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Extremely stablecoins

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ABSTRACT

In this research, I explore the factors driving extreme fluctuations in stablecoin prices concerning financial and cryptocurrency market indices. Through quantile models, I reveal the directional predictability of diverse financial variables, capturing extreme price variations and return distribution fluctuations. The outcomes highlight asymmetric pricing reactions and the impact of stablecoin stability mechanisms. The varying effects observed in stablecoin and cryptocurrency behavior imply a broader market link and potential fragility. Notably, intermediary constraints and stablecoin liquidity exhibit predictive power for subsequent price shifts in both tails, providing insights into the complex dynamics within cryptocurrency and stablecoin markets.

1. Introduction

Cryptocurrencies were initially conceived as a financial innovation to facilitate transactions free from the constraints imposed by traditional financial intermediaries and national capital controls. However, their inherent excessive volatility and speculative nature led to the development of an innovative solution, stablecoins. These digital currencies are pegged to the value of the US Dollar (USD) or other assets, designed to mitigate the volatility concerns in traditional coins. The parity is ensured through a combination of centralized and decentralized (DeFi) stability mechanisms, relying on collateralization with USD, the incorporation of liquid fixed exchange assets, and the implementation of algorithms dedicated to peg preservation (Arner et al., 2020; Catalini et al., 2022). They behave as a small economy with a fixed exchange rate and present exposition to the same problems: they require a high amount of liquid collateral reserves and are unprotected from speculative attacks. Hence, it is imperative to analyze the origins of peg deviations to design an optimal stablecoin and effective regulatory measures, particularly when considering their widespread use as a medium of exchange.

In this study, I analyze the determinants of extreme parity deviations in five of the biggest USD-pegged stablecoins through the lens of time series models, accounting for their periods of high volatility and peg-induced mean reversion. I use quantile models to test the directional predictability, in the Granger sense, within a dynamic model in which the factors exert heterogeneous effects in the tails. I apply the measure of Han et al. (2016) to analyze each explanatory variable's impact on the distribution's tails. The benefit of the methodology is that it provides a simple and robust framework to analyze the transmission of extreme fluctuations between variables. Aligning with previous studies such as those of Baur and Dimpfl (2018) and Yue et al. (2021), this paper unveils asymmetric cryptocurrency responses to different types of shocks. I construct diverse cryptocurrency and market indices, capturing

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both general and specific market characteristics. The analysis is further enriched by examining how financial and macroeconomic factors influence variations in stablecoin prices.

The cross-quantilogram reveals negative correlations in Tether, USD Coin, and Dai at the lower quantile ($\tau_1 = 0.1$) when stablecoin prices surge, indicating subsequent losses. Conversely, in the higher tail ($\tau_1 = 0.9$), the market exhibits significant predictive power, suggesting potential positive returns for Tether and USD Coin but forecasting a contraction in Binance. For the Cryptocurrency Market Index (CRYPT), the results indicate that high cryptocurrency returns predict significant losses in the lower tail or gains in the higher tail for Tether and Frax. The results are consistent with those of Balcilar et al. (2017), Griffin and Shams (2020), Kristoufek (2021), and Grobys and Huynh (2022). Intermediary constraints, as in intermediary asset pricing literature (Adrian et al., 2014; He et al., 2017; Baron and Muir, 2022), predict stablecoin prices in the higher tail, indicating that high leverage levels and low stablecoin returns predict subsequent price increases. In the lower tail, increasing both values predicts price reductions for Tether, USD Coin, Binance, and Frax. Notably, illiquidity links with higher price increases as in Mancini et al. (2013), Ranaldo and Santucci de Magistris (2019), and Brauneis et al. (2021). The model predicts higher stablecoin prices in both tails, with a more pronounced effect in the higher tail. These findings deepen the understanding of stablecoin price time dependence, substantially contributing to understanding cryptocurrency market dynamics.

This paper is relevant to researchers, policymakers, and investors, as it provides insights into stablecoin price determinants, the characteristics of the stabilization mechanisms, and the systemic risk market implications as stablecoins gain traction worldwide. The gained understanding can inform Central Banks in developing Central Bank Digital Currencies, manage potential shocks, and navigate efficient portfolio management strategies. It especially emphasizes the need for regulatory adaptability in the face of decentralized, opaque, and traceability-limited stablecoin markets.

