Multi-Factor Accounting and Credit Risk Optimization (MACRO)

February 2020

Abstract

Factor models historically sought to improve on the single-variable regression proposed by the CAPM by incorporating additional factors. The Fama-French model proposed a novel asset pricing method which incorporated two new pricing factors in addition to equity β: High-minus-Low (HML) and Small-minus-Big (SMB). These two factors are based on the hypothesis that a stock's β fails to explain significant variation in an asset's price (Fama and French 1992). The proposed strategy in this paper builds on the work done by Fama and French by proposing two novel firm-specific factors: Accurate-minus-Inaccurate (AMI) and 1-Year Implied Credit Default Risk (GMB).

The first novel factor is AMI. Unlike cash accounting, accrual accounting uses the revenue recognition and matching principles, so net income is not reflective of cash flows for the year. The accrual quality (or AMI) of a firm is determined by compared the the predicted versus actual cash flow from operations on a Year-over-Year (YoY) basis. A firm's accrual accounting metrics that more accurately predict its future cash flows from operations rank highly in AMI. Existing literature has established a notable relationship between accrual quality and future earnings. Specifically, companies that rank highly in AMI see more consistent and higher earnings overall; this remains true across industries (Dechow & Dichev 2002). A struggling company has an incentive to obscure its true financial health through accounting manipulations. Thus, by ranking companies based on AMI, the strategy is able to identify more stable and potentially rewarding investments. The second novel factor is the 1-year implied credit default risk (GMB) of any given company. The strategy then ranks each stock based on the company's likelihood of a credit default within one-year (one being least likely). The model then ranks the universe by aggregating the four indicators to calculate the long / short potential of each security.

Although these factors assist in selecting long and short positions on stocks out of the universe, there is little indication of optimal position timing. To improve upon this, the model incorporates the Purchasing Managers Index (PMI) to differentiate between times of accelerating and decelerating macroeconomic conditions. PMI is an index provided by surveying private-sector purchasing managers on their belief of whether the economy is expanding or not. In times when monthly PMI has increased on a Quarter-over-Quarter (QoQ) basis, the strategy identifies the economy as accelerating. The model dynamically adjusts net investment exposure based on predicted macroeconomic acceleration or deceleration.

Economic Hypothesis

MACRO is based on the economic hypothesis that correct asset pricing is derived from reducing information risk - risk incurred when inaccurate or incomplete data is used in asset pricing. Since information risk often leads to incorrect positions in the market, the strategy seeks to offer a more granular and robust indication of correct asset pricing (Aboody 2005). The strategy builds on the Fama-French three-factor model that hypothesizes that β is an inadequate determinant of an asset's price. The strategy adds AMI and GMB as factors to the Fama-French model to help isolate company specific characteristics that drive stock prices. In total, the strategy encompasses four factors: HML, SMB, AMI, and GMB,

$$E[R_i] = \alpha_i + \beta_1(R_m - R_f) + \beta_2 HML + \beta_3 SMB + \beta_4 AMI + \beta_5 GMB + \epsilon_i$$

To best time investment positions, the strategy uses PMI as a proxy for global macroeconomic health. PMI contains unique information about the future movement in GDP as confirmed by Granger causality tests (Afshar et al. 2007). The industrials sector is typically more highly levered, and tracks closely to GDP growth and PMI because purchasing managers work closely with manufacturers and industrial companies. The model takes short positions on industrial companies because of their cyclical nature and poor performance during times of economic contraction. These positions on industrials increase the strategy's returns and consequently insulate the strategy from recessionary periods (Çiftçi 2014). In addition, information risk sits at the core of our economic hypothesis, and the use of PMI offers insights into managerial sentiment and information. PMI combined with the four outward facing factors significantly reduces information risk and thus asset mispricing.

Implementation

Universe Selection - The universe includes all constituents of the Russell 1000 Index from February 14, 2000 to January 19, 2019 for which there exists a complete data set. Defunct or otherwise delisted companies have been included as well for historical accuracy. The Russell 1000 Index allows for the strategy to trade various companies across sectors that have a wide range of credit and accounting qualities.

