



HAL
open science

From bottom ten to top ten: The role of cryptocurrencies in enhancing portfolio return of poorly performing stocks

Roman Matkovskyy, Akanksha Jalan, Michael Dowling, Taoufik Bouraoui

► To cite this version:

Roman Matkovskyy, Akanksha Jalan, Michael Dowling, Taoufik Bouraoui. From bottom ten to top ten: The role of cryptocurrencies in enhancing portfolio return of poorly performing stocks. *Finance Research Letters*, 2021, 38, pp.101405. 10.1016/j.frl.2019.101405 . hal-04273124

HAL Id: hal-04273124

<https://hal.science/hal-04273124>

Submitted on 22 Jul 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

From bottom ten to top ten: the role of cryptocurrencies in enhancing portfolio return of poorly performing stocks

Roman Matkovskyy, Akanksha Jalan, Michael Dowling, Taoufik Bouraoui

Rennes School of Business, Department of Finance and Accounting, 2 rue Robert d'Arbrissel,
CS 76522, Rennes, 35065, France

Emails: roman.matkovskyy@rennes-sb.com, akanksha.jalan@rennes-sb.com,
michael.dowling@rennes-sb.com, taoufik.bouraoui@rennes-sb.com

Abstract

This study attempts to analyze the ability of the top 10 cryptocurrencies in enhancing portfolio returns of the 10 worst-performing stocks in the S&P600, S&P400 and S&P100 indexes, to match those of the 10 best-performing stocks therein. Applying probabilistic utility approach with different algorithms and time horizons, we find that addition of cryptocurrencies to traditional stock portfolios adds value in terms of enhancing returns. This is consistent with the growing literature on the hedging properties of cryptocurrencies against traditional financial assets.

Keywords: cryptocurrency, S&P, market capitalization, portfolio allocation, diversification

From bottom ten to top ten: the role of cryptocurrencies in enhancing portfolio return of poorly performing stocks

Abstract

This study attempts to analyze the ability of the top 10 cryptocurrencies in enhancing portfolio returns of the 10 worst-performing stocks in the S&P600, S&P400 and S&P100 indexes, to match those of the 10 best-performing stocks therein. Applying probabilistic utility approach with different algorithms and time horizons, we find that addition of cryptocurrencies to traditional stock portfolios adds value in terms of enhancing returns. This is consistent with the growing literature on the hedging properties of cryptocurrencies against traditional financial assets.

Keywords: cryptocurrency; portfolio allocation; diversification; S&P; market capitalization.

Acknowledgements: We are grateful to Jonathan Batten, the Editor-in-Chief, and the anonymous reviewer for the kind and helpful comments to the manuscript.

1. Introduction

In this study we analyze the role of the top 10 cryptocurrencies by capitalization in enhancing portfolio returns of the bottom 10 large, medium and small market cap S&P companies to match those of the top 10 performers in their respective indices. This is motivated by the hedging and diversification properties of cryptocurrencies against traditional asset classes such as equities, currencies and commodities.

The role of alternative investments in enhancing returns of traditional stock-bond portfolios has for long, been the subject of academic research. However, results so far have been largely mixed and sometimes, even conflicting. The utility of alternative investments is confirmed by Conover et al. (2010) who document that a tactical asset allocation among various asset classes consistently outperforms both a strategic-commodities' and an all-equity portfolio. Similarly, Gao & Nardari (2018) document that commodities add economic value in asset allocation.

On the other hand, another stream of literature documents diminishing hedging and diversification potential of traditional financial asset classes. For instance, Ciner et al. (2013) and Li and Lucey (2017) document that the diversification abilities of gold and crude oil seem to vary with time. In terms of commodities, results remain mixed. While some studies demonstrate that commodity futures may no longer be considered as an effective risk-hedging tool (Silvennoinen and Thorp, 2013; Baur and Dimpfl, 2018; Sharma and Rodriguez, 2019), others argue that commodities add no value to portfolio diversification at all (Bessler and Wolff, 2015; Platanakis et al. 2019). Belousova and Dorfleitner (2012) and Liu et al. (2018) conclude that the diversification benefits of commodities depend upon their type.

In addition, recent studies argue that there now appears to be a shortage of alternative assets that can be used for reducing the downside risk of equity investments (Bouri, Shahzad and Roubaud 2019; Baur and Glover, 2012), especially after the global financial crisis (Shahzad et al, 2019).