2. Econometric model

In this paper, I will follow the cross-Quantilogram model to analyze the time-series relationship and directional predictability of the most relevant variables in the price deviations of the cryptocurrencies. Then, I can have an approximation to a view of the factors that explain stablecoin deviations. I will use the model of Han et al. (2016) to determine the directional predictability between the selected regressors and the stablecoins. Their model is a generalization of the quantilogram model of Linton and Whang (2007) into a multivariate setting, where we can see the cross-correlation between series in a conditional quantile framework.

For two time series defined as a pair $(x_t, y_t) \in (\{x_{1t}, x_{2t}\}, \{y_{1t}, y_{2t}\})$, which are strictly stationary with time $t = 1, 2, \ldots, T$, we can define the conditional distribution function as $F_{y|x}(\cdot|x_{it})$ and density function $f_{y|x}(\cdot|x_{it})$ for $i = 1, 2$. From these functions, we can define the conditional quantile function as $q_{it}(\tau_i) = \inf\{z : F_{y|x}(z|x_{it}) \geq \tau_i\}$ for a defined percentile value of $\tau_i \in (0, 1)$ for each of the i series. Han et al. (2016) defines the Cross-quantilogram as the serial dependence between two events such that for a pair $\{y_{1t}, y_{2t}\}$ it defined by $\{y_{1t} \leq q_{1t}(\tau_1)$ and $\{y_{2t-p} \leq q_{2t-p}(\tau_2)$ where p is a defined lag and percentiles τ_i. We can define the cross-Quantilogram as a cross-correlation measure with conditional quantiles as follows:

$$\rho_\tau(p) = \frac{E[I_{\tau_1}(y_{1t} - q_{1t}(\tau_1))I_{\tau_2}(y_{2t-p} - q_{2t-p}(\tau_2))]}{\sqrt{I^2_{\tau_1} y_{1t} - q_{1t}(\tau_1)}\sqrt{I^2_{\tau_2}(y_{2t-p} - q_{2t-p}(\tau_2))}} \tag{1}$$

where I_{τ_i} denotes an indicator function such that $I(S)_{\tau_i} = 1[S < 0] - \tau_i$ and $p = 0, 1, 2, 3, \ldots, P$ are the established number of P lags. To calculate the cross-quantilogram, we must estimate $q_{it}(\tau_i)$ using a linear quantile regression. Once estimated, we can then turn to the sample cross-quantilogram, which approximately estimates the expectations to the sample averages:

$$\widetilde{\rho_\tau}(p) = \frac{\sum_{t=p+1}^{T} I_{\tau_1}(y_{1t} - q_{1t}(\tau_1))I_{\tau_2}(y_{2t-p} - q_{2t-p}(\tau_2))}{\sqrt{\sum_{t=p+1}^{T} I^2_{\tau_1} y_{1t} - q_{1t}(\tau_1)}\sqrt{\sum_{t=p+1}^{T} I^2_{\tau_2}(y_{2t-p} - q_{2t-p}(\tau_2))}} \tag{2}$$

The cross-quantilogram measures the correlation regarding deviations of the determined quantile between the series. As the lag structure defines the measure, it relates the directional predictability of the quantile in the lag p from the reference explanatory series to the dependent variable. The measure also provides a magnitude of correlation $\widetilde{\rho_\tau}(p)$ bounded in the set of $\widetilde{\rho_\tau}(p) \in [-1, 1]$, where a value of -1 implies the perfect inverse linear relationship, whereas 1 is a perfect linear relationship. A value of 0 implies no statistical relationship. From these values, we can then determine the directional predictability based on the estimation of each lag to determine the relationship structure at different times of the series.

3. Results

I collected the data on the available cryptocurrencies from Coinmarketcap.com, the primary data source used in the literature. The data correspond to daily data from December 2020 to December 2022, with 507 data points for each stablecoin. The date span is the maximum amount of data available for the stablecoins considered. The analysis is limited to the main five stablecoins in terms of market capitalization as they contribute the most to the overall variation of the cryptocurrency economy. Then, I estimated the model with Tether, USD Coin, Binance, Dai, and Frax stablecoins.[2] In Table 1, I present some descriptive statistics of the stablecoin data used in the model. We can see that the stablecoins used are 92% of the total market capitalization of the stablecoin market in

[2] In Online Appendix A, I present a detailed description of the data used in the model and the construction of the different parts of the paper

Table 1
Descriptive statistics of stablecoins.
Source: Coinmarketcap.com and Author's calculations.