After universe selection, securities were sorted along four factors: HML, SMB, AMI, and GMB.

***HML* (High minus Low) -** The HML factor included from the Fama-French model compares value and growth companies. By taking the difference between value and growth stocks the original Fama-French model sought to disprove the Sharpe, Litner, and Black model which based asset pricing only on equity β, a measure of exposure to systematic risk. Traditionally, HML produces long position signals when the asset is classified as a value stock and a short position is indicated when a stock is marked as growth. MACRO then ranks all stocks in the universe based on their P/B ratio, giving preference to those that are considered value stocks.

***SMB*(Small minus Big) -** The SMB factor allows for the strategy to rank the stocks in the universe based on the market capitalization of the company. The Fama-French model finds that for a given β, smaller companies produce returns in excess of larger companies. The strategy thus ranks equities in the universe by market capitalization and produces long signals for smaller companies, and short signals for larger companies to seek market out-performance at a given level of risk.

***AMI*(Accurate minus Inaccurate) -** As discussed above, AMI provides an indication of the stability of a stock and its future returns based on the quality of a company's accrual accounting. This is based on two hypotheses:

- Companies with good financials have no need to use misrepresentative methods in their financial statements
- Companies with efficient conversions of accruals to cash are rewarded by investors

The model performs a general linear regression relating current accruals with cash flows (Francis et al. 2005). This linear regression uses accrual accounting to predict the cash flows in the future; these will differ from the actual cash flows generated in the future creating residuals.

$$CFO_{i,t} = \alpha_i + \Gamma_1 CFO_{i,t-1} + \Gamma_2 ACC_{i,t-1}$$

The model then takes these residuals and then calculates their standard deviation and ranks every stock in the universe by their standard deviation, where the lowest is indexed as one.

$$AccountingQuality_i = \sqrt{\frac{\Sigma(CFO_t - C\hat{F}O_t)^2}{n-2}}$$

This gives the strategy a rank ordered list of which companies are most transparent in their accounting practices.

***GMB* (Good minus Bad) -** The GMB parameter is calculated using data from Bloomberg following the Merton Default Model. The equity of any given firm is transformed into a call option where the strike price is equal to the liabilities of the company and the expiry is the weighted maturity date of company's total debt (T).

$$E_T = max(A_T - L, 0)$$

By assuming a lognormal distribution for the asset returns, the Black-Scholes-Merton options pricing formulae can be used to infer the value of the asset. Letting N be the cumulative standard normal distribution,

$$d_1 = \frac{ln(\frac{A}{L}) + (r_f + 0.5\sigma_A^2)T}{\sigma_A \sqrt{T}}$$

$$d_2 = d_1 - \sigma_A \sqrt{T}$$

The Merton Model is then used to solve for (A,σ_A),

$$\sigma_E = \frac{A}{E} N(d_1) \sigma_A$$

where σ_E is the observable volatility of equity market prices, and σ_A is the unobservable volatility of the firm's assets.

Now computing the distance to default *(DD)* (Merton 1974), which captures all expected volatility of assets during the included time period. Taking as the number of standard deviations between the expected asset value at maturity and the current liability threshold,

$$DD = \frac{logA + (\mu_A - \sigma_A^2/2)T - log(L)}{\sigma_A \sqrt{T}}$$

The probability of default *(PD)* is defined as the probability of asset value falling below the liability threshold at the time of maturity

$$PD = 1 - N(DD)$$

This metric is then ranked for each stock in the universe ordered from least likely to default to most likely. The strategy then aggregates these four indicators into a single rank. Next the strategy determines position timing and sizing.

PMI and Leverage - MACRO dynamically adjusts net exposure based on historical returns and macroeconomic conditions. As discussed above, PMI is calculated through a survey of purchasing managers and serves as proxy for economic strength. When PMI has risen QoQ, the economy is marked as accelerating, and inversely, a falling QoQ PMI indicates a decelerating economy. When the economy is accelerating the strategy takes long positions only, which are then levered 150%. Alternatively, when the economy is decelerating, the strategy takes equally weighted long and short position to achieve a net exposure of zero levered by a total of 200%.

