Determinants of Cryptocurrency Returns:

A Lasso Quantile Regression Approach

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Abstract

We consider a relatively large set of predictors and investigate the determinants of cryptocurrency returns at different quantiles. Our analysis exclusively focuses on the highly volatile period of Covid-19. The innovation in the paper stems from the fact that we employ the Lasso penalty in a quantile regression framework to select informative variables. We find that US government bond indices and small company stock returns, a new predictor introduce in this study, significantly impact the tail behavior of the cryptocurrency returns.

Keywords: lasso, quantile regression, cryptocurrency, Covid-19

Determinants of Cryptocurrency Returns: A Lasso Quantile Regression Analysis

1. Introduction

Panagiotidis et al. (2018) use a data set with many predictors from stock, commodity, bond, and exchange rate markets to investigate the determinants of bitcoin (BTC). They employ a penalized regression approach, the least absolute selection and shrinkage operator (Lasso), introduced by Tibshirani (1996), to construct their model.[1] The Lasso method is designed to remove redundant variables by imposing a penalty in the objective function and thus, provide variable selection, which, in turn, should result in more efficient models.

In this study, we also consider a large set of explanatory variables and employ the Lasso approach; however, we conduct our analysis in a quantile regression framework by utilizing the work by Belloni and Chernozhukov (2011). Our analysis can provide a richer understanding of the determinants of cryptocurrencies by identifying risk factors associated with extreme market movements, rather than solely focusing on the mean as an ordinary Lasso regression does. [2] This is particularly relevant as we focus on the volatile Covid-19 era. Several articles argue that the economic turbulence generated by the pandemic impacted financial market dependencies and that Covid-19 has been a source of systematic risk, Corbet et al. (2020).[3]

Furthermore, in addition to BTC, we examine the determinants of two additional cryptocurrencies: ethereum (ETH) and Ripple (XRP). As Hardle et al. (2020) discusses, ETH allows for distributed computation and has a tangible component. XRP, on the other hand, is designed to work on the Ripple network, a payment system and currency exchange network

[1] Panagiotidis et al. (2018) find that gold and search intensity, measured by Google Trends, are the main explanatory variables for BTC, between 2010 and 2017.

[22] Nguyen et al. (2020) use Lasso quantile regression to investigate tail risk dependency between cryptocurrency markets.
[3] Ciner (2021) also uses the Lasso regression to examine the predictors of the US stock index returns during the Covid-19 period.

that can enable transactions to serve the international banking system. It should be of interest to investigate whether the risk factors are similar across the cryptocurrency markets.

In the next section, we discuss the statistical method of analysis. In Section 3, we present the data set and the empirical findings. In the final section, we provide the concluding remarks of the article.

2. Statistical Method

Consider a standard parametric quantile regression model:

$$Y_{i,t}(\tau) = \alpha(\tau) + \sum_{i=1}^{p} \beta_i(\tau).X_{i,t} \quad (1)$$

In which, Y_i is a response variable, cryptocurrency returns in our case, and $X_{i,t}$ is a p-dimensional matrix of covariates, and τ is the conditional quantile. As noted, our goal is to consider a larger number of potential predictors and rely on a sparse regression method, the Lasso, to remove redundant predictors. The Lasso method achieves variable selection by adding a penalty term that is proportional to the sum of the absolute value of the parameters. In the quantile regression framework, Belloni and Chernozhukov (2011) show that this can be accomplished by minimizing the below measure:

$$\sum_{t=1}^{T} \rho_\tau\left(Y_{i,t}(\tau) - \alpha(\tau) + \sum_{i=1}^{p} \beta_i(\tau).X_{i,t}\right) + \lambda \frac{\sqrt{\tau(1-\tau)}}{T} \sum_{i=1}^{p} |\beta_i(\tau)| \quad (2)$$

In which, ρ_τ denotes the quantile loss function. Post-penalization, we follow Belloni and Chernozhukov (2011) and apply the standard quantile regression to estimate the parameters on the selected variables.