ID	Stablecoin	Ticker	Start	Mk. Cap. (Bill. USD)	% Mk. Cap.	Volume (Bill. USD)
825	Tether	USDT	2015–02–25	47.22	50	62.33
3408	USD Coin	USDC	2018–10–08	25.27	26	2.68
4687	Binance USD	BUSD	2019–09–20	9.52	10	4.36
4943	Dai	DAI	2019–11–22	4.37	5	0.31
6952	Frax	FRAX	2020–12–26	1.06	1	0.02

Notes: Market share is the percentage of market capitalization over the stablecoins market. ID corresponds to the Coinmarketcap ID number. Start is the first period of emission. Volume corresponds to the value of the transactions in dollars in the 24 h of the day. Market capitalization and volume correspond to the averages of the last two years, 2021–2022.

general. I use the cross-quantilogram to test if there is directional predictability from the four macroeconomic and financial variables to both the upper and lower tails of the stablecoin distributions. The variables I considered are the stablecoin market index STBL (STBL), the overall cryptocurrency market index (CRYPT), the intermediaries squared leverage (HKML) of He et al. (2017), and the illiquidity stablecoin index (ILISTBL) based on the illiquidity measures of Abdi and Ranaldo (2017)[3].

Figs. 1 to 4 illustrate directional predictability in stablecoin price deviations based on four explanatory variables across higher quantiles.[4] The Stablecoin Index shows varied relationships with the overall market across conditional quantiles, indicating potential substantial losses when stablecoin prices are high, and values are low ($\tau_1 = 0.1$), aligning with the stability mechanisms aimed at reversion to parity. Conversely, at $\tau_1 = 0.9$, elevated stablecoin prices forecast positive returns for Tether and USD Coin but suggest a potential contraction for Binance. Meanwhile, extreme market values have limited predictive power in the median ($\tau_1 = 0.5$), except for Dai. The connection of the cryptocurrency market with stablecoins, particularly Tether, shows varied correlations, with high cryptocurrency returns predicting substantial losses or gains for Tether and Frax. Intermediary squared leverage indicates directional predictability, suggesting price increases with high leverage levels and low stablecoin returns, with differing effects in the higher and lower tails. Furthermore, stablecoin illiquidity exhibits predictive power in both tails, with higher illiquidity correlating with higher prices in the upper tail and lower price predictions in the lower tail, although with relatively mild effects.[5]

Figs. 5 to 8 illustrate the cross-quantilogram focusing on the lower 10% tail of the distribution. In this tail, there appears to be a substantial impact on the higher tail of stablecoin distributions ($\tau_1 = 0.9$), suggesting that the prices of most currencies tend to increase when the overall market price falls. This effect may come from the stabilization mechanisms inherent in these currencies. Furthermore, analysis of the cryptocurrency market effect reveals a lack of a clear pattern in the cross-quantilogram. While Binance exhibits a modest increase in stablecoin prices in response to low cryptocurrency returns in the lower tail, the effect lacks considerable magnitude. A similar trend is observed in the intermediary squared leverage's lower tail, with Tether's higher tail showing the most pronounced effect. Additionally, lower tightness in intermediaries and substantial price changes in stablecoins predict a notable decrease in price within a week. Lastly, the illiquidity measure in the lower tail indicates that an increase in the liquidity in the market predicts a rise in stablecoin prices, whereas the reverse holds for higher tails. Increased liquidity forecasts a reduction in stablecoin prices accompanied by significant price increases.

4. Conclusion

In this paper, I analyzed what causes the prices of stablecoins to fluctuate. I examined both the extreme price movements and their determinants. Furthermore, I constructed different variables and indices to explain how the prices react under different percentiles and employed quantile regression to express the heterogeneous response to other factors. By examining how each explanatory variable interacts with returns and analyzing their performance across different percentiles, I obtained valuable insights into the distribution of stablecoins moving beyond a simple linear regression model.

The analysis of directional predictability supports the overall importance of this paper's contribution and methodology to capture the asymmetric response of stablecoin prices. I found that high quantiles of the stablecoin market returns and low of the currencies imply potential significant losses, aligning with their reversion to parity. Conversely, at higher quantiles, increased stablecoin prices forecast different effects for different currencies. The connection between the cryptocurrency market and the selected stablecoins exhibits varied correlations, predicting substantial gains or losses for select stablecoins. Intermediary squared leverage shows directional predictability, correlating with higher and lower-tail price changes. Stablecoin illiquidity indicates potential price impacts in both tails but with mild effects. For the lower tail, the distributions suggest that most currencies tend to rise when the overall market falls. The response to the movements of the cryptocurrency market lacks a uniform pattern, which shows the asymmetric

[3] The selection of the explanatory variables came from an extensive analysis in Online Appendix D to G of the significant variables that represent the price deviations. Online Appendix B and C, explain in detail the construction of each of the overall exogenous and illiquidity measures

[4] In Online Appendix H, I estimate the Ljung Box Q-statistic for each lag to test the directional predictability of the data. The results complement the cross-quantilogram as they provide information on the significance of the estimated quantile correlation.

