
dolvol_var_126d_x	2527340.0	1.275800e+00	7.751000e-01	0.2622	7.587000e-01	1.088500e+00	1.545100e+00	8.289100e+00
turnover_126d_x	2527415.0	4.300000e-03	6.800000e-03	0.0000	9.000000e-04	2.200000e-03	5.300000e-03	2.857000e-01
turnover_var_126d_x	2527348.0	1.251900e+00	7.609000e-01	0.2796	7.459000e-01	1.058700e+00	1.509700e+00	7.678300e+00
zero_trades_126d_x	2527415.0	9.170000e-01	2.511100e+00	0.0000	1.900000e-03	4.000000e-03	1.771000e-01	1.949730e+01
zero_trades_252d_x	2472485.0	9.236000e-01	2.470600e+00	0.0001	2.000000e-03	4.300000e-03	2.625000e-01	1.910030e+01
bidaskhl_21d_x	2474735.0	1.470000e-02	1.810000e-02	0.0011	5.600000e-03	9.400000e-03	1.710000e-02	5.318000e-01
rvolhl_21d_x	2474735.0	2.130000e-02	1.570000e-02	0.0000	1.100000e-02	1.720000e-02	2.680000e-02	1.854000e-01
beta_21d_x	2469080.0	8.736000e-01	1.205700e+00	-11.1429	2.238000e-01	8.042000e-01	1.458000e+00	1.276490e+01
ivol_capm_21d_x	2469080.0	2.710000e-02	1.960000e-02	0.0018	1.400000e-02	2.160000e-02	3.380000e-02	2.415000e-01
iskew_capm_21d_x	2469046.0	2.407000e-01	8.745000e-01	-3.5665	-2.542000e-01	2.053000e-01	7.097000e-01	3.715300e+00
coskew_21d_x	2469074.0	-1.530000e-02	3.111000e-01	-1.4678	-2.232000e-01	-2.070000e-02	1.886000e-01	1.347500e+00
beta_dimson_21d_x	2469080.0	9.503000e-01	1.950600e+00	-19.3713	4.290000e-02	8.515000e-01	1.798400e+00	2.341690e+01
ivol_ff3_21d_x	2469080.0	2.640000e-02	1.930000e-02	0.0018	1.360000e-02	2.100000e-02	3.300000e-02	2.340000e-01
iskew_ff3_21d_x	2469068.0	1.990000e-01	7.943000e-01	-3.1203	-2.632000e-01	1.696000e-01	6.344000e-01	3.455800e+00
ivol_hxz4_21d_x	2332649.0	2.680000e-02	1.960000e-02	0.0018	1.370000e-02	2.130000e-02	3.350000e-02	2.397000e-01

	count	mean	std	min	25%	50%	75%	max
iskew_hxz4_21d_x	2332643.0	1.777000e-01	7.585000e-01	-3.0805	-2.681000e-01	1.513000e-01	6.005000e-01	3.275600e+00
rmax5_21d_x	2469033.0	3.860000e-02	2.910000e-02	0.0022	1.960000e-02	3.050000e-02	4.810000e-02	3.544000e-01
rmax1_21d_x	2469033.0	6.730000e-02	5.830000e-02	0.0035	3.110000e-02	5.000000e-02	8.280000e-02	8.996000e-01
rvol_21d_x	2469080.0	2.970000e-02	2.060000e-02	0.0018	1.590000e-02	2.400000e-02	3.690000e-02	2.515000e-01
rskew_21d_x	2469038.0	2.439000e-01	8.740000e-01	-3.5810	-2.529000e-01	2.077000e-01	7.136000e-01	3.808400e+00
ami_126d_x	2427976.0	2.294900e+00	1.277990e+01	0.0000	6.300000e-03	8.310000e-02	7.621000e-01	7.242321e+02
beta_252d_x	2434576.0	8.972000e-01	6.011000e-01	-1.8325	4.682000e-01	8.481000e-01	1.259200e+00	4.013900e+00
ivol_capm_252d_x	2434576.0	2.910000e-02	1.710000e-02	0.0050	1.700000e-02	2.480000e-02	3.650000e-02	1.684000e-01
betadown_252d_x	2406390.0	1.001300e+00	7.817000e-01	-3.9821	5.127000e-01	9.352000e-01	1.414000e+00	5.699200e+00
prc_highprc_252d_x	2434268.0	7.724000e-01	1.997000e-01	0.0167	6.610000e-01	8.272000e-01	9.318000e-01	1.000000e+00
rvol_252d_x	2434576.0	3.110000e-02	1.740000e-02	0.0052	1.870000e-02	2.680000e-02	3.870000e-02	1.690000e-01
corr_1260d_x	1904407.0	3.603000e-01	1.650000e-01	-0.0374	2.362000e-01	3.573000e-01	4.786000e-01	8.219000e-01
betabab_1260d_x	1893789.0	1.075600e+00	5.871000e-01	-0.3259	6.475000e-01	1.000500e+00	1.410600e+00	4.274900e+00
rmax5_rvol_21d_x	2343331.0	1.232900e+00	5.049000e-01	0.1125	8.720000e-01	1.159900e+00	1.512600e+00	4.328700e+00
age_x	2739928.0	2.184690e+02	1.888040e+02	1.0000	7.900000e+01	1.590000e+02	3.000000e+02	1.115000e+03
qmj_x	1825615.0	8.990000e-02	9.763000e-01	-1.7027	-7.318000e-01	1.204000e-01	9.350000e-01	1.701100e+00
qmj_prof_x	2502382.0	9.110000e-02	9.846000e-01	-1.7036	-7.339000e-01	1.300000e-01	9.456000e-01	1.698800e+00
qmj_growth_x	1825622.0	3.610000e-02	9.739000e-01	-1.7018	-7.911000e-01	4.900000e-02	8.716000e-01	1.702100e+00
qmj_safety_x	2579701.0	8.730000e-02	9.713000e-01	-1.7012	-7.189000e-01	1.215000e-01	9.239000e-01	1.708800e+00

Table 8: Complete Global Factor Dataset Summary Statistics

	count	mean	std	min	25%	50%	75%	max
beta_60m_x	532218.0	1.171000e+00	4.530000e-01	-0.350	0.886	1.149	1.393000e+00	3.389000e+00
index	532218.0	8.806473e+05	4.668442e+05	651.000	528652.250	821568.500	1.220481e+06	2.733106e+06
mth	532218.0	1.976878e+05	8.005020e+02	196101.000	197103.000	197711.000	1.984030e+05	1.989120e+05
permno	532218.0	3.638201e+04	1.839758e+04	10006.000	21573.000	32302.000	4.972900e+04	9.322000e+04
permco	532218.0	1.740521e+04	8.516931e+03	4.000	8611.000	21173.000	2.289400e+04	5.628500e+04
crsp_shrcd	532218.0	1.066100e+01	5.230000e-01	10.000	10.000	11.000	1.100000e+01	1.200000e+01
crsp_exchcd	532218.0	1.509000e+00	8.170000e-01	1.000	1.000	1.000	2.000000e+00	3.000000e+00
sic	532218.0	4.147325e+03	1.685914e+03	100.000	2899.000	3721.000	5.311000e+03	9.511000e+03
ff49	532218.0	2.874800e+01	1.327400e+01	1.000	18.000	31.000	4.100000e+01	4.900000e+01
adjfct	532218.0	6.901000e+00	2.505700e+01	0.000	1.000	2.000	4.000000e+00	1.215000e+03
shares	532218.0	1.992800e+01	4.235100e+01	0.212	4.200	8.553	1.963800e+01	1.426344e+03
me	532218.0	6.983350e+02	2.292746e+03	17.030	94.162	196.351	5.360830e+02	1.020223e+05
me_company	532218.0	7.058630e+02	2.338138e+03	17.030	94.471	197.355	5.383670e+02	1.020223e+05
prc	532218.0	3.142100e+01	5.300700e+01	0.422	17.375	26.000	3.775000e+01	8.675000e+03
prc_local	532218.0	3.142100e+01	5.300700e+01	0.422	17.375	26.000	3.775000e+01	8.675000e+03
dolvol	532218.0	2.686159e+07	1.110126e+08	0.000	1586250.000	4175525.000	1.458036e+07	9.027815e+09
ret	532218.0	1.700000e-02	1.090000e-01	-0.761	-0.043	0.008	6.800000e-02	3.185000e+00
ret_local	532218.0	1.700000e-02	1.090000e-01	-0.761	-0.043	0.008	6.800000e-02	3.185000e+00
ret_exc	532218.0	1.100000e-02	1.090000e-01	-0.771	-0.049	0.003	6.200000e-02	3.180000e+00
ret_lag_dif	532218.0	1.000000e+00	0.000000e+00	1.000	1.000	1.000	1.000000e+00	1.000000e+00
ret_exc_lead1m	532218.0	5.000000e-03	1.060000e-01	-1.005	-0.052	0.000	5.800000e-02	2.472000e+00
niq_su_x	532218.0	3.200000e-02	1.438000e+00	-15.807	-0.293	0.033	4.670000e-01	1.642400e+01
ret_6_1_x	532218.0	8.100000e-02	2.470000e-01	-0.811	-0.057	0.039	1.860000e-01	2.811000e+00
ret_12_1_x	532218.0	1.810000e-01	4.100000e-01	-0.859	-0.043	0.095	3.260000e-01	6.188000e+00
saleq_su_x	532218.0	2.610000e-01	1.384000e+00	-11.313	-0.177	0.192	7.030000e-01	3.358800e+01
tax_gr1a_x	532218.0	6.000000e-03	2.200000e-02	-0.153	-0.001	0.003	1.200000e-02	1.500000e-01
ni_inc8q_x	532218.0	3.814000e+00	2.800000e+00	0.000	3.000	3.000	7.000000e+00	8.000000e+00
prc_highprc_252d_x	532218.0	8.310000e-01	1.410000e-01	0.116	0.766	0.853	9.380000e-01	1.000000e+00
resff3_6_1_x	532218.0	-4.200000e-02	5.010000e-01	-2.954	-0.282	-0.019	2.320000e-01	1.926000e+00