Position Sizing - If the economy is found to be accelerating the strategy takes long positions on the top 30^{th} percentile of ranked stocks. A decelerating economy triggers a long and short position in the top 30^{th} percentile and bottom 30^{th} percentile of ranked stocks respectively.

The strategy includes a trading halt of 5 days. After the strategy loses more than 3% in one day the strategy remains in cash for the following trading week. This forces the model to avoid periods of significant market volatility and sustained losses.

Risks & Mitigants

Macroeconomic Market Disconnect - One area of concern for the strategy is the disconnect between market conditions and macroeconomic indicators. The market, or specific stocks, can be negatively affected by macroeconomic events that are not echoed in indicators such as PMI. An example of this is the recent outbreak of COVID-19 and its subsequent effect on American airline stocks. Cancellations and suspensions of flights to and from China have dipped the prices of American Airlines (AAL) and United Airlines (UAL). However, an overall market health indicator would not have captured this recent event and macroeconomic indicators have not worsened yet. This is not troublesome for the strategy for three reasons:

- The model gives sufficient weight to shorting downward trends during decelerating periods which still provides returns for the strategy.
- Convergence eventually should occur between markets and macro data, since markets are pricing in expectations for weaker macroeconomic conditions in the future
- The PMI is one of the most significant predictors of market performance (Afshar, et al. 2007)

Leverage - MACRO employs an appropriate amount of leverage in both expansionary and contractionary environments. Significant market volatility, however, can cause losses in excess of the investment principle. Furthermore, high intraday volatility diminishes the efficacy of MACRO's risk management, namely the trading halt. The risks of leverage are offset by MACRO's historical track record of superior returns compared to standard deviation of returns. Thus, leverage is effectively used to enhance returns and achieve a desired level of risk exposure.

Analysis of Strategic Prospects

The strategy was tested between the dates February 14, 2000 and January 29, 2019 using the Russell 1000 Index as the original universe of stocks as discussed earlier. The results of our backtest demonstrate robust risk adjusted returns.

An important aspect of this model is that it trades individual stocks instead of creating portfolios. Recent research indicates that portfolio creation when testing asset pricing models destroys information because it aggregates the β across an entire portfolio (Ang 2018). The original justification for portfolio creation was that the techniques would diversify away error through aggregating individual stock's β values (Blume 1970). However, Ang (2018) disproves this notion by showing that portfolio creation removes stock specific information from the data, despite diversifying away risk. By trading individual stocks, the strategy capitalizes on information risk and mispriced assets for greater returns.

The selected time period represented a poor environment for equities. Average returns on the Russell 1000 were significantly below historical averages, and average annual SP returns were 4%. Therefore, the ability of MACRO to generate significant returns while managing risk over this time period, with a Sharpe ratio of 1.26 is convincing. Furthermore, the strategy performed exceptionally well following post-recessionary periods, capturing significant upside, without significant downside capture during recessionary periods.

Liquidity & Capital Considerations

Liquidity - The strategy minimizes liquidity risk by limiting the trading universe to the Russell 1000, the largest 1000 companies by market capitalization in the United States. These equities are traded on major US equities exchanges with robust quotation systems and market makers. Thus, spreads are minimized and positions can be entered and exited quickly at market value.

Shorting - The strategy assumes the ability to short any asset at any time. There are some potential limitations to the strategy's ability to short such as legal restrictions on the ability to short, exorbitantly high costs to borrow, and a lack of available short float. Although these are valid risks, they should not materially affect the performance of the strategy because the strategy only seeks short exposure in times of economic contraction. Additionally, equities in the Russell 1000 Index can be assumed to have sufficient liquidity and outstanding shares to be shortable. The backtester did not account for cost to borrow or short interest. However, the strategy is only long/short 52% of the time, and interest is earned on cash received from short selling.