Given the dearth of ‘traditional’ alternative investment classes, the role of the increasingly important cryptocurrency markets becomes relevant. Since the introduction of the Bitcoin in 2008, academic research has highlighted the weak correlation between the Bitcoin and traditional financial markets (Baur, Hong, & Lee, 2018; Corbet, Meegan, Larkin, Lucey, and Yarovaya, 2018). This correlation, however, becomes stronger after the introduction of bitcoin futures in December 2017 (Matkovskyy and Jalan, 2019). This finding has led to greater inquiry about the hedging and diversification properties of the Bitcoin against traditional financial assets (Guesmi et al. 2018; Urquhart and Zhang, 2019).

Bouri et al. (2017) document that the Bitcoin acts as a strong hedge against commodity indices, in particular energy commodities. Shahzad et al. (2019) find the hedging and diversification effectiveness of bitcoin to be lower than that of gold. Selmi et al. (2019) find both gold and Bitcoin to be effective hedges against oil price movements, depending on the conditions in the oil and gold market. Urquhart and Zhang (2019) investigate the hedging, diversifier and safe haven properties of the Bitcoin against world currency fluctuations. They find that the Bitcoin acts as a hedge for the CHF, EUR and the GBP, a diversifier for the AUD, CAD and JPY and a safe haven for the CAD, CHF and the GBP in times of turmoil.

Regarding portfolio diversification with cryptocurrency, Wu and Pandey (2014) show that Bitcoin can play an important role in enhancing portfolio efficiency. Using out-of-sample tests, Bouri, Lucey, and Roubaud (2019) document that hedging equities with cryptocurrencies is beneficial. Using an analysis of traditional assets and alternative investments, Brière et al (2015) and Bouri et al. (2017) show that bitcoin investment offers significant diversification benefits. Platanakis and Urquhart (2019) suggest that investors should include Bitcoin in their portfolio as it generates substantial higher risk-adjusted returns.

For the U.S. markets, to which this paper also relates, Kajtazi and Moro (2019) demonstrate that the addition of bitcoin, despite its speculative characteristics, results in improved performance of asset portfolios in the US, China and Europe. Using monthly data for

the period 2010-2017, Chan, Le and Wu (2019) document strong hedging properties of the Bitcoin against 5 international stock indices, including the S&P 500.

We contribute to existing literature by examining the role of cryptocurrencies, a rising class of alternative investments, in enhancing equity returns. For this purpose, we focus not only on one cryptocurrency, as has been the case in most academic articles so far, but the top 10 cryptocurrencies by market capitalization. In addition, our study focuses exclusively on the period after the launch of Bitcoin futures in December 2017. There is evidence to indicate that the integration between traditional and cryptocurrency markets increased significantly post the launch of Bitcoin futures (Matkovskyy and Jalan, 2019).

To investigate the return-enhancing property of cryptocurrencies, we use an applied and goal-based approach to the problem of portfolio optimization using cryptocurrencies. We analyze the role of the top 10 cryptocurrencies in enhancing returns of the 10 poorest performers in 3 S&P index portfolios to match those of the top 10 in their respective group.

For this purpose, we choose the top 10 cryptocurrencies in terms of capitalization, as on 7/06/2019. These are Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Bitcoin Cash (BCH), EOS, Litecoin (LTC), Binance Coin (BNB), Tether (USDT), Stellar and Cardano (ADA).

Traditional financial assets are represented by the equity S&P600, S&P400 and S&P100 indices, comprising small, medium and large capitalization companies, respectively.

We believe that making a distinction between companies on the basis of their size in our sample is important for various reasons. Research indicates that companies with different capitalization have different sensitivities to risk factors important for pricing assets (Hu and Li 1998). Small cap companies have greater exposure to risks (Chan, Chen and Hsieh 1985; Chan and Chen 1991).

Size is also related to profitability (Fama and French 1995). Small-cap companies tend to be balance-sheet constrained and bank-dependent (Gertler and Gilchrist 1994). Also, small capitalization companies usually have low liquidity (Menkveld and Wang, 2013), higher cost of

capital to attract investors and risks associated with the selling of low-capitalization stocks in bearish markets (Acharya and Pedersen 2005).

The dataset covers the period from 1/01/2018 to 6/06/2019. The launch of Bitcoin futures in December 2017 resulted in an increase in Bitcoin market efficiency, and higher integration of Bitcoin markets into traditional ones (Kochling et al. 2018; Matkovskyy and Jalan, 2019). Given this finding, our study focuses exclusively on the post-launch period.