[5] Based on Figure H4, in Online Appendix H, I cannot reject the null hypothesis that none of the lags provide significant information to give a statistically significant prediction.

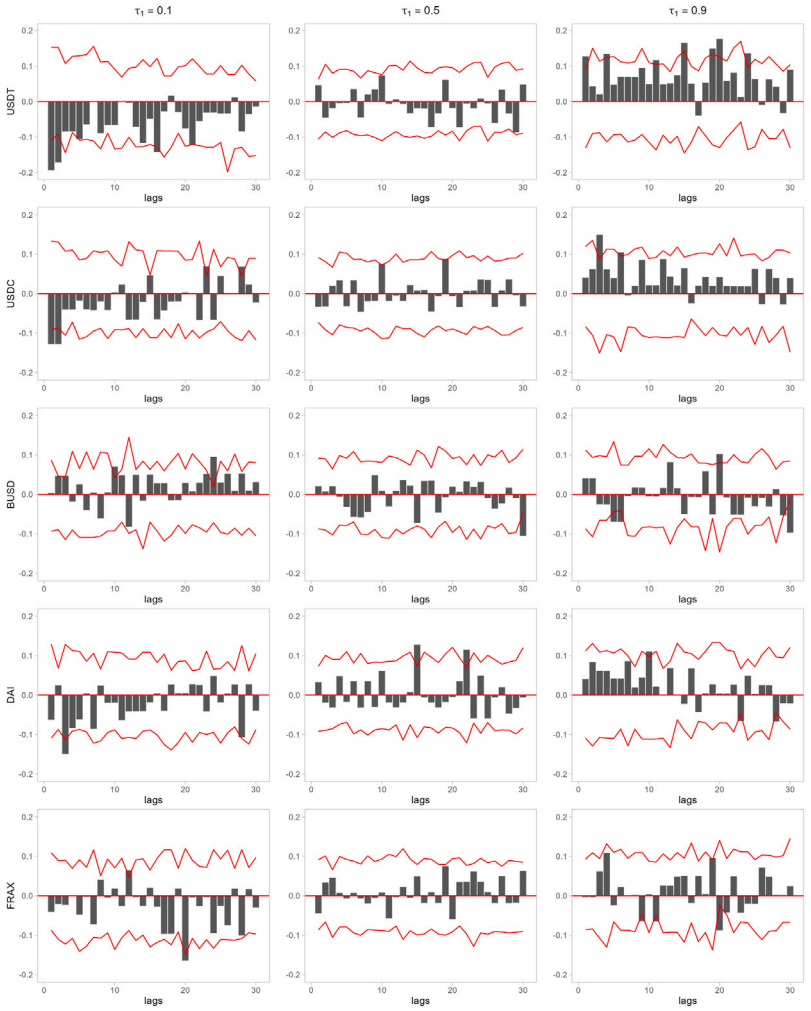


Fig. 1. Directional predictability from the higher tail of the stablecoin market index (STBL) to the stablecoins.
Notes: The graph plots the cross-quantilograms for the periods of 1 to 30 lags and different quantiles given by $\tau_1 = (0.1, 0.5, 0.9)$ and for the 90th percentile of the deviations of the stablecoins. The gray bar graphs represent the directional predictability of the τ_1 percentile index (columns) and the respective cryptocurrency deviation lag (rows). The red lines are the bootstrapped confidence intervals constructed using the stationary bootstrap method of Politis and Romano (1994) and the automatic block length selection of Politis and White (2004) and Patton et al. (2009) with 1000 bootstrap repetitions.
Source: Author's Calculations.

effects in response to different tail distributions. Lower tightness in intermediaries and substantial stablecoin price changes forecast price decreases, whereas illiquidity impacts predict varied price responses based on the tail distributions.

This study unveils vital insights for researchers, investors, and regulators. It identifies key factors driving extreme fluctuations in stablecoin prices, aiding with risk management. By revealing predictive financial variables, it enables anticipation of price variations. Additionally, it highlights asymmetrical market reactions and the impact of stability mechanisms, improving our understanding of market dynamics. The study's findings show that market connections and potential systemic fragility crucial for risk assessment. Moreover, it identifies intermediary constraints and stablecoin liquidity as predictive variables, benefiting decision-making for both investors and regulators.