Trading Fees - The strategy rebalances the portfolio daily. At scale, trading fees should not meaningfully impact returns. Furthermore, the daily transacted amount does not represent the entire portfolio. The strategy's relatively simple long/short positioning of equities on major exchanges, without using any derivatives strategies or thinly traded fixed income instruments further minimizes trading fees.

Scalability - The focus on United States listed, larger market capitalization equities in the Russell 1000 ensures MACRO is scalable to large capital deployments. At scale, trading fees and margin interest are also lowered further enhancing returns. At any given time, the strategy uses 30-60% of the universe in long or short positions. The relatively high number of securities on the book at any given time prevents large buying or selling pressures on individual securities and aids in strategy scalability.

Results

Backtesting - Data for the strategy was gathered using the Bloomberg Data API and validated with a custom Python script, ensuring complete data for all equities in the universe. A custom backtester was developed in Python and compiled into platform-native C code for performance optimization. The resulting executable was then deployed on the Microsoft Azure cloud platform, allowing fast and robust backtesting of the strategy and rapid refinements.

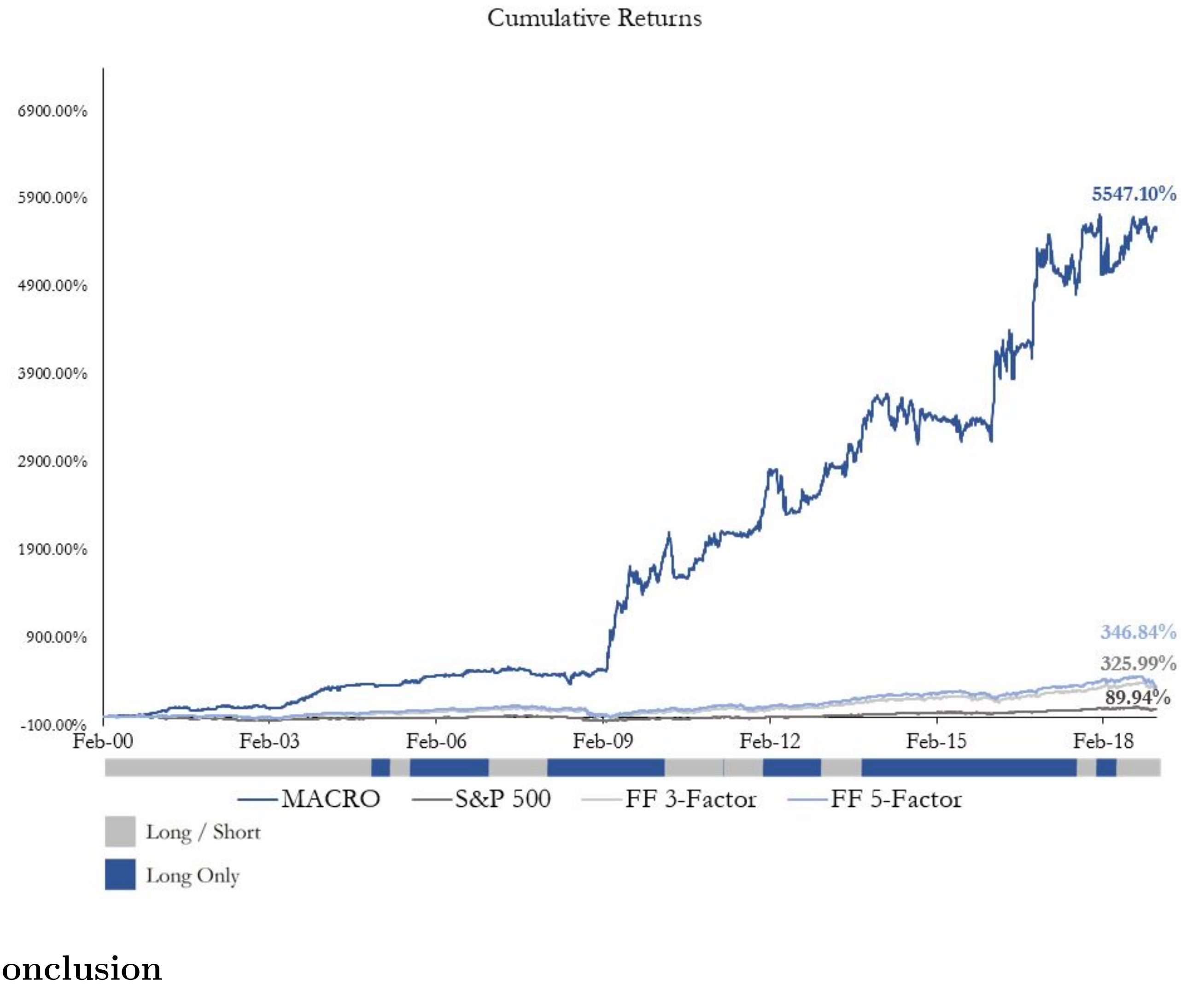
The backtest found that the strategy delivered significant risk-adjusted returns over the testing period, with a cumulative return of 5547%. The strategy delivered average annual returns of 23.00%, compared to the SP 500's period annual returns of 5.22%. Over the test period, the strategy exhibited an annual standard deviation of 18.37%, slightly lower than the SP's 19.12% over the same period. The table below shows annual returns of the strategy, as well as annual returns of the SP 500. A Sharpe ratio was calculated using average returns in excess of the risk free rate of 1.3% and the average annual standard deviation of the strategy (18.37%.) The Sharpe ratio of the strategy is 1.26, demonstrating significant value creation and superior risk-adjusted returns. Adjusting for dividends paid by long positions during the testing period, and dividends owed on the short positions, the adjusted Sharpe ratio of MACRO was 1.26. During the period, the strategy was long-only 48% of the time, and long/short 52% of the time.