We apply the Probabilistic Utility (hereafter, PU) approach using different estimates, which is best-suited to the study because it: (i) is less sensitive to sample size than Maximization of Expected Utility (hereafter, MEU) and (ii) yields less concentrated portfolio solutions.

To address the issue of uncertainty in parameter determination, we apply the Bayesian approach of Rossi et al. (2002). In this case, the parameters describing the distribution of the cryptocurrency and the selected equity indices are defined by the distributions themselves. This approach allows for taking into account uncertainty that states explicitly the errors associated with the determination of the portfolio.

We document significant ability of cryptocurrencies in boosting equity returns. This is in line with the results of Platanakis and Urquhart (2019) who document higher risk-adjusted returns on the inclusion of the Bitcoin in the asset portfolio. Since our focus is on poorly performing stocks only, we can treat our results as evidence in favor of the hedging properties of cryptocurrencies. This is consistent with the findings of Chan, Le and Wu (2019) and Bouri, Lucey and Roubaud (2019) who document strong hedging properties of the Bitcoin against equity. To the best of our knowledge, however, we are the first paper to not only consider the impact of the ten largest cryptocurrencies (most papers focus only on the Bitcoin), but also investigate the cross-sectional impact on different equity indices on the basis of firm size.

We also find that that the hedging ability of cryptocurrencies is higher for small-cap stocks, than larger ones. In addition, for medium-cap companies, the return-enhancing effect of cryptos is not only much lower, but also diminishes over time. Except the USDT, no other

cryptocurrency seems to enhance equity returns in the longer, 250-day time horizon. In our robustness tests that exclude the USDT from our cryptocurrency sample, we find that no cryptocurrency except three - BTC, ETH and LTC, boost stock returns in the longer time horizon.

In short, our results support the hypothesis that alternative investments, in this case cryptocurrencies, add value by enhancing performance of traditional financial assets. We also contribute to the growing literature on the hedging and diversification properties of cryptocurrencies.

The remainder of the paper proceeds as follows. Section 2 describes the data and methodology. In section 3, we discuss the empirical results, and in section 4 we offer our conclusions. The on-line appendix includes supplementary material.

2. Data and model set-up

Our dataset includes daily close prices of the top 10 cryptocurrencies in terms of capitalization, as on 7/06/2019. Cryptocurrency and stock data comes from www.coinmarketcap.com and Thompson EIKON, respectively.

The non-stationary behavior of stock prices can induce major drawbacks in portfolio selection. (Livan, Scalas, Inoue, 2012). We calculate returns for each stock index to ensure stationarity as follows

$$r_t = (\ln P_t - \ln P_{t-1}) \times 100 \quad (1)$$

where r_t is the daily return on day t and P_t and P_{t-1} are the prices at day t and day $t-1$. They are further used to determine the top and bottom 10 companies in each index.

The issue of uncertainty in expected returns has received significant academic attention (Barry 1974; Bawa, Brown, and Klein 1979; Brennan 1998; Stambaugh 1999; Balduzzi and Liu, 2000; Polson and Tew 2000; Barberis 2000; Xia 2001; Markowitz and Usmen, 2003; etc). Our motivation for the methodology starts with a question of ambiguity and uncertainty given, that

investors are not neutral to the ambiguity given multiple priors (Uppal and Wang, 2003; Garlappi, Uppal and Wang, 2004; etc).

Classical portfolio selection using MEU (Markowitz, 1952) suffers from various well-documented drawbacks, such as extreme and hardly plausible portfolio weights that are highly sensitive to changes in expected returns (Michaud, 1989). To overcome these drawbacks, we utilize the PU approach as in Rossi et al. (2002) and Marschinski et al. (2007). An implication of this approach interprets a utility function as the logarithm of the probability density for a portfolio. Then the optimal allocation is derived based on the expected value of the portfolio's weights that are considered to be parameters of this distribution (see on-line Appendix 1).

The probabilistic utility approach allows for deriving an improved portfolio selection procedure. The issue of ambiguity aversion is addressed as well through the introduction of a parameter that implicitly accommodates uncertainty.