	count	mean	std	min	25%	50%	75%	max
resff3_12_1_x	532218.0	-1.800000e-02	2.550000e-01	-1.155	-0.161	-0.007	1.370000e-01	7.900000e-01
be_me_x	532218.0	8.110000e-01	5.520000e-01	0.012	0.448	0.724	1.022000e+00	1.009700e+01
debt_me_x	532218.0	7.170000e-01	1.271000e+00	0.000	0.123	0.332	7.470000e-01	2.510800e+01
at_me_x	532218.0	2.978000e+00	5.266000e+00	0.037	0.831	1.482	2.495000e+00	5.293000e+01
ret_60_12_x	532218.0	9.080000e-01	1.395000e+00	-0.939	0.286	0.550	1.046000e+00	2.063600e+01
ni_me_x	532218.0	8.300000e-02	9.300000e-02	-4.344	0.054	0.074	1.150000e-01	8.570000e-01
fcf_me_x	532218.0	-1.330000e-01	3.110000e-01	-6.788	-0.149	-0.070	-1.600000e-02	2.322000e+00
div12m_me_x	532218.0	3.200000e-02	2.500000e-02	0.000	0.013	0.028	4.600000e-02	1.750000e-01
eqpo_me_x	532218.0	3.300000e-02	3.900000e-02	-0.000	0.019	0.020	3.600000e-02	6.870000e-01
eqnpo_me_x	532218.0	1.300000e-02	6.100000e-02	-1.569	0.010	0.010	2.700000e-02	5.800000e-01
sale_gr3_x	532218.0	5.970000e-01	1.045000e+00	-0.983	0.250	0.396	6.210000e-01	2.835500e+01
sale_gr1_x	532218.0	1.680000e-01	2.990000e-01	-0.911	0.061	0.121	2.020000e-01	8.495000e+00
ebitda_mev_x	532218.0	1.650000e-01	1.360000e-01	-2.840	0.109	0.143	1.960000e-01	2.712000e+00
sale_me_x	532218.0	2.020000e+00	2.490000e+00	0.000	0.786	1.518	2.269000e+00	6.705800e+01
ocf_me_x	532218.0	1.500000e-02	2.220000e-01	-4.015	-0.020	0.020	8.100000e-02	2.748000e+00
intrinsic_value_x	532218.0	4.197170e+02	8.801200e+02	0.099	65.828	113.423	3.517070e+02	9.626163e+03
bev_mev_x	532218.0	7.700000e-01	4.030000e-01	0.009	0.505	0.773	9.770000e-01	5.615000e+00
netdebt_me_x	532218.0	4.110000e-01	1.070000e+00	-3.343	0.016	0.201	5.340000e-01	2.390300e+01
eq_dur_x	532218.0	1.460200e+01	2.748000e+00	0.286	13.409	14.948	1.632600e+01	3.766200e+01
capex_abn_x	532218.0	3.600000e-02	5.400000e-01	-1.139	-0.142	-0.061	9.300000e-02	9.084000e+00
at_gr1_x	532218.0	1.790000e-01	3.130000e-01	-0.588	0.058	0.108	1.900000e-01	6.247000e+00
ppeinv_gr1a_x	532218.0	1.200000e-01	1.630000e-01	-0.566	0.058	0.088	1.370000e-01	2.396000e+00
noa_at_x	532218.0	7.700000e-01	2.170000e-01	-0.206	0.701	0.758	8.310000e-01	3.512000e+00
noa_gr1a_x	532218.0	1.000000e-01	1.790000e-01	-0.585	0.036	0.068	1.120000e-01	3.209000e+00
lnoa_gr1a_x	532218.0	2.800000e-02	4.300000e-02	-0.345	0.014	0.018	3.200000e-02	4.360000e-01
capx_gr1_x	532218.0	3.080000e-01	1.049000e+00	-1.263	-0.024	0.135	3.410000e-01	3.425000e+01
capx_gr2_x	532218.0	6.110000e-01	1.740000e+00	-1.324	0.069	0.278	5.800000e-01	4.400000e+01
capx_gr3_x	532218.0	8.810000e-01	2.349000e+00	-1.209	0.190	0.405	7.490000e-01	5.162800e+01
chcsho_12m_x	532218.0	3.300000e-02	1.100000e-01	-0.270	0.000	0.002	2.000000e-02	1.928000e+00

	count	mean	std	min	25%	50%	75%	max
eqnpo_12m_x	532218.0	7.000000e-03	9.200000e-02	-0.976	-0.000	0.021	4.500000e-02	4.740000e-01
debt_gr3_x	532218.0	1.250000e+00	5.505000e+00	-1.000	0.099	0.318	7.220000e-01	1.709550e+02
inv_gr1_x	532218.0	1.780000e-01	4.590000e-01	-1.000	0.032	0.106	1.960000e-01	8.957000e+00
inv_gr1a_x	532218.0	1.800000e-02	4.400000e-02	-0.353	0.000	0.008	2.700000e-02	2.980000e-01
oaccruals_at_x	532218.0	6.800000e-02	9.900000e-02	-1.094	0.031	0.055	9.600000e-02	6.720000e-01
taccruals_at_x	532218.0	4.600000e-02	8.300000e-02	-1.068	0.024	0.038	6.400000e-02	7.950000e-01
cowc_gr1a_x	532218.0	2.300000e-02	5.700000e-02	-0.546	0.001	0.018	3.600000e-02	4.190000e-01
coa_gr1a_x	532218.0	4.500000e-02	7.000000e-02	-0.618	0.015	0.036	6.000000e-02	4.920000e-01
col_gr1a_x	532218.0	2.100000e-02	4.100000e-02	-0.372	0.005	0.017	3.200000e-02	3.650000e-01
nncoa_gr1a_x	532218.0	4.600000e-02	7.400000e-02	-0.951	0.017	0.031	6.200000e-02	5.960000e-01
ncoa_gr1a_x	532218.0	5.400000e-02	7.700000e-02	-0.965	0.022	0.037	7.200000e-02	5.770000e-01
ncol_gr1a_x	532218.0	7.000000e-03	1.700000e-02	-0.180	0.001	0.003	1.000000e-02	1.700000e-01
nfna_gr1a_x	532218.0	-2.100000e-02	9.400000e-02	-0.807	-0.049	-0.008	1.000000e-02	7.900000e-01
lti_gr1a_x	532218.0	5.000000e-03	3.000000e-02	-0.496	0.000	0.000	0.000000e+00	3.480000e-01
fnl_gr1a_x	532218.0	2.700000e-02	8.600000e-02	-0.726	-0.005	0.008	4.900000e-02	6.180000e-01
be_gr1a_x	532218.0	5.700000e-02	7.900000e-02	-0.977	0.022	0.045	7.500000e-02	7.450000e-01
oaccruals_ni_x	532218.0	1.258000e+00	4.084000e+00	-32.889	0.431	0.794	1.390000e+00	8.515800e+01
taccruals_ni_x	532218.0	6.240000e-01	2.539000e+00	-84.700	0.425	0.640	8.670000e-01	4.606200e+01
netis_at_x	532218.0	2.000000e-02	9.400000e-02	-0.939	0.001	0.007	1.900000e-02	1.385000e+00
eqnetis_at_x	532218.0	1.100000e-02	6.000000e-02	-0.201	0.000	0.000	2.000000e-03	1.283000e+00
dbnetis_at_x	532218.0	1.700000e-02	8.400000e-02	-0.933	-0.008	0.000	4.000000e-02	6.460000e-01
niq_be_x	532218.0	3.200000e-02	3.600000e-02	-1.486	0.029	0.030	3.900000e-02	3.710000e-01
niq_be_chg1_x	532218.0	-1.000000e-03	3.500000e-02	-1.288	-0.001	-0.000	1.000000e-03	8.180000e-01
niq_at_x	532218.0	1.500000e-02	1.600000e-02	-0.401	0.012	0.013	1.900000e-02	1.470000e-01
niq_at_chg1_x	532218.0	-0.000000e+00	1.300000e-02	-0.279	-0.000	-0.000	0.000000e+00	3.050000e-01
ebit_bev_x	532218.0	2.100000e-01	2.350000e-01	-7.292	0.118	0.153	2.450000e-01	2.122000e+00
ebit_sale_x	532218.0	1.260000e-01	2.260000e-01	-17.327	0.077	0.103	1.770000e-01	5.410000e-01
sale_bev_x	532218.0	2.096000e+00	1.939000e+00	0.000	1.145	1.796	2.305000e+00	2.035900e+01
at_turnover_x	532218.0	1.283000e+00	9.470000e-01	0.000	0.654	1.253	1.600000e+00	9.298000e+00