Sharpe Ratio by Year

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Avg.
MACRO Ex. Returns	42.2%	33.8%	14.5%	71.1%	18.7%	21.2%	11.3%	-9.8%	8.2%	182.0%	17.0%	19.5%	5.9%	39.1%	-5.7%	-4.5%	53.3%	1.8%	-2.2%	23.2%
S&P 500 Ex. Returns	*-6.3%*	*-11.8%*	*-25.1%*	*21.0%*	*8.0%*	*2.5%*	*10.5%*	*2.4%*	*-38.9%*	*18.4%*	*9.7%*	*-2.4%*	*10.4%*	*25.1%*	*11.1%*	*-2.0%*	*9.9%*	*17.1%*	*-8.3%*	*3.9%*
MACO Yearly St. Dev	17.7%	18.5%	20.1%	20.0%	12.8%	14.4%	9.7%	12.6%	22.0%	40.7%	19.1%	15.7%	15.6%	15.8%	14.3%	8.4%	21.0%	13.0%	13.5%	18.4%
S&P 500 Yearly St. Dev	*22.1%*	*21.6%*	*26.0%*	*17.1%*	*11.1%*	*10.3%*	*10.0%*	*16.0%*	*41.0%*	*27.3%*	*18.1%*	*23.3%*	*12.8%*	*11.1%*	*11.4%*	*15.5%*	*13.1%*	*6.7%*	*17.1%*	*19.1%*
MACRO Sharpe Ratio	**2.4**	**1.8**	**0.7**	**3.6**	**1.5**	**1.5**	**1.2**	**-0.8**	**0.4**	**4.5**	**0.9**	**1.2**	**0.4**	**2.5**	**-0.4**	**-0.5**	**2.5**	**0.1**	**-0.2**	**1.26**
S&P 500 Sharpe Ratio	*-0.3*	*-0.5*	*-1.0*	*1.2*	*0.7*	*0.2*	*1.0*	*0.1*	*-0.9*	*0.7*	*0.5*	*-0.1*	*0.8*	*2.3*	*1.0*	*-0.1*	*0.8*	*2.6*	*-0.5*	**0.21**