For portfolio weights, we choose a utility function which ensures the direct impact of time horizon on portfolio allocation (Consiglia et al., 2001; Rossi et al. 2002; Marschinski et al. 2007 etc.):

$$E[u(a, L, \lambda, T)] = \sum_{n=1}^{N_T} \Delta t [E(U(n\Delta t)) - \lambda E(D(n\Delta t))], \quad (2)$$

where $U(n\Delta t)$ is a function for the upside potential of allocation estimates, $D(n\Delta t)$ is a function for emulating the downside risk of this allocation for a portfolio return at time $n\Delta t$, L is the target return, λ is the degree of risk aversion, and T is the investment horizon. This setup implies that longer the time horizon, the more funds are allocated to riskier assets and vice versa.

This function is superior to the standard maximization of expected utility in several ways. It reduces excessive sensitivity to external parameters, avoids concentration on too few assets and helps in accounting for the incompleteness of information and uncertainty-aversion in its estimates (Marschinski et al., 2007).

Given that risk averse investors tend to stay closer to the targeted return, it is assumed that longer the investment horizon, higher the number of investors that intend to allocate funds

to risky assets and vice versa. Thus, applying a Gaussian integration to the adjusted Eq. (1) (Rossi et al. 2002)

$$E[u(a, L, \lambda, T)] = \sum_{n=1}^{N_T} \Delta t [n \Delta t M f_2(n \Delta t) - \sqrt{n \Delta t} S f_1(n \Delta t)], \quad (3)$$

where,

the expected downside utility is

$$f_1(t) = (\lambda - 1) \frac{e^{-t\eta^2}}{\sqrt{2\pi}} \quad (4)$$

the expected upside utility is

$$f_2(t) = \frac{1+\lambda}{2} - \frac{1-\lambda}{2} \operatorname{erfc}(\sqrt{t\eta}) \quad (5)$$

$$\eta = \frac{M}{2S} \quad (6)$$

$$M = \alpha^T \cdot \mu - L \quad (7)$$

$$S^2 = \alpha^T \cdot \Sigma \cdot \alpha \quad (8)$$

where $\operatorname{erfc}()$ is the complementary error function, μ is the expected returns of cryptocurrencies, Σ is the variance-covariance matrix of the returns and L is the target return.

We derive the distributions for the period log-return weights ω :

$$\omega \sim \exp\left(-\frac{(\omega-\mu)^T \Sigma^{-1} (\omega-\mu)}{2}\right) \frac{1}{\sqrt{(2\pi)^J |\Sigma|}}, N(\mu, \Sigma) \quad (9)$$

where ω is the weight vector.

As one can see above, another advantage is the possibility to incorporate time-dependency in the allocation process, i.e., longer time horizons (*ceteris paribus*) result in more aggressive portfolio weights.

Portfolio allocations based on utility-maximizing portfolio choices require the evaluation of a high-dimensional unknown density using dynamic Monte Carlo integration and Markov Chain Monte Carlo (MCMC) techniques. To enhance the credibility of our results, we use variations of the Metropolis-Hastings method. Three different algorithms are further used and

compared. The motivation is that no single Markov chain method should dominate all others in all problems (Tierney, 1994).

The first algorithm is a random walk Metropolis (Tierney, 1994) with a multivariate normal proposal to produce a Markov chain with equilibrium distribution having a specified unnormalized density. Also, this approach allows for controlling an animation in which a function of the parameters is considered to be the parameters that are moved through the posterior distribution by the chain.

The second algorithm used produces a sample from a defined distribution using a random walk Metropolis algorithm with a multivariate normal proposal distribution as in Gelman et al. (2003) and Robert and Casella (2004).

The third is an implementation of the robust adaptive Metropolis sampler of Vihola (2012) that estimates the shape of the target distribution simultaneously coercing the acceptance rate. It tunes the covariance matrix of the jump distribution to achieve the desired acceptance rate. The adaptation rule is computationally simple adding no extra cost compared with the adaptive Metropolis algorithm of Haario, Saksman and Tamminen (2001).

In general, this algorithm's adaptation strategy is a multidimensional extension that adapts the scale of the proposal distribution to attain a given acceptance rate. This algorithm derives robust empirical results with different target distributions having no finite second moment. Thus, it ensures that the Markovian property of convergence to the target (stationary) distribution is guaranteed.