	count	mean	std	min	25%	50%	75%	max
gp_at_x	532218.0	3.330000e-01	2.380000e-01	-1.266	0.156	0.313	4.450000e-01	1.350000e+00
gp_atl1_x	532218.0	3.940000e-01	2.990000e-01	-1.629	0.179	0.360	5.150000e-01	2.081000e+00
ope_be_x	532218.0	2.690000e-01	1.900000e-01	-5.541	0.213	0.245	3.270000e-01	1.636000e+00
ope_bel1_x	532218.0	3.220000e-01	2.540000e-01	-4.721	0.240	0.277	3.740000e-01	3.210000e+00
op_at_x	532218.0	1.550000e-01	9.900000e-02	-1.233	0.107	0.140	2.010000e-01	5.210000e-01
op_atl1_x	532218.0	1.830000e-01	1.300000e-01	-1.902	0.121	0.159	2.320000e-01	9.190000e-01
cop_at_x	532218.0	1.010000e-01	1.210000e-01	-1.188	0.065	0.098	1.490000e-01	8.660000e-01
cop_atl1_x	532218.0	1.010000e-01	1.800000e-01	-3.468	0.074	0.107	1.620000e-01	8.260000e-01
f_score_x	532218.0	4.987000e+00	1.462000e+00	0.000	4.000	5.000	6.000000e+00	9.000000e+00
o_score_x	532218.0	-2.600000e+00	1.428000e+00	-8.827	-3.333	-2.108	-2.063000e+00	1.890400e+01
z_score_x	532218.0	4.292000e+00	3.950000e+00	-4.581	2.871	3.583	4.396000e+00	1.279700e+02
pi_nix_x	532218.0	1.711000e+00	4.590000e-01	0.188	1.526	1.726	1.887000e+00	8.722000e+00
at_be_x	532218.0	3.303000e+00	4.371000e+00	1.000	1.592	1.971	2.618000e+00	4.812300e+01
saleq_gr1_x	532218.0	1.670000e-01	3.690000e-01	-0.986	0.066	0.117	1.900000e-01	1.273600e+01
opex_at_x	532218.0	1.020000e+00	8.020000e-01	0.030	0.473	1.019	1.282000e+00	7.158000e+00
emp_gr1_x	532218.0	6.200000e-02	1.610000e-01	-1.301	0.006	0.043	8.400000e-02	1.483000e+00
age_x	532218.0	2.681630e+02	1.779190e+02	1.000	129.000	234.000	3.870000e+02	7.680000e+02
dsale_dinv_x	532218.0	-9.000000e-03	3.880000e-01	-5.274	-0.051	0.016	8.300000e-02	3.661000e+00
dsale_drec_x	532218.0	-2.200000e-02	3.390000e-01	-6.314	-0.079	-0.002	6.700000e-02	3.915000e+00
dgp_dsale_x	532218.0	2.300000e-02	3.430000e-01	-3.695	-0.045	0.001	5.100000e-02	1.201100e+01
dsale_dsga_x	532218.0	-1.000000e-03	1.860000e-01	-2.225	-0.034	-0.006	2.500000e-02	3.436000e+00
sale_emp_gr1_x	532218.0	8.900000e-02	1.970000e-01	-0.812	0.029	0.074	1.220000e-01	6.027000e+00
tangibility_x	532218.0	6.880000e-01	1.050000e-01	0.137	0.650	0.685	7.300000e-01	1.389000e+00
kz_index_x	532218.0	-3.152000e+00	7.543000e+00	-121.722	-3.120	-1.111	-5.090000e-01	1.529200e+01
cash_at_x	532218.0	9.400000e-02	1.010000e-01	0.000	0.031	0.062	1.180000e-01	8.810000e-01
ni_ar1_x	532218.0	2.880000e-01	4.890000e-01	-2.015	0.080	0.243	4.840000e-01	3.490000e+00
ni_ivol_x	532218.0	1.500000e-02	2.000000e-02	0.000	0.006	0.013	1.500000e-02	6.330000e-01
earnings_variability_x	532218.0	3.330000e-01	2.800000e-01	0.024	0.181	0.269	3.420000e-01	3.436000e+00
aliq_at_x	532218.0	7.560000e-01	2.310000e-01	0.240	0.666	0.727	7.750000e-01	5.901000e+00

	count	mean	std	min	25%	50%	75%	max
aliq_mat_x	532218.0	5.760000e-01	2.150000e-01	0.041	0.477	0.586	6.460000e-01	3.973000e+00
seas_1_1an_x	532218.0	1.500000e-02	1.020000e-01	-0.591	-0.041	0.008	6.300000e-02	1.250000e+00
seas_1_1na_x	532218.0	1.600000e-02	2.700000e-02	-0.141	0.005	0.013	2.500000e-02	2.410000e-01
seas_2_5an_x	532218.0	1.500000e-02	4.400000e-02	-0.252	-0.002	0.012	2.900000e-02	5.730000e-01
ivol_ff3_21d_x	532218.0	1.800000e-02	9.000000e-03	0.004	0.012	0.016	2.100000e-02	1.330000e-01
ivol_capm_252d_x	532218.0	2.000000e-02	8.000000e-03	0.007	0.014	0.019	2.300000e-02	1.030000e-01
ivol_capm_21d_x	532218.0	1.800000e-02	9.000000e-03	0.004	0.012	0.017	2.200000e-02	1.340000e-01
ivol_hxz4_21d_x	532218.0	1.900000e-02	8.000000e-03	0.005	0.013	0.020	2.000000e-02	1.290000e-01
rvol_21d_x	532218.0	2.000000e-02	1.100000e-02	0.004	0.013	0.019	2.400000e-02	1.560000e-01
betabab_1260d_x	532218.0	1.152000e+00	4.620000e-01	0.106	0.874	1.109	1.340000e+00	4.226000e+00
beta_dimson_21d_x	532218.0	9.880000e-01	1.424000e+00	-19.371	0.274	0.848	1.630000e+00	2.341700e+01
turnover_126d_x	532218.0	2.000000e-03	2.000000e-03	0.000	0.001	0.001	2.000000e-03	1.500000e-02
turnover_var_126d_x	532218.0	1.131000e+00	5.060000e-01	0.344	0.813	1.059	1.254000e+00	6.403000e+00
dolvol_126d_x	532218.0	1.040906e+06	2.747060e+06	175.564	85266.781	208631.680	6.878182e+05	2.997359e+07
dolvol_var_126d_x	532218.0	1.160000e+00	5.200000e-01	0.363	0.834	1.090	1.288000e+00	6.326000e+00
ami_126d_x	532218.0	3.380000e-01	1.263000e+00	0.000	0.033	0.128	3.250000e-01	2.019330e+02
zero_trades_21d_x	532218.0	3.070000e-01	1.367000e+00	0.000	0.002	0.005	7.000000e-03	2.009700e+01
zero_trades_126d_x	532218.0	3.050000e-01	1.240000e+00	0.000	0.003	0.006	8.000000e-03	1.904100e+01
zero_trades_252d_x	532218.0	3.050000e-01	1.201000e+00	0.000	0.003	0.006	9.000000e-03	1.861000e+01
rmax1_21d_x	532218.0	4.600000e-02	3.100000e-02	0.006	0.026	0.040	5.500000e-02	4.290000e-01
rskew_21d_x	532218.0	2.520000e-01	7.770000e-01	-2.611	-0.195	0.247	6.720000e-01	3.177000e+00
iskew_capm_21d_x	532218.0	2.350000e-01	7.530000e-01	-2.841	-0.202	0.227	6.370000e-01	3.099000e+00
iskew_ff3_21d_x	532218.0	1.930000e-01	6.900000e-01	-2.111	-0.212	0.186	5.650000e-01	2.802000e+00
iskew_hxz4_21d_x	532218.0	1.690000e-01	6.030000e-01	-2.064	-0.115	0.165	4.170000e-01	2.680000e+00
coskew_21d_x	532218.0	-1.700000e-02	3.000000e-01	-1.437	-0.206	-0.026	1.660000e-01	1.300000e+00
ret_1_0_x	532218.0	1.600000e-02	1.040000e-01	-0.606	-0.041	0.008	6.500000e-02	1.167000e+00
betadown_252d_x	532218.0	1.050000e+00	6.690000e-01	-3.043	0.615	0.938	1.373000e+00	5.248000e+00
bidaskhl_21d_x	532218.0	7.000000e-03	5.000000e-03	0.001	0.004	0.006	8.000000e-03	2.540000e-01
ret_3_1_x	532218.0	3.200000e-02	1.480000e-01	-0.717	-0.049	0.014	1.030000e-01	1.556000e+00

	count	mean	std	min	25%	50%	75%	max
ret_9_1_x	532218.0	1.310000e-01	3.340000e-01	-0.836	-0.054	0.066	2.600000e-01	4.818000e+00
ret_12_7_x	532218.0	7.700000e-02	2.420000e-01	-0.779	-0.055	0.041	1.770000e-01	2.934000e+00
corr_1260d_x	532218.0	4.190000e-01	9.900000e-02	0.040	0.376	0.389	4.820000e-01	7.180000e-01
rmax5_21d_x	532218.0	2.700000e-02	1.500000e-02	0.003	0.016	0.024	3.200000e-02	2.040000e-01
rmax5_rvol_21d_x	532218.0	1.246000e+00	4.630000e-01	0.141	0.933	1.193	1.486000e+00	3.492000e+00
ni_be_x	532218.0	1.210000e-01	1.370000e-01	-7.189	0.098	0.116	1.570000e-01	6.490000e-01
ocf_at_x	532218.0	1.200000e-02	1.070000e-01	-1.358	-0.022	0.015	6.500000e-02	5.980000e-01
ocf_at_chg1_x	532218.0	-3.000000e-03	1.240000e-01	-1.078	-0.038	-0.001	3.100000e-02	1.153000e+00
mispricing_perf_x	532218.0	5.500000e-01	1.990000e-01	0.010	0.413	0.555	6.980000e-01	9.880000e-01
mispricing_mgmt_x	532218.0	4.850000e-01	1.800000e-01	0.015	0.376	0.503	6.060000e-01	9.430000e-01
qmj_x	532218.0	1.900000e-01	8.050000e-01	-1.703	-0.249	0.127	7.640000e-01	1.701000e+00
qmj_prof_x	532218.0	1.690000e-01	8.830000e-01	-1.704	-0.471	0.124	8.850000e-01	1.699000e+00
qmj_growth_x	532218.0	5.500000e-02	7.940000e-01	-1.701	-0.429	0.043	5.710000e-01	1.702000e+00
qmj_safety_x	532218.0	2.720000e-01	8.670000e-01	-1.701	-0.336	0.270	9.970000e-01	1.705000e+00