One limitation of this study is partially explored the stablecoins, focusing on specific stability mechanisms without considering their full spectrum, which restricts the ability to identify comprehensive patterns. From the results, we can conclude that the main stablecoins behave differently rather than being a model-fits-all type. Future research should delve deeper into this aspect, aiming to unravel the transmission channels of shocks through stability mechanisms. Furthermore, extending the analysis to encompass the impact of events, such as the recent Security Exchange Commission filings against Binance, holds potential interest in discerning the interconnections and dependencies among stablecoins.

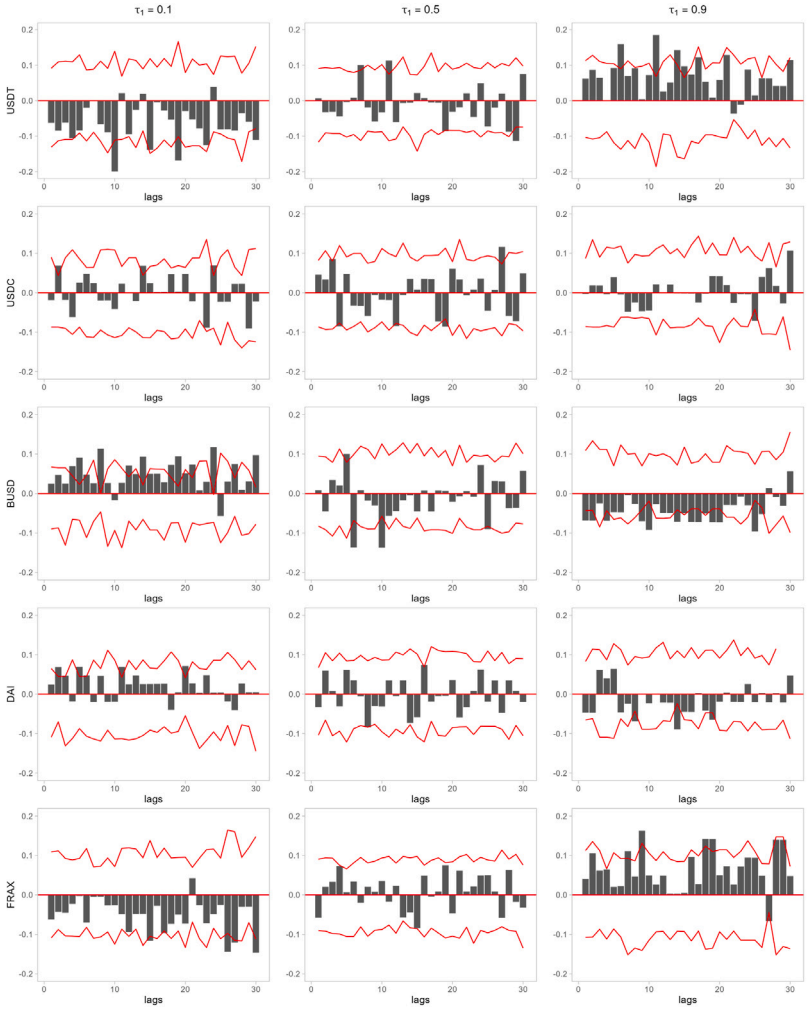


Fig. 2. Directional predictability from the higher tail of cryptocurrency market index (CRYPT) to stablecoins.
Notes: The graph plots the cross-quantilograms for the periods of 1 to 30 lags and different quantiles given by $\tau_1 = (0.1, 0.5, 0.9)$ and for the 90th percentile deviations of the stablecoins. The gray bar graphs represent the directional predictability of the τ_1 percentile index (columns) and the respective cryptocurrency deviation lag (rows). The red lines are the bootstrapped confidence intervals constructed using the stationary bootstrap method of Politis and Romano (1994) and the automatic block length selection of Politis and White (2004) and Patton et al. (2009) with 1000 bootstrap repetitions.
Source: Author's Calculations.

CRediT authorship contribution statement

Julian Fernandez-Mejia: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.frl.2024.105268.