3. Empirical results

General return statistics for selected companies and cryptocurrencies are presented in Tables A1-A2. Table A1 indicates that BCH, offers the highest maximum (and mean) return and one of the highest variances. USDT, however, offers both the lowest minimum return among the cryptocurrencies, and the lowest skewness and variance, making it a rather 'safe' but low-yielding

investment. On the other hand, USDT is price-stable. This can potentially render it unnecessary for inclusion in our portfolio allocation. To ensure robustness of our results, we calculate portfolio weights for two cases, with and without the USDT.¹

Mean values of returns of the top and bottom 10 companies presented in Tables A2-A4 indicate that average stock performance diminishes with market cap. Also, small-cap companies seem to be rather extreme in their performance – while the best performers in this group generate the highest average return among all indices, the poor ones report the highest overall loss. Table A4 reveals a rather poor overall performance of cryptocurrencies during the sample period. Except EOS and BNB, all other cryptos end up losing money on an average.

Portfolio optimization is undertaken using the MEU and PU, with a targeted return equal to the average return of the respective top 10 companies.

The length of the Markov chains is set to 50,000. Risk aversion determines the proportion of wealth allocated between risky and risk-free assets and is set to 3 (moderate). The investment horizon spans 30 days. Allocations based on PU are presented in Tables A5-7.

The MEU optimization yields highly concentrated portfolio solutions with allocations only to BTC, XRP and LTC for the S&P600 and S&P100 indices and only BTC and XRP for S&P400. The other cryptocurrencies are ignored.

We counteract the problem of concentration by using the PU approach with three different algorithms: Vihola (2012), Gelman et al. (2003) and Robert & Casella (2004), and Tierney (1994).

In contrast, these results show a rather equitable allocation of weights across ‘all’ stocks and cryptos, each ranging between 3 and 8%. Among cryptos, BTC and LTC continue to have the highest shares. Interestingly, we find that the solution portfolio weights assigned to cryptocurrencies decrease progressively with the market cap of the companies - the total share of cryptocurrencies in the portfolio allocation is 39.1%, 31.9% and 27.7% for small-cap, mid-cap

¹ Even with exclusion of the USDT, results remain qualitatively similar. Cryptocurrencies continue to remain efficient in enhancing portfolio returns (see Tables 7-10 in on-line appendix).

and large-cap companies, respectively. This seems to suggest a more effective role of cryptos in boosting returns of small-cap stocks, than larger ones.

Tables A8-A10 present PU results over different time horizons, starting from 5 to 250 days. In case of the bottom 10 S&P600 companies, the role of cryptocurrencies is seen to diminish over time in terms of allocation of weights. The only exceptions are ETH and LTC, weights on which remain stable over time, while an increase is observed for BTC.

For the S&P400 companies, portfolio weights in cryptos show a general decline over time. The weight on BTC however, remains largely constant over time, indicating its ability to add value consistently over the 250-day time horizon. In portfolio allocation with S&P100, even when cryptocurrencies exhibit diminishing portfolio weights over the 250-day time horizon, the BTC shows the most stable contribution.

Tables A11-12 present average Sharpe ratios for different portfolios. We observe that the Robert and Casella (2004) algorithm generates portfolios with the most favorable Sharpe ratios for all companies, irrespective of size.

4. Conclusion

In this study we analyze the ability of the top 10 cryptocurrencies in terms of capitalization in improving portfolio returns of the bottom 10 companies in the S&P600, S&P400 and S&P100 indices, to reach the average return of the top 10 stocks in their respective index.

Using both MEU and PU approaches, we find that the addition of cryptocurrencies to a portfolio of the worst-performing stocks in three different indices indeed helps improve performance in terms of returns. The highest efficacy of cryptos in boosting returns is noted for small-cap stocks. Moreover, for medium -cap companies the role of cryptocurrencies is much lower and diminishing over time. Except the BTC, ETH and LTC, no other cryptocurrency seems to maintain its efficacy in boosting stock returns in the longer time horizon.

Overall, our results support the hypothesis that alternative investments in traditional stock portfolios add value and also contribute to the growing stream of literature on the hedging and diversifier properties of cryptocurrencies. These results can be of value to market participants in general and fund managers in particular. Our findings can enable the common investor to better understand and appreciate the rising integration between traditional and cryptocurrency markets, particularly after the launch of the Bitcoin futures in December 2017.

More so, global fund managers with significant amounts in assets under management can apply these findings to include cryptocurrencies in their asset portfolios – particularly in small cap stocks - not only to diversify risk but also enhance fund returns. This is particularly relevant since fund managers are typically paid as a percentage of returns generated on assets managed.