Table 9: Revised Global Factor Dataset Summary Statistics: Training Set

	count	mean	std	min	25%	50%	75%	max
beta_60m_x	294581.0	1.096000e+00	5.200000e-01	-1.747	8.060000e-01	1.075000e+00	1.300000e+00	3.873000e+00
index	294581.0	1.362950e+06	6.892364e+05	1202.000	7.803110e+05	1.500595e+06	1.905059e+06	2.733128e+06
mth	294581.0	1.994940e+05	2.842530e+02	199001.000	1.992120e+05	1.995080e+05	1.997110e+05	1.999120e+05
permno	294581.0	5.554521e+04	2.573578e+04	10010.000	3.027700e+04	6.277000e+04	7.797600e+04	9.322000e+04
permco	294581.0	1.494868e+04	8.865682e+03	4.000	7.662000e+03	1.419100e+04	2.128600e+04	5.701800e+04
crsp_shrcd	294581.0	1.105000e+01	2.420000e-01	10.000	1.100000e+01	1.100000e+01	1.100000e+01	1.200000e+01
crsp_exchcd	294581.0	1.860000e+00	9.660000e-01	1.000	1.000000e+00	1.000000e+00	3.000000e+00	3.000000e+00
sic	294581.0	4.670888e+03	1.847487e+03	100.000	3.330000e+03	4.813000e+03	6.153000e+03	9.997000e+03
ff49	294581.0	3.098800e+01	1.313100e+01	1.000	2.100000e+01	3.400000e+01	4.300000e+01	4.900000e+01
adjfct	294581.0	2.352000e+00	4.866000e+00	0.000	1.000000e+00	1.000000e+00	2.000000e+00	2.880000e+02
shares	294581.0	6.768500e+01	1.581650e+02	0.542	1.463600e+01	2.761800e+01	6.018400e+01	5.160025e+03
me	294581.0	2.685416e+03	1.012770e+04	62.992	2.917890e+02	6.017040e+02	1.685533e+03	6.024329e+05
me_company	294581.0	2.745729e+03	1.033108e+04	62.992	2.934430e+02	6.080760e+02	1.703233e+03	6.024329e+05
prc	294581.0	4.176600e+01	7.262160e+02	0.172	1.700000e+01	2.525000e+01	3.687500e+01	7.830500e+04
prc_local	294581.0	4.176600e+01	7.262160e+02	0.172	1.700000e+01	2.525000e+01	3.687500e+01	7.830500e+04
dolvol	294581.0	1.878977e+08	7.930779e+08	0.000	1.077097e+07	3.501225e+07	1.211556e+08	8.464558e+10
ret	294581.0	2.400000e-02	1.420000e-01	-0.982	-4.600000e-02	1.200000e-02	7.900000e-02	9.374000e+00
ret_local	294581.0	2.400000e-02	1.420000e-01	-0.982	-4.600000e-02	1.200000e-02	7.900000e-02	9.374000e+00
ret_exc	294581.0	2.000000e-02	1.420000e-01	-0.986	-5.000000e-02	8.000000e-03	7.500000e-02	9.370000e+00
ret_lag_dif	294581.0	1.000000e+00	0.000000e+00	1.000	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
ret_exc_lead1m	294581.0	1.000000e-02	1.340000e-01	-0.998	-5.600000e-02	5.000000e-03	6.900000e-02	6.404000e+00
niq_su_x	294581.0	-9.000000e-02	1.850000e+00	-17.871	-4.600000e-01	3.000000e-03	5.610000e-01	5.228000e+00
ret_6_1_x	294581.0	1.000000e-01	3.090000e-01	-0.838	-5.900000e-02	4.700000e-02	2.060000e-01	3.244000e+00
ret_12_1_x	294581.0	2.220000e-01	5.210000e-01	-0.907	-3.200000e-02	9.900000e-02	3.560000e-01	5.633000e+00
saleq_su_x	294581.0	2.490000e-01	1.562000e+00	-4.939	-5.680000e-01	1.380000e-01	9.630000e-01	8.854000e+00
tax_gr1a_x	294581.0	5.000000e-03	2.200000e-02	-0.132	-1.000000e-03	2.000000e-03	1.100000e-02	1.170000e-01
ni_inc8q_x	294581.0	3.200000e+00	3.102000e+00	0.000	0.000000e+00	2.000000e+00	7.000000e+00	8.000000e+00
prc_highprc_252d_x	294581.0	8.250000e-01	1.580000e-01	0.074	7.520000e-01	8.630000e-01	9.490000e-01	1.000000e+00
resff3_6_1_x	294581.0	-3.500000e-02	4.830000e-01	-2.692	-2.600000e-01	-2.500000e-02	2.170000e-01	1.705000e+00

	count	mean	std	min	25%	50%	75%	max
resff3_12_1_x	294581.0	-1.500000e-02	2.450000e-01	-0.946	-1.480000e-01	-1.300000e-02	1.260000e-01	7.460000e-01
be_me_x	294581.0	5.250000e-01	4.100000e-01	0.006	2.500000e-01	4.460000e-01	6.950000e-01	1.020500e+01
debt_me_x	294581.0	5.460000e-01	1.217000e+00	0.000	3.700000e-02	2.120000e-01	5.900000e-01	5.045200e+01
at_me_x	294581.0	2.217000e+00	4.123000e+00	0.009	4.800000e-01	1.022000e+00	2.134000e+00	1.278460e+02
ret_60_12_x	294581.0	8.620000e-01	1.375000e+00	-0.964	2.690000e-01	3.870000e-01	9.770000e-01	1.328900e+01
ni_me_x	294581.0	3.500000e-02	1.150000e-01	-8.106	2.000000e-02	4.700000e-02	7.200000e-02	4.830000e-01
fcf_me_x	294581.0	5.000000e-03	1.600000e-01	-5.425	-2.000000e-02	1.600000e-02	4.900000e-02	2.588000e+00
div12m_me_x	294581.0	1.400000e-02	1.900000e-02	0.000	0.000000e+00	6.000000e-03	2.300000e-02	2.000000e-01
eqpo_me_x	294581.0	2.600000e-02	4.200000e-02	-0.001	0.000000e+00	1.200000e-02	3.300000e-02	7.260000e-01
eqnpo_me_x	294581.0	-2.000000e-03	8.400000e-02	-1.644	-4.000000e-03	5.000000e-03	2.700000e-02	6.710000e-01
sale_gr3_x	294581.0	8.400000e-01	2.577000e+00	-0.988	1.720000e-01	3.570000e-01	6.530000e-01	5.854700e+01
sale_gr1_x	294581.0	2.460000e-01	6.080000e-01	-0.895	3.300000e-02	1.160000e-01	2.550000e-01	1.088600e+01
ebitda_mev_x	294581.0	1.100000e-01	9.900000e-02	-1.984	6.400000e-02	1.050000e-01	1.450000e-01	1.386000e+00
sale_me_x	294581.0	1.201000e+00	1.595000e+00	0.000	3.790000e-01	7.530000e-01	1.424000e+00	5.494600e+01
ocf_me_x	294581.0	7.700000e-02	1.570000e-01	-3.829	2.400000e-02	6.800000e-02	1.190000e-01	3.793000e+00
intrinsic_value_x	294581.0	1.027543e+03	2.258605e+03	0.141	1.283670e+02	2.713090e+02	7.443850e+02	2.371766e+04
bev_mev_x	294581.0	5.360000e-01	3.550000e-01	0.001	2.680000e-01	5.140000e-01	7.610000e-01	6.841000e+00
netdebt_me_x	294581.0	3.810000e-01	1.060000e+00	-2.464	-3.000000e-02	1.210000e-01	4.720000e-01	4.390200e+01
eq_dur_x	294581.0	1.648500e+01	2.528000e+00	1.790	1.538700e+01	1.673400e+01	1.760300e+01	5.375100e+01
capex_abn_x	294581.0	6.200000e-02	6.730000e-01	-1.147	-1.480000e-01	-8.000000e-02	1.250000e-01	9.274000e+00
at_gr1_x	294581.0	3.000000e-01	7.580000e-01	-0.663	3.100000e-02	1.060000e-01	2.690000e-01	1.121900e+01
ppeinv_gr1a_x	294581.0	1.150000e-01	2.250000e-01	-0.533	3.300000e-02	5.800000e-02	1.290000e-01	2.601000e+00
noa_at_x	294581.0	7.040000e-01	4.150000e-01	-0.509	5.610000e-01	6.720000e-01	8.010000e-01	4.641000e+00
noa_gr1a_x	294581.0	1.380000e-01	3.540000e-01	-0.612	1.100000e-02	5.200000e-02	1.450000e-01	4.058000e+00
lnoa_gr1a_x	294581.0	3.000000e-02	7.000000e-02	-0.351	7.000000e-03	1.200000e-02	3.400000e-02	5.060000e-01
capx_gr1_x	294581.0	4.830000e-01	1.638000e+00	-1.337	-4.900000e-02	1.380000e-01	4.700000e-01	3.033300e+01
capx_gr2_x	294581.0	1.010000e+00	3.574000e+00	-1.428	3.200000e-02	2.730000e-01	7.390000e-01	6.113600e+01
capx_gr3_x	294581.0	1.387000e+00	5.155000e+00	-1.199	1.450000e-01	3.660000e-01	8.780000e-01	1.076800e+02
chcsho_12m_x	294581.0	6.800000e-02	2.060000e-01	-0.245	0.000000e+00	9.000000e-03	4.300000e-02	2.658000e+00