CAPM Alpha by Year

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Avg.
MACRO Yearly CAPM Alpha	**42.9%**	**36.0%**	**14.7%**	**71.4%**	**19.6%**	**22.4%**	**12.9%**	**-8.2%**	**8.3%**	**184.8%**	**17.4%**	**20.7%**	**6.6%**	**42.4%**	**-3.4%**	**-3.2%**	**53.1%**	**5.0%**	**-0.1%**	**23.1%**
MACRO Yearly Beta	*-0.14*	*0.08*	*-0.05*	*0.05*	*0.03*	*0.02*	*-0.02*	*-0.09*	*-0.03*	*-0.07*	*0.08*	*-0.10*	*0.05*	*-0.08*	*-0.09*	*0.03*	*0.13*	*-0.10*	*0.11*	*-0.02*



Conclusion

The strategy in this paper seeks to reduce information risk and capitalize on subsequent mispricing of assets by using an improved version of the Fama-French model. The strategy retains two of the original Fama-French model factors (HML and SMB) and it incorporated two novel factors, AMI and GMB. AMI measured accrual accounting quality while GMB measured a company's Implied 1-Year Default Risk. Using a rolling five-day trading halt and PMI in tandem, the model was able to produce significant cumulative returns over 19 years with cumulative returns of 5547% and a Sharpe ratio of 1.26. These results support the original economic hypothesis: firm specific information is a better indicator of future returns than beta. Utilizing macroeconomic indicators like PMI greatly improves risk-adjusted returns by allowing the strategy to weight positions appropriately with macroeconomic conditions.

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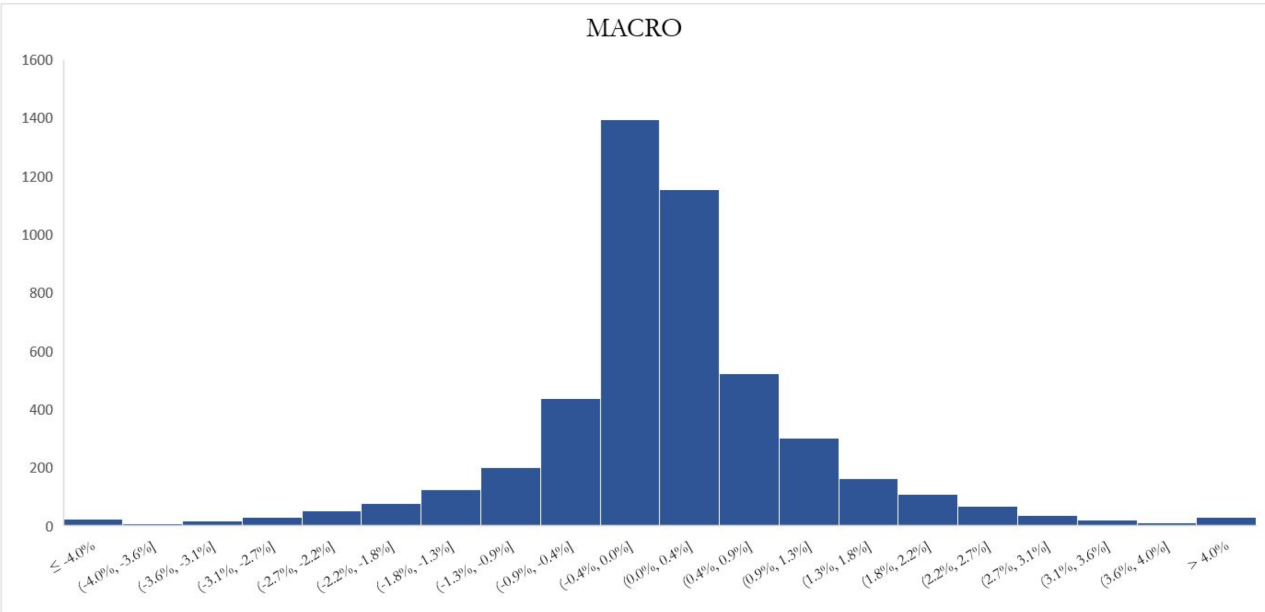