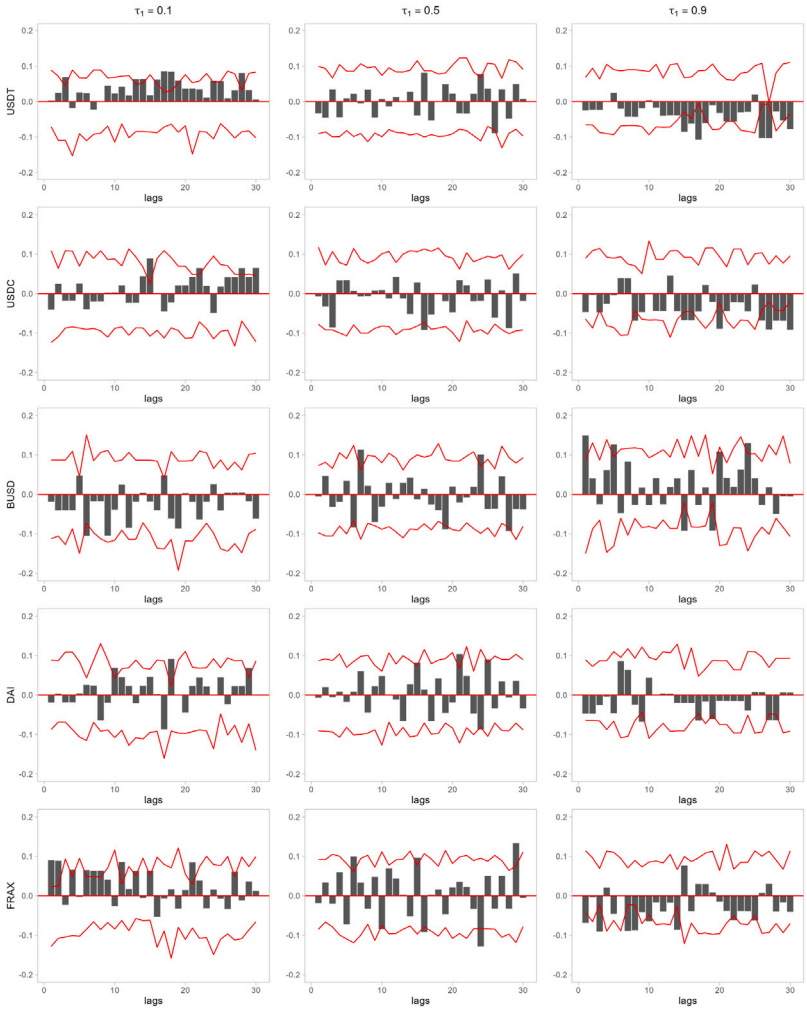


Fig. 3. Directional predictability from the higher tail of intermediary squared leverage (HKML) to stablecoins.
Notes: The graph plots the cross-quantilograms for the periods of 1 to 30 lags and different quantiles given by $\tau_1 = (0.1, 0.5, 0.9)$ and for the 90th percentile deviations of the stablecoins. The gray bar graphs represent the directional predictability of the τ_1 percentile index (columns) and the respective cryptocurrency deviation lag (rows). The red lines are the bootstrapped confidence intervals constructed using the stationary bootstrap method of Politis and Romano (1994) and the automatic block length selection of Politis and White (2004) and Patton et al. (2009) with 1000 bootstrap repetitions.
Source: Author's Calculations.