	count	mean	std	min	25%	50%	75%	max
eqnpo_12m_x	294581.0	-3.500000e-02	1.480000e-01	-1.255	-3.300000e-02	-2.000000e-03	2.700000e-02	4.210000e-01
debt_gr3_x	294581.0	2.550000e+00	1.542700e+01	-1.000	-3.300000e-02	1.920000e-01	7.310000e-01	3.188620e+02
inv_gr1_x	294581.0	2.290000e-01	8.790000e-01	-1.000	-4.000000e-03	9.000000e-02	2.020000e-01	1.302400e+01
inv_gr1a_x	294581.0	1.100000e-02	4.100000e-02	-0.357	-0.000000e+00	0.000000e+00	1.500000e-02	2.630000e-01
oaccruals_at_x	294581.0	-3.400000e-02	9.600000e-02	-0.935	-6.800000e-02	-3.800000e-02	2.000000e-03	5.230000e-01
taccruals_at_x	294581.0	-5.100000e-02	1.640000e-01	-1.432	-9.400000e-02	-4.300000e-02	9.000000e-03	9.610000e-01
cowc_gr1a_x	294581.0	1.400000e-02	6.700000e-02	-0.605	-8.000000e-03	8.000000e-03	3.300000e-02	4.170000e-01
coa_gr1a_x	294581.0	3.900000e-02	8.300000e-02	-0.791	4.000000e-03	2.200000e-02	6.200000e-02	4.540000e-01
col_gr1a_x	294581.0	2.400000e-02	5.300000e-02	-0.471	3.000000e-03	1.500000e-02	3.800000e-02	3.440000e-01
nncoa_gr1a_x	294581.0	5.400000e-02	1.210000e-01	-1.080	7.000000e-03	2.700000e-02	8.000000e-02	6.480000e-01
ncoa_gr1a_x	294581.0	6.400000e-02	1.250000e-01	-0.943	1.200000e-02	3.300000e-02	9.400000e-02	6.630000e-01
ncol_gr1a_x	294581.0	8.000000e-03	2.900000e-02	-0.224	-0.000000e+00	2.000000e-03	1.100000e-02	2.190000e-01
nfna_gr1a_x	294581.0	-1.700000e-02	1.370000e-01	-0.983	-5.000000e-02	0.000000e+00	2.000000e-02	9.650000e-01
lti_gr1a_x	294581.0	9.000000e-03	4.200000e-02	-0.360	0.000000e+00	0.000000e+00	1.000000e-03	2.940000e-01
fnl_gr1a_x	294581.0	2.400000e-02	1.260000e-01	-0.831	-1.200000e-02	0.000000e+00	4.900000e-02	9.140000e-01
be_gr1a_x	294581.0	6.900000e-02	1.440000e-01	-1.017	9.000000e-03	3.600000e-02	9.700000e-02	7.940000e-01
oaccruals_ni_x	294581.0	-1.254000e+00	4.986000e+00	-60.944	-1.275000e+00	-5.450000e-01	2.200000e-02	3.908000e+01
taccruals_ni_x	294581.0	-2.223000e+00	8.905000e+00	-112.262	-1.845000e+00	-6.590000e-01	1.330000e-01	3.405000e+01
netis_at_x	294581.0	1.700000e-02	2.100000e-01	-1.171	-3.900000e-02	-1.000000e-03	3.500000e-02	1.489000e+00
eqnetis_at_x	294581.0	4.400000e-02	1.550000e-01	-0.216	-0.000000e+00	1.000000e-03	1.300000e-02	1.389000e+00
dbnetis_at_x	294581.0	-2.400000e-02	1.460000e-01	-1.135	-4.200000e-02	-3.000000e-03	1.500000e-02	6.040000e-01
niq_be_x	294581.0	2.400000e-02	9.700000e-02	-1.913	1.500000e-02	3.000000e-02	4.900000e-02	4.290000e-01
niq_be_chg1_x	294581.0	-5.000000e-03	9.600000e-02	-1.766	-9.000000e-03	-1.000000e-03	6.000000e-03	9.390000e-01
niq_at_x	294581.0	9.000000e-03	4.200000e-02	-0.555	3.000000e-03	1.100000e-02	2.300000e-02	1.120000e-01
niq_at_chg1_x	294581.0	-0.000000e+00	3.500000e-02	-0.349	-4.000000e-03	-0.000000e+00	3.000000e-03	4.710000e-01
ebit_bev_x	294581.0	1.310000e-01	8.300000e-01	-16.386	9.500000e-02	1.520000e-01	2.550000e-01	2.332000e+00
ebit_sale_x	294581.0	-1.000000e-02	1.335000e+00	-32.364	6.200000e-02	1.110000e-01	1.940000e-01	5.370000e-01
sale_bev_x	294581.0	2.200000e+00	2.665000e+00	0.000	8.240000e-01	1.530000e+00	2.507000e+00	2.745100e+01
at_turnover_x	294581.0	1.044000e+00	8.280000e-01	0.000	4.160000e-01	9.120000e-01	1.411000e+00	4.719000e+00

	count	mean	std	min	25%	50%	75%	max
gp_at_x	294581.0	3.160000e-01	2.760000e-01	-0.853	1.120000e-01	2.570000e-01	4.710000e-01	1.412000e+00
gp_atl1_x	294581.0	3.960000e-01	3.830000e-01	-1.018	1.300000e-01	3.020000e-01	5.580000e-01	2.455000e+00
ope_be_x	294581.0	2.480000e-01	3.340000e-01	-5.705	1.720000e-01	2.240000e-01	3.330000e-01	2.299000e+00
ope_bel1_x	294581.0	3.220000e-01	4.980000e-01	-5.420	2.020000e-01	2.470000e-01	3.970000e-01	4.618000e+00
op_at_x	294581.0	1.470000e-01	1.280000e-01	-1.058	7.700000e-02	1.370000e-01	2.080000e-01	5.660000e-01
op_atl1_x	294581.0	1.830000e-01	1.990000e-01	-1.949	9.200000e-02	1.520000e-01	2.450000e-01	1.125000e+00
cop_at_x	294581.0	1.890000e-01	1.500000e-01	-1.029	1.120000e-01	1.700000e-01	2.590000e-01	8.800000e-01
cop_atl1_x	294581.0	2.280000e-01	2.250000e-01	-1.844	1.330000e-01	1.880000e-01	3.000000e-01	1.507000e+00
f_score_x	294581.0	5.173000e+00	1.413000e+00	1.000	5.000000e+00	5.000000e+00	6.000000e+00	9.000000e+00
o_score_x	294581.0	-2.721000e+00	2.068000e+00	-8.385	-3.800000e+00	-2.767000e+00	-2.092000e+00	1.799600e+01
z_score_x	294581.0	5.789000e+00	8.539000e+00	-7.856	2.387000e+00	3.525000e+00	5.488000e+00	9.787600e+01
pi_nix_x	294581.0	1.623000e+00	6.310000e-01	0.244	1.468000e+00	1.544000e+00	1.657000e+00	9.259000e+00
at_be_x	294581.0	3.946000e+00	4.895000e+00	1.023	1.596000e+00	2.137000e+00	3.387000e+00	5.215100e+01
saleq_gr1_x	294581.0	2.800000e-01	7.890000e-01	-0.988	2.200000e-02	1.130000e-01	2.780000e-01	1.052800e+01
opex_at_x	294581.0	8.560000e-01	7.380000e-01	0.036	3.030000e-01	7.170000e-01	1.156000e+00	4.588000e+00
emp_gr1_x	294581.0	9.700000e-02	2.260000e-01	-1.333	2.000000e-03	6.200000e-02	1.390000e-01	1.440000e+00
age_x	294581.0	2.577090e+02	2.162820e+02	7.000	8.100000e+01	1.780000e+02	3.920000e+02	8.880000e+02
dsale_dinv_x	294581.0	-1.700000e-02	7.120000e-01	-9.498	-4.700000e-02	3.000000e-02	1.140000e-01	3.472000e+00
dsale_drec_x	294581.0	-3.200000e-02	5.320000e-01	-6.378	-1.010000e-01	2.000000e-03	9.500000e-02	3.597000e+00
dgp_dsale_x	294581.0	3.200000e-02	4.350000e-01	-4.610	-4.300000e-02	2.000000e-03	6.500000e-02	4.688000e+00
dsale_dsga_x	294581.0	2.200000e-02	2.700000e-01	-1.680	-2.400000e-02	2.000000e-03	4.000000e-02	3.562000e+00
sale_emp_gr1_x	294581.0	8.300000e-02	3.340000e-01	-0.841	-4.000000e-03	4.000000e-02	1.100000e-01	4.904000e+00
tangibility_x	294581.0	6.350000e-01	1.730000e-01	0.111	5.600000e-01	6.440000e-01	7.300000e-01	1.390000e+00
kz_index_x	294581.0	-6.962000e+00	2.127700e+01	-352.632	-5.199000e+00	-1.327000e+00	2.110000e-01	1.127800e+01
cash_at_x	294581.0	1.330000e-01	1.820000e-01	0.000	1.700000e-02	5.600000e-02	1.650000e-01	9.310000e-01
ni_ar1_x	294581.0	1.810000e-01	4.900000e-01	-1.898	1.000000e-02	1.240000e-01	3.310000e-01	3.331000e+00
ni_ivol_x	294581.0	3.000000e-02	4.600000e-02	0.000	1.000000e-02	2.400000e-02	3.100000e-02	7.070000e-01
earnings_variability_x	294581.0	7.750000e-01	6.210000e-01	0.027	3.660000e-01	7.820000e-01	9.030000e-01	6.427000e+00
aliq_at_x	294581.0	8.390000e-01	6.100000e-01	0.181	6.100000e-01	6.980000e-01	8.330000e-01	1.083700e+01

	count	mean	std	min	25%	50%	75%	max
aliq_mat_x	294581.0	4.510000e-01	1.870000e-01	0.050	3.440000e-01	4.330000e-01	5.490000e-01	1.842000e+00
seas_1_1an_x	294581.0	2.000000e-02	1.160000e-01	-0.578	-3.700000e-02	9.000000e-03	6.900000e-02	1.407000e+00
seas_1_1na_x	294581.0	1.900000e-02	3.300000e-02	-0.160	7.000000e-03	1.400000e-02	2.800000e-02	2.910000e-01
seas_2_5an_x	294581.0	1.500000e-02	4.400000e-02	-0.276	5.000000e-03	1.200000e-02	2.600000e-02	5.270000e-01
ivol_ff3_21d_x	294581.0	2.300000e-02	1.400000e-02	0.005	1.300000e-02	1.900000e-02	2.800000e-02	1.910000e-01
ivol_capm_252d_x	294581.0	2.500000e-02	1.200000e-02	0.007	1.600000e-02	2.200000e-02	3.100000e-02	1.360000e-01
ivol_capm_21d_x	294581.0	2.300000e-02	1.400000e-02	0.005	1.400000e-02	2.000000e-02	2.900000e-02	1.910000e-01
ivol_hxz4_21d_x	294581.0	2.300000e-02	1.400000e-02	0.005	1.300000e-02	1.900000e-02	2.800000e-02	1.920000e-01
rvol_21d_x	294581.0	2.500000e-02	1.500000e-02	0.006	1.500000e-02	2.200000e-02	3.100000e-02	1.990000e-01
betabab_1260d_x	294581.0	1.025000e+00	5.100000e-01	-0.326	7.170000e-01	9.110000e-01	1.255000e+00	3.650000e+00
beta_dimson_21d_x	294581.0	9.630000e-01	1.780000e+00	-17.092	7.100000e-02	8.230000e-01	1.721000e+00	1.921100e+01
turnover_126d_x	294581.0	3.000000e-03	3.000000e-03	0.000	1.000000e-03	3.000000e-03	4.000000e-03	2.900000e-02
turnover_var_126d_x	294581.0	1.143000e+00	6.230000e-01	0.405	7.510000e-01	9.860000e-01	1.324000e+00	6.770000e+00
dolvol_126d_x	294581.0	6.536392e+06	1.464928e+07	486.102	5.446526e+05	1.610104e+06	5.476749e+06	1.547992e+08
dolvol_var_126d_x	294581.0	1.148000e+00	6.240000e-01	0.383	7.540000e-01	1.002000e+00	1.333000e+00	6.601000e+00
ami_126d_x	294581.0	2.060000e-01	1.300000e+00	0.000	4.000000e-03	1.800000e-02	7.700000e-02	1.666870e+02
zero_trades_21d_x	294581.0	2.430000e-01	1.301000e+00	0.000	2.000000e-03	3.000000e-03	5.000000e-03	2.009600e+01
zero_trades_126d_x	294581.0	2.490000e-01	1.223000e+00	0.000	2.000000e-03	3.000000e-03	6.000000e-03	1.791600e+01
zero_trades_252d_x	294581.0	2.580000e-01	1.216000e+00	0.000	2.000000e-03	3.000000e-03	6.000000e-03	1.752300e+01
rmax1_21d_x	294581.0	5.700000e-02	4.400000e-02	0.007	2.900000e-02	4.500000e-02	6.900000e-02	6.240000e-01
rskew_21d_x	294581.0	2.430000e-01	8.120000e-01	-2.818	-2.200000e-01	2.130000e-01	6.900000e-01	3.243000e+00
iskew_capm_21d_x	294581.0	2.440000e-01	7.890000e-01	-2.563	-2.120000e-01	2.130000e-01	6.800000e-01	3.091000e+00
iskew_ff3_21d_x	294581.0	1.980000e-01	7.250000e-01	-2.308	-2.310000e-01	1.730000e-01	6.050000e-01	2.800000e+00
iskew_hxz4_21d_x	294581.0	1.780000e-01	6.920000e-01	-2.037	-2.370000e-01	1.550000e-01	5.730000e-01	2.748000e+00
coskew_21d_x	294581.0	-1.900000e-02	3.120000e-01	-1.468	-2.240000e-01	-2.200000e-02	1.840000e-01	1.154000e+00
ret_1_0_x	294581.0	2.300000e-02	1.300000e-01	-0.619	-4.400000e-02	1.100000e-02	7.600000e-02	1.600000e+00
betadown_252d_x	294581.0	9.990000e-01	7.080000e-01	-3.514	5.370000e-01	9.180000e-01	1.339000e+00	5.699000e+00
bidaskhl_21d_x	294581.0	1.000000e-02	7.000000e-03	0.002	5.000000e-03	7.000000e-03	1.200000e-02	1.790000e-01
ret_3_1_x	294581.0	4.100000e-02	1.820000e-01	-0.707	-5.200000e-02	2.000000e-02	1.160000e-01	2.077000e+00