References

- Acharya, V., Pedersen, L. (2005) Asset pricing with liquidity risk. *J. Financial Economics* 77 (2), 375–410.
- Balduzzi, P. and L. Liu. (2000). Parameter Uncertainty and International Investment. Working Paper, Boston College.
- Barberis, N. (2000). Investing for the long run when returns are predictable. *Journal of Finance* 55, 225-264.
- Barry, C.B. (1974). Portfolio Analysis under Uncertain Means, Variances and Covariances. *Journal of Finance* 29, 515-522.
- Baur, D. G., & Glover, K. (2012). The destruction of a safe haven asset? *Applied Finance Letters*, 1(1), 8–15.
- Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of Exchange or Speculative Assets? *Journal of International Financial Markets Institutions and Money*, 54, 177–189.
- Baur, D.G. and Dimpfl, T. (2018). The asymmetric return-volatility relationship of commodity prices. *Energy Economics* 76, 378-387.

- Bawa, V., S. Brown, and R. Klein. (1979). *Estimation Risk and Optimal Portfolio Choice*. North Holland, Amsterdam.
- Belousova, J. & Dorfleitner, G. (2012). On the diversification benefits of commodities from the perspective of euro investors. *Journal of Banking and Finance* 36 (9), 2455 – 2472.
- Bessler, W., & Wolff, D. (2015). Do commodities add value in multi-asset portfolios? An out-of-sample analysis for different investment strategies. *Journal of Banking and Finance* 60, 1 – 20.
- Bouri, E., Jalkh, N., Molnar, P., and Roubaud, D. (2017). Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven? *Applied Economics* 49(50), 5063 – 5073.
- Bouri, E., Lucey, B., Roubaud, D. (2019). Cryptocurrencies and the downside risk in equity investments. *Finance research letters*, In press.
- Bouri, E., Molnar, P., Azzi, G., Roubaud, D., Hagfors, L.I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance research letters* 20, 192-198.
- Bouri, E., Shahzad, S.J.H. and Roubaud, D. (2019). Cryptocurrencies as hedges and safe-havens for US equity sectors. *The Quarterly Review of Economics and Finance*, In press.
- Brennan, M. (1998). The role of learning in dynamic portfolio decisions. *European Finance Review* 1, 295-306.
- Brière, M., Oosterlinck, K., Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management* 16, 365-373.
- Chan, K, and Chen, N. (1991). Structural and Return Characteristics of Small and Large Firms. *Journal of Finance*, pp. 1467-83.
- Chan, W.H., Le, M., Wu, Y.W. (2019). Holding Bitcoin longer: The dynamic hedging abilities of Bitcoin. *The Quarterly Review of Economics and Finance* 71, 107 – 113.
- Ciner, C., Gurdgiev, C., Lucey, B.M. (2013). Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. *Int. Rev. Financ. Anal.* 29, 202–211.

Conover, M., Jensen, G., Johnson, R., & Mercer, J. (2010). Is Now the Time to Add Commodities to Your Portfolio? *The Journal of Investing* 19 (3), 10-19.

Consiglia A., Cocco F., and Zenios S. (2001). The value of integrative risk management for insurance products with guarantees. *Journal of Risk Finance* 2, 6–16.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, 28–34.

Fama, E., and French, K (1995). Size and Book-Market Factors in Earnings and Returns. *The Journal of Finance*, 131-55.

Gao, X., Nardari, F. (2018). Do Commodities Add Economic Value in Asset Allocation? New Evidence from Time-Varying Moments. *Journal of Financial and Quantitative Analysis* (in press).

Garlappi, L., Uppal, R. and Wang, T. (2004). “Portfolio Selection with Parameter and Model Uncertainty: A Multi-Prior Approach.” Conference paper, 2004 UBC Finance Conference

Gelman, A., Carlin, J. B., Stern, H. S., and Rubin, D. B. (2003). *Bayesian Data Analysis*. 2nd Edition. Boca Raton: Chapman & Hall/CRC.

Gertler, M. and Gilchrist, S. (1994). Monetary Policy, Business Cycles, and The Behavior of Small Manufacturing Firms. *The Quarterly Journal of Economics*, 309-40.

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2018). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis* 63, 431-437.

Haario, H., Saksman, E., and Tamminen, J. (2001). An adaptive Metropolis algorithm. *Bernoulli* 7(2), 223–242.

Hastings, W. (1970). Monte Carlo sampling methods using Markov chains and their applications. *Biometrika* 57, 97–109.