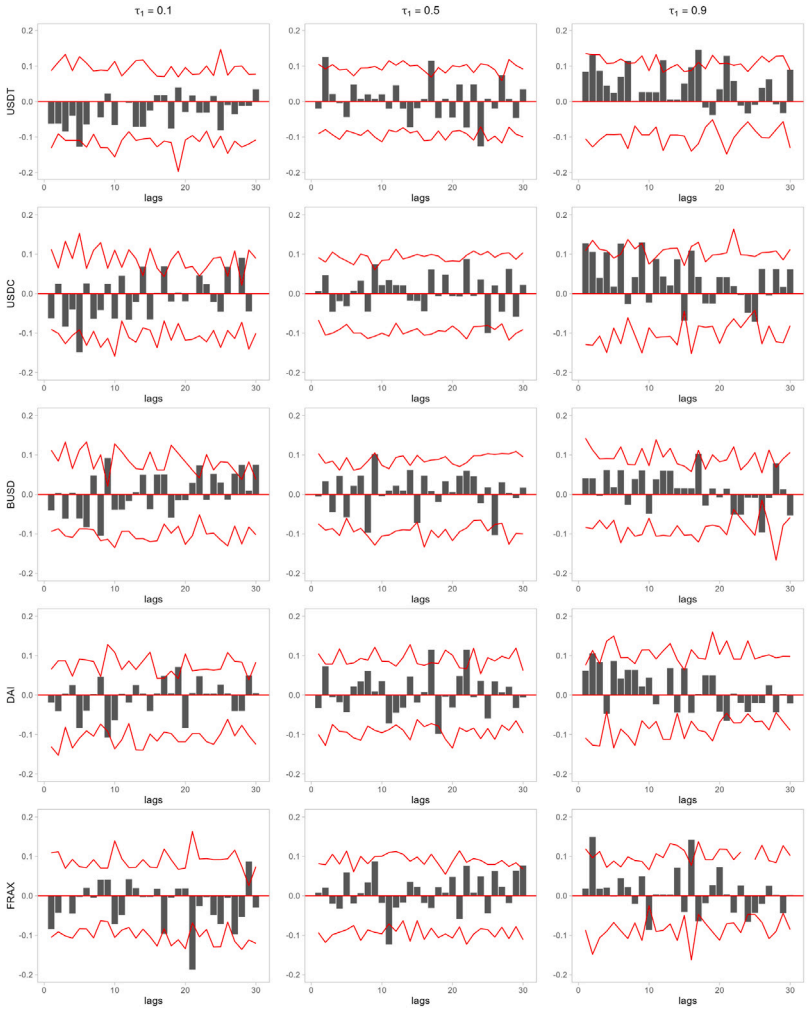


Fig. 4. Directional predictability from the higher tail of illiquidity index (ILISTL) to the stablecoins.
Notes: The graph plots the cross-quantilograms for the periods of 1 to 30 lags and different quantiles given by $\tau_1 = (0.1, 0.5, 0.9)$ and for the 90th percentile deviations of the stablecoins. The gray bar graphs represent the directional predictability of the τ_1 percentile index (columns) and the respective cryptocurrency deviation lag (rows). The red lines are the bootstrapped confidence intervals constructed using the stationary bootstrap method of Politis and Romano (1994) and the automatic block length selection of Politis and White (2004) and Patton et al. (2009) with 1000 bootstrap repetitions.
Source: Author's Calculations.