The tuning parameter, λ, determines the stiffness of the penalty, for which we use the Bayesian Information Criteria (BIC). Also, we employ the Adaptive version of the Lasso, developed by Zou (2006), as it can lead to more efficient estimates. The Adaptive Lasso first fits the full model without penalty, and then uses a weighted penalty, where the weights are the reciprocals of the corresponding coefficients from the full model.

3. Data and Empirical Findings

The variables in our data set are provided in Table 1. We use exchange traded funds as these instruments are liquid and are synchronously traded on financial markets. Our predictors are similar to those considered by Panagiotidis et al. (2018), and, also by Corbet et al. (2019, 2018). However, there are also notable differences. Firstly, while Panagiotidis et al. (2018) only include central bank interest rates, we include corporate bonds, inflation protected securities and emerging market bonds.

The primary reason we include more variables from the bond market is due to the actions of the US Federal Reserve following the Covid-19 crisis. Specifically, the Fed introduced the Secondary Market Corporate Credit Facility (SMCCF) on March 23rd to purchase corporate bonds and extended it on April 9th to include even the high yield corporate bonds as unprecedented responses to the Covid-19 crash.[4]

Secondly, we do not include Google Trends search index as a potential explanatory variable. This is due to Medeiros and Pires (2021), who suggest that each Google search data is different from the other even when the same search terms are used. Therefore, arbitrary

[4] Gilchrist et al. (2021) find that Fed's forceful response shored up market confidence and stabilized conditions.

conclusions may be reached by chance. Finally, we include the clean energy stock index (PBW), since cryptocurrencies are large consumers of energy, Ren and Lucey (2022), and as a new variable to the literature, the small company stock index (SLY), as a further proxy for risk in particular, financial distress in financial markets; see, Van Dijk (2011) and the articles referenced therein.

Our dataset covers the period between January 2, 2020 and April 23, 2021. All variables, save for the economic policy uncertainty index (EPU), are transformed by taking log first differences. For cryptocurrencies, following the literature, only weekday returns are calculated, and the dataset is obtained from Yahoo Finance!

In Table 2, we provide some summary statistics for the data. Importantly, we observe the presence of excess kurtosis in cryptocurrency returns and that the assumption of normal distribution is comfortably rejected, in each case. This initial evidence further supports utilizing the quantile regression framework.

In Table 3, we report the main findings of the study. We estimate the Adaptive Lasso quantile regressions to examine cryptocurrencies at the 50th, 90th and the 10th quantiles to investigate the risk factors in bullish and bearish markets, as well as at the median. Firstly, at the 50th quantile, the three cryptocurrencies are affected by the same variables, gold (GLD) and the S&P 500 index (SPY). Note that Panagiotidis et al. (2018) also detect gold as a significant variable for the BTC. On the other hand, the significance of the stock market is not commonly detected and may be unique to the Covid-19 era.

We proceed to examine the risk factors for cryptocurrency returns at the tails of their distributions. We find that in bearish markets, at the 10th quantile, corporate investment grade bonds (LQD) and the stock market volatility index (VIX) are significant for BTC. For ETH and XRP, the small company stock index (SLY), emerges as a significant determinant as well as the US government bond index (TLH). Also, the uncertainty measures we use, VIX and EPU, are significant for BTC and ETH, respectively, and the coefficient estimates are negative, as expected. Moreover, an exchange rate variable, the Australian dollar (FXA), emerges as significant for XRP at the 10th quantile.

On the other hand, at the 90th quantile, we observe that SLY is the only statistically significant variable for BTC. Bond market indices continue to play significant roles as the government bond index (TLT) is the only significant variable for ETH, and the Treasury bond index (SHY) is significant for XRP. The Japanese yen (FXY) and another new variable introduced in this paper, clean energy stock index (PBW), are also significant for XRP at the 90th quantile. The influence of exchange rates on XRP returns is consistent with the view that this cryptocurrency is tailored to facilitate international payments on a global network.