Hu, Z., Li, L. (1998). Responses of the Stock Market to Macroeconomic Announcements Across Economic States. *IMF Working Papers* vol. 98(79), 1-29.

Kajtazi, A. & Moro, A. (2019) The role of bitcoin in well diversified portfolios: A comparative global study. *International Review of Financial Analysis* (in press).

Kochling, G., Muller, J., & Posch, P. N. (2018). Does the introduction of futures improve the efficiency of Bitcoin? *Finance Research Letters* (in press)

Li, S., Lucey, B.M., 2017. Reassessing the role of precious metals as safe havens—What colour is your haven and why? *J. Commodity Markets* 7, 1–14.

Liu, Q., Tse, Y., & Zhang, L. (2018). Including commodity futures in asset allocation in China. *Quantitative Finance* 18, 1487 – 1499.

Livan, G., Scalas, E., Inoue, J.-I. (2012) On the non-stationarity of financial time series: Impact on optimal portfolio selection. *Journal of Statistical Mechanics Theory and Experiment* 07.

Markowitz, H. and Usmen, N. (2003). Resampled Frontiers vs Diffuse Bayes: An Experiment. *Journal of Investment Management* 1 (4), 9-25

Marschinski R., Rossi P., Tavoni M., and Cocco F. (2007). Portfolio selection with probabilistic utility. *Annals of Operations Research* 151, 223–239.

Matkovskyy, R., Jalan, A. (2019a). From Financial Markets to Bitcoin Markets: a Fresh Look at the Contagion Effect. *Finance research letters* 31, 93-97.

Menkveld, A.J., Wang, T. (2013). How do designated market makers create value for small-caps? *J. Financial Markets* 16, 571–603.

Michaud R. (1989). The Markowitz optimization enigma: Is optimized optimal. *Financial Analyst Journal* 45, 31–42.

Platanakis, E., Sakkas, A. & Sutcliffe, C. (2019). Harmful diversification: Evidence from alternative investments. *The British Accounting Review* 51(1), 1 – 23.

Platanakis, E., Urquhart, A. (2019). Should Investors Include Bitcoin in Their Portfolios? A Portfolio Theory Approach. *The British Accounting Review* (in press).

Polson, N.G. and Tew, B.V. (2000). Bayesian Portfolio Selection: An Empirical Analysis of the S&P 500 Index 1970-1996. *Journal of Business and Economic Statistics* 18 (2), 164-173.

Robert, C. P. & Casella, G. (2004). *Monte Carlo Statistical Methods*. 2nd Edition. New York: Springer.

Rossi P., Tavoni M., Cocco F., and Marschinski R. 2002 Portfolio selection with probabilistic utility, Bayesian statistics and Markov chain Monte Carlo. arXiv:cond-mat/0211480

Selmi, R., Mensi, W., Hammoudeh, S., Bouoiyour, J. (2018). Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. *Energy Economics* 74, 787 – 801.

Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019). Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis* 63, 322-330.

Shahzad, S., J., H., Bouri, E., Roubaud, D., Kristoufek, L.(2019). Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin. *Economic Modelling*, In Press.

Sharma, S. and Rodriguez, I. (2019). The diminishing hedging role of crude oil: Evidence from time varying financialization. *Journal of Multinational Financial Management*, In press.

Silvennoinen, A., and S. Thorp (2013). Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions and Money* 24, 42-65.

Stambaugh, R. (1999). Predictive regressions. *Journal of Financial Economics* 54, 375-421.

Tierney, L. (1994). Markov chains for exploring posterior distributions (with discussion). *Annals of Statistics* 22, 1701–1762.

Uppal, R. and Wang, T. (2003). Model Misspecification and Under-diversification. *Journal of Finance* 58, 2465-2486.

Urquhart, A., Zhang, H. (2019). Is Bitcoin a hedge or safe haven for currencies? An intraday analysis. *International Review of Financial Analysis* 63, 49 – 57.

Vihola, M. (2012). Robust adaptive Metropolis algorithm with coerced acceptance rate. *Statistics and Computing* 22(5), 997–1008.

Wu, C. Y., Pandey, V. K. (2014). The Value of Bitcoin in Enhancing the Efficiency of an Investor's Portfolio. *Journal of Financial Planning* 27, 44-52.

Xia, Y. (2001). Learning about predictability: the effect of parameter uncertainty on optimal dynamic asset allocation. *Journal of Finance* 56, 205-246.