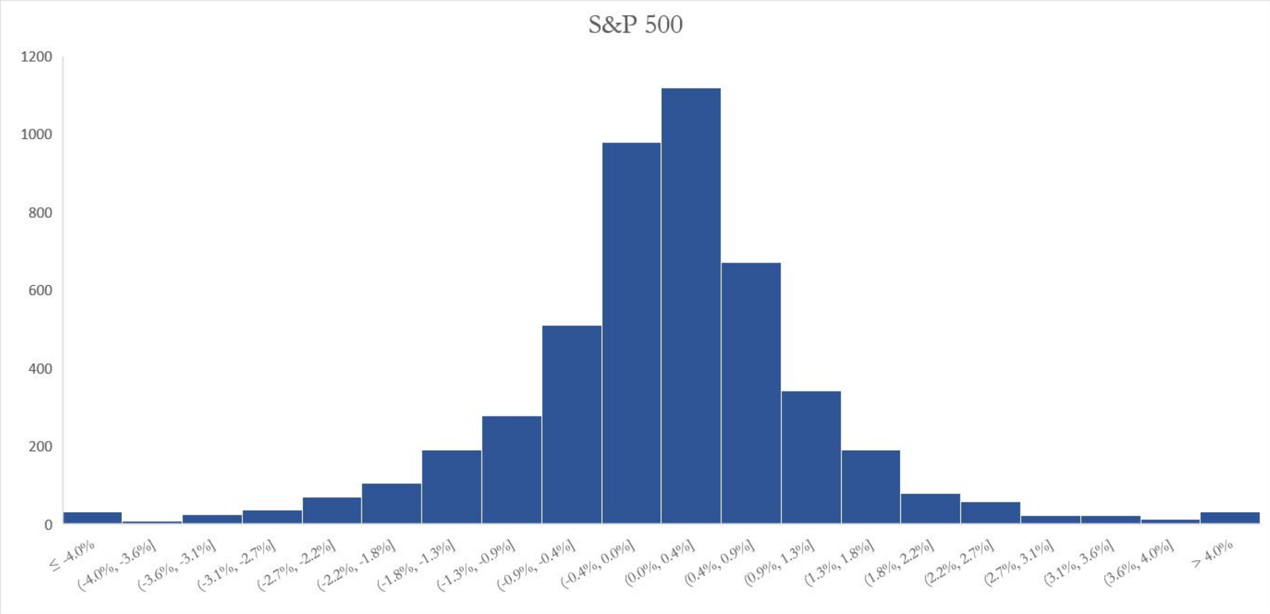
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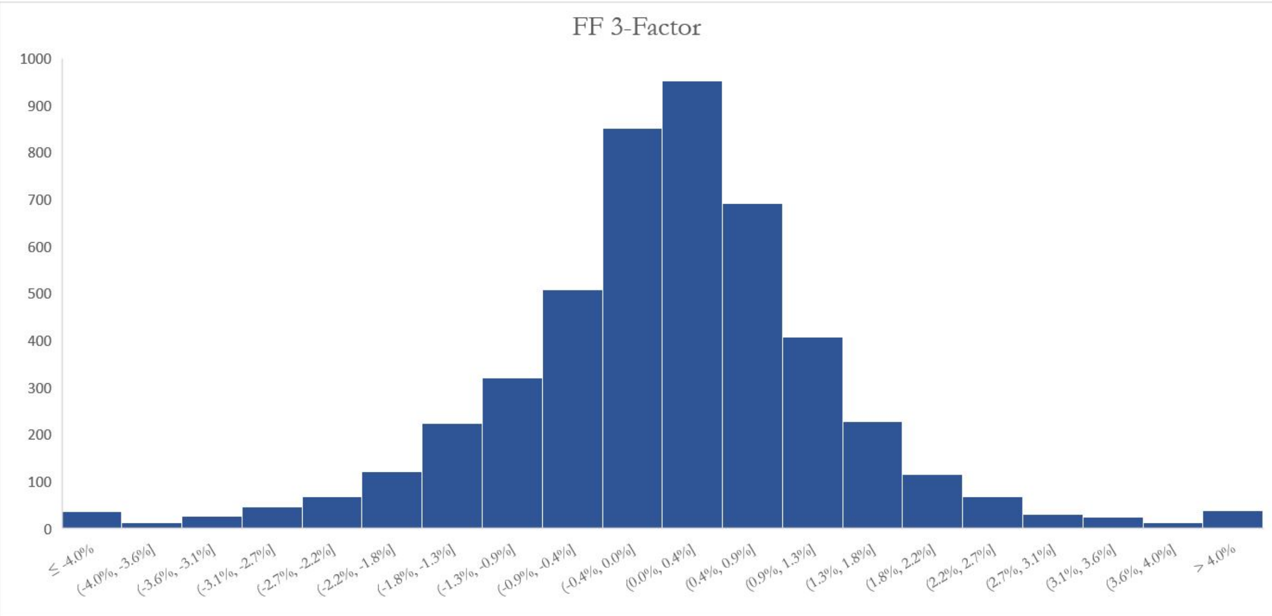
