**2. Related Literature**

Detailed summaries

**1. “Common Risk Factors in the Returns on Stocks and Bonds” by Fama & French (1993)**

**Summary**: This seminal paper by Eugene Fama and Kenneth French introduced the three-factor model, which expanded on the Capital Asset Pricing Model (CAPM) by adding two additional factors: size (SMB, small minus big) and value (HML, high minus low). The model demonstrated that small-cap stocks and high book-to-market ratio stocks tend to outperform the market.

**2. “On Persistence in Mutual Fund Performance” by Carhart (1997)**

**Summary**: Mark Carhart’s study extended the Fama-French model by adding a momentum factor (MOM) to account for the tendency of stocks that have performed well in the past to continue performing well in the short term. Carhart found that mutual fund performance persistence is largely driven by common factors in stock returns and investment expenses, rather than fund managers’ stock-picking skills.

**3. “Common Risk Factors in Cryptocurrency” by Liu et al. (2019)**

**Summary**: Liu and colleagues developed a three-factor model for cryptocurrencies, analogous to the Fama-French model for equities. They identified three key factors: cryptocurrency market, size, and momentum, which capture the cross-sectional expected returns of cryptocurrencies. Their model showed that these factors could form successful long-short strategies, generating significant excess returns.

**4. “Risks and Returns of Cryptocurrency” by Liu et al. (2020)**

**Summary**: In this paper, Liu and Tsyvinski explored the risk exposures of major cryptocurrencies, such as Bitcoin, Ripple, and Ethereum. They found that cryptocurrency returns are driven by factors specific to the cryptocurrency market, such as network factors (user adoption) and production factors (costs of production), rather than traditional asset factors.

**5. “Risks and Returns of Cryptocurrency” by Liu & Tsyvinski (2020)**

**Summary**: This paper investigates the risk factors specific to the cryptocurrency market. Liu and Tsyvinski identify that cryptocurrency returns are influenced by network factors, such as user adoption, rather than production factors like mining costs. They also find a strong momentum effect and that proxies for investor attention can predict future returns.

**6. “A Systematic Literature Review on the Determinants of Cryptocurrency Pricing” by Peng et al. (2023)**

**Summary**: This systematic review identifies key factors influencing cryptocurrency pricing, including supply and demand, technology, economics, market volatility, investor attributes, and social media.

**7. “Optimizing Cryptocurrency Returns: A Quantitative Study on Factor-Based Investing” by Verweij (2024)**

**Summary**: Verweij extends the traditional three-factor model by adding seven additional factors that significantly affect cryptocurrency returns.

**8. “Pro Forma Modeling of Cryptocurrency Returns, Volatilities, Linkages” by Sarker et al. (2022)**

**Summary**: This paper uses traditional econometric techniques to forecast cryptocurrency prices and analyzes the top six cryptocurrencies as a group to understand cross-sectional effects.

**2.2 Almost Stochastic Dominance**

[1] Bali, T.G., Demirtas, K.O., Levy, H. and Wolf, A., 2009. Bonds versus stocks: Investors’ age

and risk taking. *Journal of Monetary Economics,* 56(6), pp. 817-830.

Almost stochastic dominance (ASD) and almost mean–variance (AMV) approaches are used to examine the dominance of stock and bond portfolios. ASD and AMV rules unambiguously support the popular practice of **advising higher stock to bond ratio for long investment horizons. \*using ASD find when people ages, they should buy more stocks**

[2] Levy, H. and Levy, M., 2019. Stocks versus Bonds and the Investment Horizon. *Available at*

*SSRN 3458828*.

We employ the distribution-free First-degree Stochastic Dominance with a Riskless asset (FSDR) criterion to compare stocks to bonds for various investment horizons. We find that for any horizon greater than 3 years, stocks dominate bonds by FSDR. This implies that for any combination of bonds with the risk-free asset (TIPS), there exists a combination of stocks with TIPS that dominates it for any investor with non-decreasing preferences. Hence, the dominance of stocks over bonds for the long-run holds not only for all expected

utility maximizers, but for all Prospect Theory investors as well.

**\*The same result as Bali (2009)**

[3] Post, T., 2003. Empirical tests for stochastic dominance efficiency. *Journal of Finance,* 58(5),

pp. 1905-1931.

Using our tests, the Fama and French market portfolio is significantly inefficient relative to benchmark portfolios formed on market capitalization and book-to-market equity ratio.

**\* SSD (Second-Order Stochastic Dominance) is better than Fama-French**

[4] Board, J.L. and Sutcliffe, C.M., 1994. Estimation methods in portfolio selection and the

effectiveness of short sales restrictions: UK evidence. *Management Science,* 40(4), pp. 516-

534.