	count	mean	std	min	25%	50%	75%	max
ret_9_1_x	294581.0	1.590000e-01	4.120000e-01	-0.879	-4.800000e-02	7.300000e-02	2.810000e-01	4.691000e+00
ret_12_7_x	294581.0	9.700000e-02	2.910000e-01	-0.797	-4.400000e-02	4.200000e-02	1.960000e-01	3.295000e+00
corr_1260d_x	294581.0	3.380000e-01	1.280000e-01	-0.037	2.630000e-01	3.170000e-01	4.110000e-01	7.320000e-01
rmax5_21d_x	294581.0	3.300000e-02	2.200000e-02	0.005	1.900000e-02	2.800000e-02	4.100000e-02	2.990000e-01
rmax5_rvol_21d_x	294581.0	1.265000e+00	4.620000e-01	0.234	9.530000e-01	1.190000e+00	1.522000e+00	3.545000e+00
ni_be_x	294581.0	6.800000e-02	3.810000e-01	-7.304	6.100000e-02	1.110000e-01	1.650000e-01	8.470000e-01
ocf_at_x	294581.0	6.500000e-02	1.280000e-01	-1.240	1.900000e-02	7.100000e-02	1.260000e-01	4.950000e-01
ocf_at_chg1_x	294581.0	6.000000e-03	1.090000e-01	-0.852	-2.600000e-02	-0.000000e+00	3.000000e-02	1.036000e+00
mispricing_perf_x	294581.0	5.780000e-01	1.820000e-01	0.021	4.540000e-01	5.790000e-01	7.130000e-01	9.610000e-01
mispricing_mgmt_x	294581.0	4.900000e-01	1.790000e-01	0.052	3.680000e-01	4.950000e-01	6.230000e-01	8.840000e-01
qmj_x	294581.0	2.170000e-01	7.590000e-01	-1.698	-7.800000e-02	1.140000e-01	7.470000e-01	1.698000e+00
qmj_prof_x	294581.0	3.300000e-01	9.150000e-01	-1.698	-3.660000e-01	4.030000e-01	1.126000e+00	1.698000e+00
qmj_growth_x	294581.0	7.200000e-02	7.390000e-01	-1.698	-2.810000e-01	3.500000e-02	5.130000e-01	1.698000e+00
qmj_safety_x	294581.0	2.230000e-01	8.930000e-01	-1.698	-4.430000e-01	2.640000e-01	9.700000e-01	1.701000e+00

Table 10: Revised Global Factor Dataset Summary Statistics: Validation Set

	count	mean	std	min	25%	50%	75%	max
beta_60m_x	531461.0	1.143000e+00	6.650000e-01	-0.762	7.160000e-01	1.081000e+00	1.428000e+00	4.912000e+00
index	531461.0	1.639772e+06	8.608909e+05	1495.000	8.349320e+05	1.872142e+06	2.405852e+06	2.739927e+06
mth	531461.0	2.009810e+05	6.308130e+02	200001.000	2.004070e+05	2.010030e+05	2.015100e+05	2.020120e+05
permno	531461.0	6.249862e+04	2.927243e+04	10012.000	3.294200e+04	7.752600e+04	8.648900e+04	9.343600e+04
permco	531461.0	2.536554e+04	1.682836e+04	7.000	1.205800e+04	2.098100e+04	4.099800e+04	5.766700e+04
crsp_shrcd	531461.0	1.110400e+01	3.060000e-01	10.000	1.100000e+01	1.100000e+01	1.100000e+01	1.200000e+01
crsp_exchcd	531461.0	1.820000e+00	9.770000e-01	1.000	1.000000e+00	1.000000e+00	3.000000e+00	3.000000e+00
sic	531461.0	4.731309e+03	1.973094e+03	100.000	3.312000e+03	4.813000e+03	6.211000e+03	9.999000e+03
ff49	531461.0	3.088900e+01	1.275800e+01	1.000	2.100000e+01	3.400000e+01	4.200000e+01	4.900000e+01
adjfct	531461.0	1.190000e+00	1.201000e+00	0.000	1.000000e+00	1.000000e+00	1.000000e+00	1.120000e+02
shares	531461.0	2.183130e+02	6.077150e+02	1.009	3.797500e+01	7.258200e+01	1.709880e+02	2.920640e+04
me	531461.0	9.114197e+03	3.153046e+04	178.093	9.360740e+02	2.009547e+03	5.793820e+03	2.255969e+06
me_company	531461.0	9.284112e+03	3.274782e+04	178.093	9.401740e+02	2.023393e+03	5.869141e+03	2.255969e+06
prc	531461.0	6.448400e+01	1.368034e+03	0.120	1.815000e+01	3.059000e+01	4.950000e+01	1.416000e+05
prc_local	531461.0	6.448400e+01	1.368034e+03	0.120	1.815000e+01	3.059000e+01	4.950000e+01	1.416000e+05
dolvol	531461.0	1.430663e+09	5.379275e+09	0.000	1.191406e+08	3.596018e+08	1.153573e+09	8.441730e+11
ret	531461.0	1.800000e-02	1.510000e-01	-0.984	-4.800000e-02	1.200000e-02	7.300000e-02	1.988400e+01
ret_local	531461.0	1.800000e-02	1.510000e-01	-0.984	-4.800000e-02	1.200000e-02	7.300000e-02	1.988400e+01
ret_exc	531461.0	1.600000e-02	1.510000e-01	-0.985	-4.900000e-02	1.000000e-02	7.200000e-02	1.988200e+01
ret_lag_dif	531461.0	1.000000e+00	0.000000e+00	1.000	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
ret_exc_lead1m	531461.0	7.000000e-03	1.370000e-01	-1.001	-5.400000e-02	7.000000e-03	6.700000e-02	4.100000e+00
niq_su_x	531461.0	-9.700000e-02	1.914000e+00	-50.846	-6.530000e-01	-1.100000e-02	6.410000e-01	2.019500e+01
ret_6_1_x	531461.0	8.200000e-02	3.500000e-01	-0.917	-7.900000e-02	4.600000e-02	1.920000e-01	8.412000e+00
ret_12_1_x	531461.0	1.800000e-01	5.820000e-01	-0.973	-8.800000e-02	8.600000e-02	3.200000e-01	1.223100e+01
saleq_su_x	531461.0	1.380000e-01	1.682000e+00	-16.096	-7.990000e-01	1.300000e-01	1.062000e+00	8.648000e+00
tax_gr1a_x	531461.0	2.000000e-03	2.800000e-02	-0.216	-4.000000e-03	1.000000e-03	9.000000e-03	2.050000e-01
ni_inc8q_x	531461.0	2.918000e+00	3.092000e+00	0.000	0.000000e+00	2.000000e+00	6.000000e+00	8.000000e+00
prc_highprc_252d_x	531461.0	8.110000e-01	1.820000e-01	0.017	7.290000e-01	8.640000e-01	9.510000e-01	1.000000e+00
resff3_6_1_x	531461.0	-2.900000e-02	4.950000e-01	-2.363	-2.870000e-01	-2.200000e-02	2.540000e-01	1.833000e+00