4. Concluding Remarks

We investigate the determinants of three cryptocurrency returns during the Covid-19 era by using Adaptive Lasso quantile regressions. Our methodology selects informative predictors, and eliminates weak ones, at different parts of the return distribution. We show that gold and S&P 500 index prices consistently impact the cryptocurrencies in our sample at the median of their return distributions. However, unique variables are significant in the tails of their distributions. We particularly note that developments in bond markets are highly influential, consistent with the unusual actions of the Federal Reserve in the Covid-19 period.

It is also noteworthy that small company stocks, a new predictor to the literature, impacts the extreme quantiles of the cryptocurrencies in our sample. This is consistent with the view that small company stocks may act as a risk proxy in financial markets. Overall, our results support the argument that investigating the full spectrum of the return distribution, and using a statistical learning method for variable selection, provides a richer understanding of the determinants of cryptocurrency returns.

References

Belloni, A. and Chernozhukov, V., 2011. ℓ1-penalized quantile regression in high-dimensional sparse models. *The Annals of Statistics*, *39*(1), pp.82-130.

Ciner, C., 2021. Stock return predictability in the time of COVID-19. *Finance Research Letters*, *38*, p.101705.

Corbet, S., Larkin, C. and Lucey, B., 2020. The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, *35*, p.101554.

Corbet, S., Lucey, B., Urquhart, A. and Yarovaya, L., 2019. Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, pp.182-199.

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

Gilchrist, S., Wei, B., Yue, V.Z. and Zakrajšek, E., 2020. *The Fed takes on corporate credit risk: An analysis of the efficacy of the SMCCF* (No. w27809). National Bureau of Economic Research.

Härdle, W.K., Harvey, C.R. and Reule, R.C., 2020. Understanding cryptocurrencies. *Journal of Financial Econometrics*, *18*(2), pp.181-208.

Medeiros, M.C. and Pires, H.F., 2021. The Proper Use of Google Trends in Forecasting Models. *arXiv preprint arXiv:2104.03065*.

Nguyen, L.H., Chevapatrakul, T. and Yao, K., 2020. Investigating tail-risk dependence in the cryptocurrency markets: A LASSO quantile regression approach. *Journal of Empirical Finance*, *58*, pp.333-355.

Panagiotidis, T., Stengos, T. and Vravosinos, O., 2018. On the determinants of bitcoin returns: A LASSO approach. *Finance Research Letters*, *27*, pp.235-240.

Ren, B. and Lucey, B., 2022. A clean, green haven? Examining the relationship between clean energy, clean and dirty cryptocurrencies. *Energy Economics*, p.105951.

Tibshirani, R., 1996. Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), pp.267-288.

Van Dijk, M.A., 2011. Is size dead? A review of the size effect in equity returns. *Journal of Banking & Finance*, *35*(12), pp.3263-3274.

Zou, H., 2006. The adaptive lasso and its oracle properties. *Journal of the American statistical association*, *101*(476), pp.1418-1429.

Table 1- Data Set

USO	US Oil Fund, LP
GLD	SPDR Gold Shares
SPY	SPDR S&P 500 ETF Trust
SLY	SPDR S&P 600 Small Cap
PBW	Invesco WilderHill Clean Energy

TLH	iShares 10-20 Year Treasury Bond
HYG	iShares iBoxx $ High Yield Corporate Bond
EMB	iShares J.P. Morgan USD Emerging Markets Bond
TLT	iShares 20+ Year Treasury Bond
IEI	iShares 3-7 Year Treasury Bond
TIP	iShares Treasury Inflation Protected Securities Bond
LQD	iShares iBoxx $ Investment Grade Corporate Bond
SHY	iShares 1-3 Year Treasury Bond
FXY	Invesco Currency Shares Japanese Yen Trust
FXE	Invesco Currency Shares Euro Currency Trust
FXB	Invesco Currency Shares British Pound Trust
FXF	Invesco Currency Shares Swiss Franc Trust
FXA	Invesco Currency Shares Australian Dollar Trust
FXC	Invesco Currency Sahres Canadian Dollar Trust
EPU	Economic Policy Uncertainty Index
VIX	CBOE Volatility Index

Note- This table provides the definitions of the variables included in the dataset.