[5] Bali, T.G., Brown, S.J. and Demirtas, K.O., 2013. Do hedge funds outperform stocks and bonds? *Management Science,* 59(8), pp. 1887-1903.

Hedge funds employ a wide variety of dynamic trading strategies, and make extensive use of derivatives, short selling, and leverage.

The article uses both classic and ASD rules to find dominance and because the return distribution of hedge fund portfolios as well as the distribution of equity and bond returns exhibit significant departures from normality, the classical selection rules do not provide an appropriate framework to explain investors’ preferences. But ASD works and it does not require a parametric specification of investors’ preferences and does not make any assumptions about asset returns.

The results indicate that popular hedge fund strategies (long/short equity hedge and emerging markets) outperform the U.S. equity market. However, the remaining nine hedge fund strategies considered in this paper do not generate superior performance over the S&P 500 index. **\*in the hedge funds to SP500, ASD works better than classic**

**Conclusion: ASD is good when modeling not normal, but no strategies**

**2.3 Long/Short Legs of Zero-Investment Portfolios**

[1] Israel, R. and Moskowitz, T.J., 2013. The role of shorting, firm size, and time on market

anomalies. *Journal of Financial Economics,* 108(2), pp. 275-301.

Long positions make up almost all of size, 60% of value, and half of momentum profits. Shorting becomes less important for momentum and more important for value as firm size decreases. The value premium decreases with firm size and is weak among the largest stocks. Momentum profits, however, exhibit no reliable relation with size.

Find no evidence that shorting profits are more important for momentum.

Overall, the premium for momentum, whether long-short or long-only, appears to be consistently higher than that of value, especially among large cap stocks in which the value premium is weakest. **\* Long is better**

[2] Blitz, D., Baltussen, G. and van Vliet, P., 2019. When Equity Factors Drop Their Shorts.

*Available at SSRN 3493305*.

Standard academic factor portfolios take hypothetical long positions in stocks with attractive characteristics and combine them with short positions in stocks with unattractive characteristics. Therefore, factor premiums can be disentangled into a long-leg premium and a short-leg premium. We found that factor premiums originate in both legs but are typically stronger on the long side. **\* Long is better**

[3] Frazzini, A. and Pedersen, L.H., 2014. Betting against beta. *Journal of Financial Economics,*

111(1), pp. 1-25.

Portfolios of high-beta assets have lower alphas and Sharpe ratios than portfolios of low-beta assets.

[4] Barroso, P. and Santa-Clara, P., 2015. Momentum has its moments. *Journal of Financial*

*Economics,* 116(1), pp. 111-120.

**Momentum** has offered investors the highest Sharpe ratio while it has also had the worst crashes. However, it can be predicted and managing the risk of momentum leads to substantial economic gains.

Scaling the portfolio to have constant volatility over time is a more natural way of implementing the strategy than having a constant amount in the long and short leg with varying volatility. **\* Use and study about long-short legs**

[5] Daniel, K. and Moskowitz, T.J., 2016. Momentum crashes. *Journal of Financial Economics,*

122(2), pp. 221-247.

Also the **momentum** predicting.

A momentum strategy is a bet on past returns predicting the cross section of future returns, typically implemented by buying past winners and selling past losers.

**Conclusion: Factor premiums originate stronger on the long side.**

Moskowitz & Israel 2013

**The role of shorting, firm size, and time on market anomalies**

The long positions make up almost all of size, 60% of value, and half of momentum profits. Long-only versions of value and momentum also consistently yield positive alphas across size groups, across markets and asset classes, and across time.

David Blitz, Guido Baltussen, Pim van Vliet

**When equity factors drop their shorts**

It finds that **most of the value added comes from the long legs**, while the short legs offer limited value. Long legs tend to offer better diversification and higher risk-adjusted returns, especially in small caps.

Frazzini and Pedersen, 2014

Barroso and Santa-Clara, 2015

Daniel and Moskowitz, 2016

These articles explore methods of adjusting portfolio allocations, particularly in managing risk and optimizing returns across different markets, but they do not cover the Bitcoin or cryptocurrency markets.

**Common Risk Factors in Cryptocurrency**

This paper identifies three key factors—market, size, and momentum—that explain the cross-sectional expected returns of cryptocurrencies.

**Risks and Returns of Cryptocurrency**

This paper examines the risk-return tradeoff of cryptocurrencies, focusing on Bitcoin, Ripple, and Ethereum. It demonstrates that cryptocurrency returns are largely driven by cryptocurrency-specific factors such as momentum and investor attention, rather than traditional stock market or macroeconomic factors.