	count	mean	std	min	25%	50%	75%	max
resff3_12_1_x	531461.0	-1.300000e-02	2.530000e-01	-1.046	-1.600000e-01	-1.200000e-02	1.440000e-01	7.740000e-01
be_me_x	531461.0	5.420000e-01	5.170000e-01	0.005	2.440000e-01	4.390000e-01	6.890000e-01	2.516300e+01
debt_me_x	531461.0	5.270000e-01	1.260000e+00	0.000	4.300000e-02	2.080000e-01	5.440000e-01	6.550600e+01
at_me_x	531461.0	1.997000e+00	3.652000e+00	0.010	4.730000e-01	9.520000e-01	2.011000e+00	1.923120e+02
ret_60_12_x	531461.0	7.400000e-01	1.402000e+00	-0.996	1.350000e-01	3.530000e-01	9.310000e-01	1.791400e+01
ni_me_x	531461.0	1.900000e-02	2.300000e-01	-18.929	1.300000e-02	4.200000e-02	6.600000e-02	9.920000e-01
fcf_me_x	531461.0	2.900000e-02	1.710000e-01	-7.856	2.000000e-03	3.700000e-02	7.200000e-02	4.202000e+00
div12m_me_x	531461.0	1.200000e-02	1.900000e-02	0.000	0.000000e+00	2.000000e-03	1.900000e-02	4.020000e-01
eqpo_me_x	531461.0	3.400000e-02	5.400000e-02	-0.000	1.000000e-03	1.600000e-02	4.500000e-02	1.725000e+00
eqnpo_me_x	531461.0	9.000000e-03	9.600000e-02	-3.911	-3.000000e-03	9.000000e-03	3.800000e-02	1.443000e+00
sale_gr3_x	531461.0	7.190000e-01	2.545000e+00	-1.000	6.800000e-02	2.950000e-01	6.090000e-01	8.620400e+01
sale_gr1_x	531461.0	1.910000e-01	6.470000e-01	-0.996	4.000000e-03	8.700000e-02	2.090000e-01	1.370600e+01
ebitda_mev_x	531461.0	9.300000e-02	1.190000e-01	-5.587	5.500000e-02	9.000000e-02	1.290000e-01	1.983000e+00
sale_me_x	531461.0	9.930000e-01	1.606000e+00	0.000	2.740000e-01	5.560000e-01	1.105000e+00	7.507500e+01
ocf_me_x	531461.0	9.300000e-02	1.560000e-01	-4.343	3.900000e-02	7.500000e-02	1.280000e-01	5.711000e+00
intrinsic_value_x	531461.0	3.673158e+03	9.322883e+03	0.515	2.746770e+02	6.616840e+02	2.401336e+03	1.130984e+05
bev_mev_x	531461.0	5.450000e-01	4.310000e-01	0.001	2.580000e-01	4.990000e-01	7.490000e-01	1.692600e+01
netdebt_me_x	531461.0	3.480000e-01	1.073000e+00	-3.496	-5.200000e-02	1.000000e-01	4.220000e-01	5.866300e+01
eq_dur_x	531461.0	1.683500e+01	5.240000e+00	1.053	1.565800e+01	1.686700e+01	1.783200e+01	3.430350e+02
capex_abn_x	531461.0	4.500000e-02	6.920000e-01	-1.028	-2.420000e-01	-6.700000e-02	1.680000e-01	1.196300e+01
at_gr1_x	531461.0	2.660000e-01	1.181000e+00	-0.740	3.000000e-03	7.700000e-02	2.080000e-01	3.163800e+01
ppeinv_gr1a_x	531461.0	7.400000e-02	1.740000e-01	-0.449	1.000000e-02	4.000000e-02	8.300000e-02	3.079000e+00
noa_at_x	531461.0	6.120000e-01	4.870000e-01	-1.152	4.460000e-01	6.240000e-01	7.550000e-01	1.038800e+01
noa_gr1a_x	531461.0	1.040000e-01	4.220000e-01	-0.737	-1.300000e-02	3.300000e-02	1.020000e-01	1.075200e+01
lnoa_gr1a_x	531461.0	3.500000e-02	1.020000e-01	-0.578	-4.000000e-03	1.200000e-02	4.500000e-02	7.540000e-01
capx_gr1_x	531461.0	3.700000e-01	1.543000e+00	-1.021	-1.390000e-01	1.030000e-01	4.080000e-01	3.277600e+01
capx_gr2_x	531461.0	7.800000e-01	3.210000e+00	-1.010	-1.390000e-01	2.160000e-01	6.650000e-01	7.697200e+01
capx_gr3_x	531461.0	1.128000e+00	4.517000e+00	-1.000	-1.030000e-01	2.930000e-01	8.460000e-01	1.128460e+02
chcsho_12m_x	531461.0	4.600000e-02	2.130000e-01	-0.227	-9.000000e-03	7.000000e-03	2.600000e-02	8.477000e+00

	count	mean	std	min	25%	50%	75%	max
eqnpo_12m_x	531461.0	-2.000000e-02	1.340000e-01	-2.249	-2.100000e-02	1.000000e-03	3.300000e-02	3.470000e-01
debt_gr3_x	531461.0	4.136000e+00	2.614000e+01	-1.000	-9.000000e-02	1.730000e-01	7.340000e-01	4.310000e+02
inv_gr1_x	531461.0	1.820000e-01	8.460000e-01	-1.000	-1.300000e-02	7.700000e-02	1.570000e-01	1.698100e+01
inv_gr1a_x	531461.0	6.000000e-03	2.900000e-02	-0.288	-0.000000e+00	0.000000e+00	9.000000e-03	2.080000e-01
oaccruals_at_x	531461.0	-5.600000e-02	1.000000e-01	-2.264	-8.100000e-02	-4.400000e-02	-1.400000e-02	3.810000e-01
taccruals_at_x	531461.0	-6.900000e-02	1.810000e-01	-2.480	-1.150000e-01	-4.900000e-02	-4.000000e-03	1.294000e+00
cowc_gr1a_x	531461.0	3.000000e-03	5.500000e-02	-0.605	-1.400000e-02	3.000000e-03	2.000000e-02	3.410000e-01
coa_gr1a_x	531461.0	2.000000e-02	6.500000e-02	-0.777	-2.000000e-03	1.400000e-02	3.900000e-02	4.190000e-01
col_gr1a_x	531461.0	1.700000e-02	5.000000e-02	-0.485	-2.000000e-03	1.100000e-02	3.000000e-02	3.830000e-01
nncoa_gr1a_x	531461.0	4.100000e-02	1.340000e-01	-1.884	-8.000000e-03	2.000000e-02	7.000000e-02	7.690000e-01
ncoa_gr1a_x	531461.0	4.900000e-02	1.420000e-01	-1.884	-4.000000e-03	2.600000e-02	8.100000e-02	7.490000e-01
ncol_gr1a_x	531461.0	7.000000e-03	3.600000e-02	-0.360	-2.000000e-03	2.000000e-03	1.500000e-02	3.340000e-01
nfna_gr1a_x	531461.0	-1.400000e-02	1.460000e-01	-1.108	-4.800000e-02	-0.000000e+00	2.700000e-02	1.384000e+00
lti_gr1a_x	531461.0	5.000000e-03	3.500000e-02	-0.231	0.000000e+00	0.000000e+00	1.000000e-03	2.570000e-01
fnl_gr1a_x	531461.0	2.200000e-02	1.270000e-01	-1.230	-1.400000e-02	0.000000e+00	4.300000e-02	1.130000e+00
be_gr1a_x	531461.0	4.500000e-02	1.460000e-01	-2.072	1.000000e-03	2.800000e-02	8.100000e-02	8.560000e-01
oaccruals_ni_x	531461.0	-2.033000e+00	5.721000e+00	-71.442	-1.715000e+00	-7.240000e-01	-2.420000e-01	1.429400e+01
taccruals_ni_x	531461.0	-2.755000e+00	9.625000e+00	-131.510	-2.469000e+00	-8.370000e-01	-6.300000e-02	6.728600e+01
netis_at_x	531461.0	-2.800000e-02	2.270000e-01	-1.368	-8.500000e-02	-1.800000e-02	1.300000e-02	1.593000e+00
eqnetis_at_x	531461.0	2.100000e-02	1.510000e-01	-0.351	-1.500000e-02	0.000000e+00	7.000000e-03	1.489000e+00
dbnetis_at_x	531461.0	-4.800000e-02	1.610000e-01	-1.362	-6.200000e-02	-6.000000e-03	0.000000e+00	5.670000e-01
niq_be_x	531461.0	1.800000e-02	1.130000e-01	-2.022	9.000000e-03	2.600000e-02	4.600000e-02	6.990000e-01
niq_be_chg1_x	531461.0	-2.000000e-03	1.130000e-01	-2.004	-1.100000e-02	-1.000000e-03	1.000000e-02	1.228000e+00
niq_at_x	531461.0	6.000000e-03	4.700000e-02	-0.667	2.000000e-03	1.000000e-02	2.200000e-02	1.820000e-01
niq_at_chg1_x	531461.0	1.000000e-03	4.500000e-02	-0.455	-5.000000e-03	0.000000e+00	5.000000e-03	8.410000e-01
ebit_bev_x	531461.0	5.600000e-02	1.346000e+00	-41.056	7.400000e-02	1.310000e-01	2.330000e-01	2.800000e+00
ebit_sale_x	531461.0	-2.370000e-01	4.578000e+00	-185.045	5.700000e-02	1.170000e-01	2.090000e-01	6.150000e-01
sale_bev_x	531461.0	2.041000e+00	3.073000e+00	0.000	6.210000e-01	1.261000e+00	2.224000e+00	3.887100e+01
at_turnover_x	531461.0	8.410000e-01	7.220000e-01	0.000	3.210000e-01	6.760000e-01	1.141000e+00	4.267000e+00