Table 2- Summary Statistics

	Mean	Std. Dev.	Skewness	Kurtosis	A2	SW
BTC	0.0066	0.0321	-2.4552	24.3763	8.052	0.8143
XRP	0.0061	0.0939	0.6858	14.532	16.4999	0.7737

ETH	0.0089	0.0692	-1.4594	16.9571	7.1603	0.8463
USO	-0.0027	0.0422	-2.1921	15.1519	14.2659	0.7929
GLD	0.0004	0.0192	-0.5898	3.4585	4.2603	0.9451
SPY	0.0008	0.0192	-0.9648	9.4913	12.5658	0.8414
SLY	0.0008	0.0358	-0.9004	5.1851	5.6726	0.9137
PBW	0.0029	0.0358	-0.679	2.8246	2.585	0.9593
TLH	0.0001	0.0093	-0.1564	9.8222	8.5446	0.856
HYG	-0.0001	0.0097	-0.1374	14.0592	24.9661	0.7339
EMB	-0.0001	0.0111	-3.6843	29.7848	28.648	0.6406
TLT	0.0001	0.0127	0.2412	9.4361	6.9855	0.8677
IEI	0.0001	0.002	0.6433	10.4045	12.6186	0.8337
TIP	0.0002	0.0051	0.5076	23.9542	21.6812	0.7037
LQD	0.0001	0.0096	0.4484	20.004	28.3308	0.663
SHY	0.0001	0.0007	1.4558	19.5552	25.6534	0.7087
FXE	0.0001	0.0045	-0.2427	1.4309	0.3358	0.9861
FXY	-0.0001	0.0054	-0.3844	9.8317	9.635	0.85
FXB	0.0001	0.0065	-0.7547	6.6182	2.5869	0.9333
FXF	0.0001	0.0046	-0.2943	1.749	1.0653	0.9785
FXA	0.0002	0.0075	-0.4527	2.4784	2.0501	0.9666
FXC	0.0001	0.0048	-0.3773	2.1736	2.2586	0.9695
EPU	5.3893	0.5858	-0.3171	-0.1208	1.1476	0.9856
VIX	0.0007	0.0905	0.0007	5.7341	8.457	0.8817

Note- This table provides the summary statistics of the variables in the data set. A2 and SW denote Andersen-Darling and Shapiro-Wilk tests, respectively, for normality.

Table 3- Lasso Quantile Regressions

	BTC			*ETH*			*XRP*		
	0.1	0.5	0.9	0.1	0.5	0.9	0.1	0.5	0.9

USO	-	-	-	-	-	-	-	-	-
GLD	-	**0.64**	-	-	**0.79**	-	-	**0.54**	-
SPY	-	**0.25**	-	**0.71**	**0.81**	0.31	-	**0.61**	-
SLY	-	-	**0.54**	**0.49**	-	0.48	**0.59**	-	-
PBW	0.28	-	-	-	-	-	-	-	**0.57**
TLH	-	-	-	**1.48**	-	-	**4.1**	-	-
HYG	-	-	-	-	-	-	-	-	-
EMB	-	-	-	-	-	-	-	-	-
TLT	-	-0.15	-	-	-	**1.05**	-	-	-
IEI	-3.04	-	-	-	-	-7.58	-12.55	-	-
TIP	-	-	-	-	-	-	-	-	-
LQD	**0.79**	-	-	-	-	-	-	-	-
SHY	-15.89	-	-	-	-	-	-	-	**1.54**
FXY	2.76	-	-	-	-	-	-	-	**-1.54**
FXE	-	-	-	-	-	-	-	-	-
FXB	-	-	-	-	-	-	-	-	-
FXF	-	-	-1.18	-	-	-0.98	-	-	-
FXA	-0.38	-	-	-	-	-	**2.11**	-	-
FXC	-	1.4	-	0.78	-	-	-	-	-
EPU	-	-	-	**-0.03**	-	-	-	-	-
VIX	**-0.19**	-	-	-0.16	-	-	-0.22	-	-

Note- This table provides the estimation results of adaptive Llasso quantile regressions. The bold entries signify significance at five percent.