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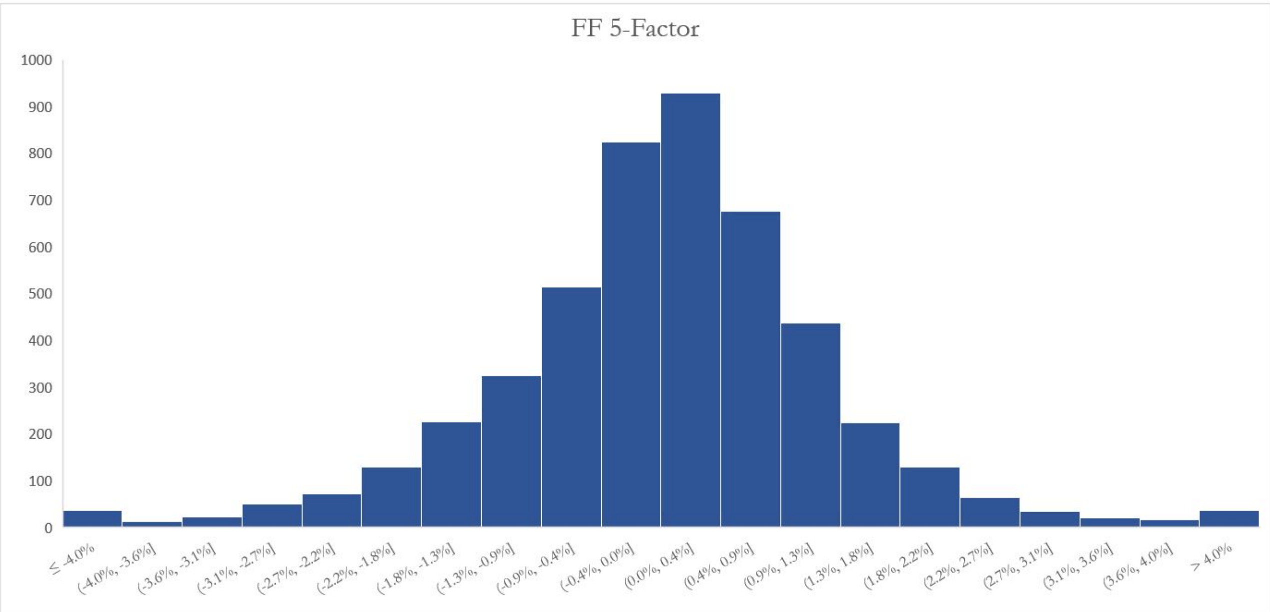
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