	count	mean	std	min	25%	50%	75%	max
gp_at_x	531461.0	2.740000e-01	2.480000e-01	-1.169	1.000000e-01	2.390000e-01	3.990000e-01	1.293000e+00
gp_atl1_x	531461.0	3.240000e-01	3.250000e-01	-1.904	1.130000e-01	2.680000e-01	4.630000e-01	2.788000e+00
ope_be_x	531461.0	2.340000e-01	4.400000e-01	-8.815	1.450000e-01	2.040000e-01	3.170000e-01	3.725000e+00
ope_bel1_x	531461.0	2.740000e-01	5.480000e-01	-13.628	1.680000e-01	2.280000e-01	3.610000e-01	4.420000e+00
op_at_x	531461.0	1.320000e-01	1.220000e-01	-1.224	6.700000e-02	1.260000e-01	1.940000e-01	5.380000e-01
op_atl1_x	531461.0	1.470000e-01	2.450000e-01	-6.946	7.400000e-02	1.400000e-01	2.240000e-01	1.018000e+00
cop_at_x	531461.0	1.910000e-01	1.510000e-01	-0.924	1.070000e-01	1.760000e-01	2.650000e-01	1.940000e+00
cop_atl1_x	531461.0	2.190000e-01	2.240000e-01	-3.834	1.190000e-01	1.960000e-01	3.020000e-01	1.923000e+00
f_score_x	531461.0	5.234000e+00	1.422000e+00	1.000	4.000000e+00	5.000000e+00	6.000000e+00	9.000000e+00
o_score_x	531461.0	-2.944000e+00	2.326000e+00	-9.387	-4.243000e+00	-3.020000e+00	-2.185000e+00	2.287000e+01
z_score_x	531461.0	5.413000e+00	9.607000e+00	-37.336	1.997000e+00	3.275000e+00	5.180000e+00	1.744240e+02
pi_nix_x	531461.0	1.519000e+00	6.770000e-01	0.106	1.334000e+00	1.488000e+00	1.589000e+00	1.989400e+01
at_be_x	531461.0	3.707000e+00	4.571000e+00	1.023	1.582000e+00	2.157000e+00	3.430000e+00	5.963100e+01
saleq_gr1_x	531461.0	2.020000e-01	7.530000e-01	-1.000	-7.000000e-03	8.500000e-02	2.150000e-01	1.574800e+01
opex_at_x	531461.0	7.050000e-01	6.560000e-01	0.003	2.430000e-01	5.380000e-01	9.460000e-01	4.437000e+00
emp_gr1_x	531461.0	7.300000e-02	2.000000e-01	-1.165	-1.000000e-02	5.100000e-02	1.190000e-01	1.442000e+00
age_x	531461.0	3.164250e+02	2.392710e+02	10.000	1.300000e+02	2.440000e+02	4.400000e+02	1.115000e+03
dsale_dinv_x	531461.0	-2.300000e-02	7.480000e-01	-19.478	-6.100000e-02	2.500000e-02	9.800000e-02	5.598000e+00
dsale_drec_x	531461.0	-2.200000e-02	5.420000e-01	-7.400	-1.120000e-01	4.000000e-03	1.160000e-01	7.638000e+00
dgp_dsale_x	531461.0	3.700000e-02	4.720000e-01	-5.970	-4.200000e-02	5.000000e-03	6.500000e-02	7.188000e+00
dsale_dsga_x	531461.0	2.300000e-02	2.880000e-01	-2.001	-4.200000e-02	3.000000e-03	5.400000e-02	6.964000e+00
sale_emp_gr1_x	531461.0	7.800000e-02	3.670000e-01	-0.956	-3.000000e-02	3.900000e-02	1.070000e-01	7.027000e+00
tangibility_x	531461.0	5.840000e-01	2.060000e-01	0.002	4.580000e-01	6.190000e-01	7.020000e-01	1.685000e+00
kz_index_x	531461.0	-1.475800e+01	5.964000e+01	-1723.572	-9.717000e+00	-2.274000e+00	2.400000e-01	8.730000e+01
cash_at_x	531461.0	1.680000e-01	2.030000e-01	0.000	2.900000e-02	8.300000e-02	2.240000e-01	9.800000e-01
ni_ar1_x	531461.0	1.460000e-01	5.670000e-01	-3.964	-1.330000e-01	1.060000e-01	3.650000e-01	9.144000e+00
ni_ivol_x	531461.0	4.200000e-02	8.300000e-02	0.000	1.000000e-02	2.300000e-02	3.700000e-02	1.757000e+00
earnings_variability_x	531461.0	1.119000e+00	1.132000e+00	0.044	5.490000e-01	8.810000e-01	1.192000e+00	1.145300e+01
aliq_at_x	531461.0	7.410000e-01	9.790000e-01	0.104	5.050000e-01	6.250000e-01	7.440000e-01	2.804000e+01

	count	mean	std	min	25%	50%	75%	max
aliq_mat_x	531461.0	3.770000e-01	1.890000e-01	0.027	2.380000e-01	3.610000e-01	4.780000e-01	2.246000e+00
seas_1_1an_x	531461.0	1.600000e-02	1.280000e-01	-0.670	-4.500000e-02	7.000000e-03	6.800000e-02	1.824000e+00
seas_1_1na_x	531461.0	1.600000e-02	3.900000e-02	-0.235	-2.000000e-03	1.200000e-02	3.000000e-02	3.870000e-01
seas_2_5an_x	531461.0	1.500000e-02	5.600000e-02	-0.297	-9.000000e-03	1.100000e-02	3.500000e-02	6.340000e-01
ivol_ff3_21d_x	531461.0	2.000000e-02	1.500000e-02	0.002	1.000000e-02	1.600000e-02	2.400000e-02	2.280000e-01
ivol_capm_252d_x	531461.0	2.300000e-02	1.300000e-02	0.005	1.400000e-02	2.000000e-02	2.800000e-02	1.410000e-01
ivol_capm_21d_x	531461.0	2.100000e-02	1.600000e-02	0.002	1.100000e-02	1.600000e-02	2.600000e-02	2.420000e-01
ivol_hxz4_21d_x	531461.0	2.000000e-02	1.500000e-02	0.002	1.000000e-02	1.500000e-02	2.400000e-02	2.310000e-01
rvol_21d_x	531461.0	2.500000e-02	1.800000e-02	0.002	1.400000e-02	2.000000e-02	3.100000e-02	2.520000e-01
betabab_1260d_x	531461.0	1.071000e+00	4.730000e-01	-0.029	7.670000e-01	1.029000e+00	1.303000e+00	3.831000e+00
beta_dimson_21d_x	531461.0	1.175000e+00	1.449000e+00	-13.953	4.250000e-01	1.041000e+00	1.786000e+00	1.954200e+01
turnover_126d_x	531461.0	9.000000e-03	8.000000e-03	0.000	4.000000e-03	7.000000e-03	1.200000e-02	2.800000e-01
turnover_var_126d_x	531461.0	7.410000e-01	4.240000e-01	0.280	4.880000e-01	6.180000e-01	8.450000e-01	7.510000e+00
dolvol_126d_x	531461.0	5.434158e+07	9.867098e+07	2317.257	5.641453e+06	1.690584e+07	5.411359e+07	1.038495e+09
dolvol_var_126d_x	531461.0	7.390000e-01	4.300000e-01	0.262	4.840000e-01	6.190000e-01	8.520000e-01	8.104000e+00
ami_126d_x	531461.0	2.500000e-02	6.470000e-01	0.000	0.000000e+00	1.000000e-03	4.000000e-03	9.796700e+01
zero_trades_21d_x	531461.0	1.100000e-02	2.260000e-01	0.000	1.000000e-03	2.000000e-03	3.000000e-03	1.575900e+01
zero_trades_126d_x	531461.0	1.300000e-02	2.210000e-01	0.000	1.000000e-03	2.000000e-03	3.000000e-03	1.400900e+01
zero_trades_252d_x	531461.0	1.500000e-02	2.330000e-01	0.000	1.000000e-03	2.000000e-03	3.000000e-03	1.359200e+01
rmax1_21d_x	531461.0	5.600000e-02	5.000000e-02	0.003	2.700000e-02	4.100000e-02	6.600000e-02	9.000000e-01
rskew_21d_x	531461.0	1.350000e-01	9.260000e-01	-3.581	-3.520000e-01	1.140000e-01	5.940000e-01	3.808000e+00
iskew_capm_21d_x	531461.0	1.560000e-01	9.940000e-01	-3.566	-3.640000e-01	1.340000e-01	6.520000e-01	3.715000e+00
iskew_ff3_21d_x	531461.0	1.300000e-01	8.940000e-01	-3.120	-3.550000e-01	1.110000e-01	5.920000e-01	3.456000e+00
iskew_hxz4_21d_x	531461.0	1.200000e-01	8.400000e-01	-3.081	-3.460000e-01	1.020000e-01	5.650000e-01	3.276000e+00
coskew_21d_x	531461.0	-3.000000e-03	3.090000e-01	-1.128	-2.090000e-01	-7.000000e-03	2.000000e-01	1.347000e+00
ret_1_0_x	531461.0	1.700000e-02	1.360000e-01	-0.724	-4.700000e-02	1.100000e-02	7.200000e-02	2.176000e+00
betadown_252d_x	531461.0	1.087000e+00	5.640000e-01	-1.626	7.370000e-01	1.024000e+00	1.371000e+00	3.822000e+00
bidaskhl_21d_x	531461.0	9.000000e-03	6.000000e-03	0.001	5.000000e-03	7.000000e-03	1.100000e-02	1.540000e-01
ret_3_1_x	531461.0	3.300000e-02	1.990000e-01	-0.831	-6.100000e-02	2.000000e-02	1.090000e-01	3.342000e+00

	count	mean	std	min	25%	50%	75%	max
ret_9_1_x	531461.0	1.300000e-01	4.620000e-01	-0.955	-8.700000e-02	6.700000e-02	2.590000e-01	9.274000e+00
ret_12_7_x	531461.0	7.800000e-02	3.330000e-01	-0.906	-7.500000e-02	3.900000e-02	1.840000e-01	8.509000e+00
corr_1260d_x	531461.0	4.620000e-01	1.510000e-01	-0.010	3.610000e-01	4.500000e-01	5.780000e-01	8.220000e-01
rmax5_21d_x	531461.0	3.200000e-02	2.400000e-02	0.002	1.700000e-02	2.500000e-02	3.900000e-02	3.380000e-01
rmax5_rvol_21d_x	531461.0	1.195000e+00	4.900000e-01	0.112	8.620000e-01	1.117000e+00	1.435000e+00	4.329000e+00
ni_be_x	531461.0	5.000000e-02	4.660000e-01	-10.754	3.800000e-02	9.600000e-02	1.630000e-01	1.451000e+00
ocf_at_x	531461.0	7.400000e-02	1.290000e-01	-1.818	3.100000e-02	8.100000e-02	1.330000e-01	3.960000e-01
ocf_at_chg1_x	531461.0	7.000000e-03	1.060000e-01	-0.912	-2.300000e-02	1.000000e-03	2.700000e-02	1.390000e+00
mispricing_perf_x	531461.0	5.800000e-01	1.740000e-01	0.031	4.650000e-01	5.890000e-01	7.090000e-01	9.240000e-01
mispricing_mgmt_x	531461.0	4.940000e-01	1.650000e-01	0.065	3.850000e-01	5.040000e-01	6.150000e-01	8.790000e-01
qmj_x	531461.0	2.090000e-01	8.600000e-01	-1.698	-3.550000e-01	1.780000e-01	9.070000e-01	1.698000e+00
qmj_prof_x	531461.0	3.650000e-01	9.230000e-01	-1.698	-3.270000e-01	4.870000e-01	1.161000e+00	1.698000e+00
qmj_growth_x	531461.0	7.800000e-02	8.590000e-01	-1.698	-5.550000e-01	1.120000e-01	7.300000e-01	1.698000e+00
qmj_safety_x	531461.0	1.040000e-01	9.040000e-01	-1.698	-6.120000e-01	1.430000e-01	8.510000e-01	1.708000e+00

Table 11: Revised Global Factor Dataset Summary Statistics: Testing Set