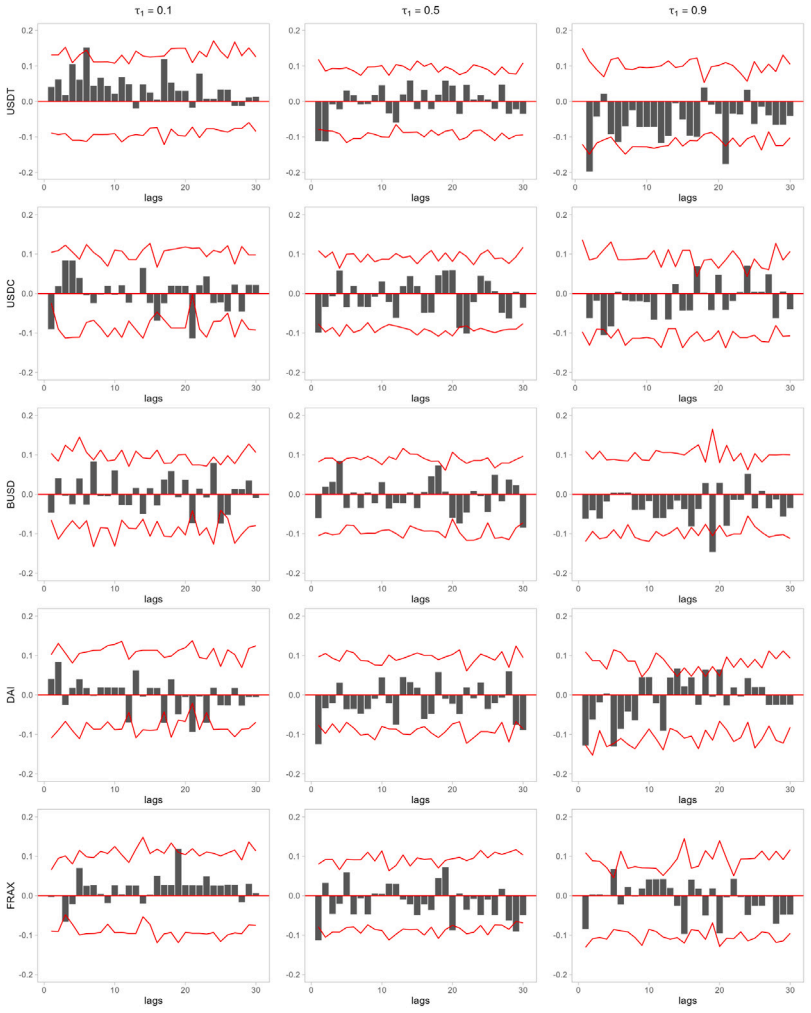


Fig. 5. Directional predictability from the lower tail of stablecoin market index (STBL) to the of stablecoins.
Notes: The graph plots the cross-quantilograms for the periods of 1 to 30 lags and different quantiles given by $\tau_1 = (0.1, 0.5, 0.9)$ and for the 90th percentile deviations of the stablecoins. The gray bar graphs represent the directional predictability of the τ_1 percentile index (columns) and the respective cryptocurrency deviation lag (rows). The red lines are the bootstrapped confidence intervals constructed using the stationary bootstrap method of Politis and Romano (1994) and the automatic block length selection of Politis and White (2004) and Patton et al. (2009) with 1000 bootstrap repetitions.
Source: Author's Calculations.

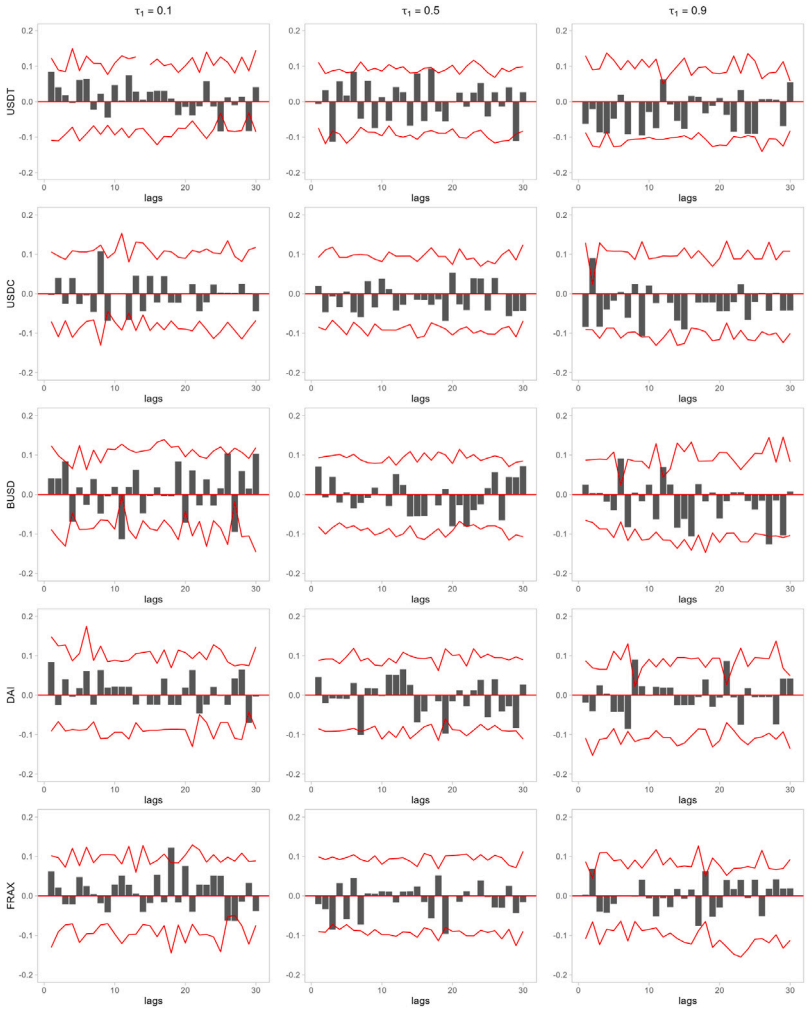


Fig. 6. Directional predictability from the lower tail of cryptocurrency market index (CRYPT) to the stablecoins.
Notes: The graph plots the cross-quantilograms for the periods of 1 to 30 lags and different quantiles given by $\tau_1 = (0.1, 0.5, 0.9)$ and for the 90th percentile deviations of the stablecoins. The gray bar graphs represent the directional predictability of the τ_1 percentile index (columns) and the respective cryptocurrency deviation lag (rows). The red lines are the bootstrapped confidence intervals constructed using the stationary bootstrap method of Politis and Romano (1994) and the automatic block length selection of Politis and White (2004) and Patton et al. (2009) with 1000 bootstrap repetitions.
Source: Author's Calculations.

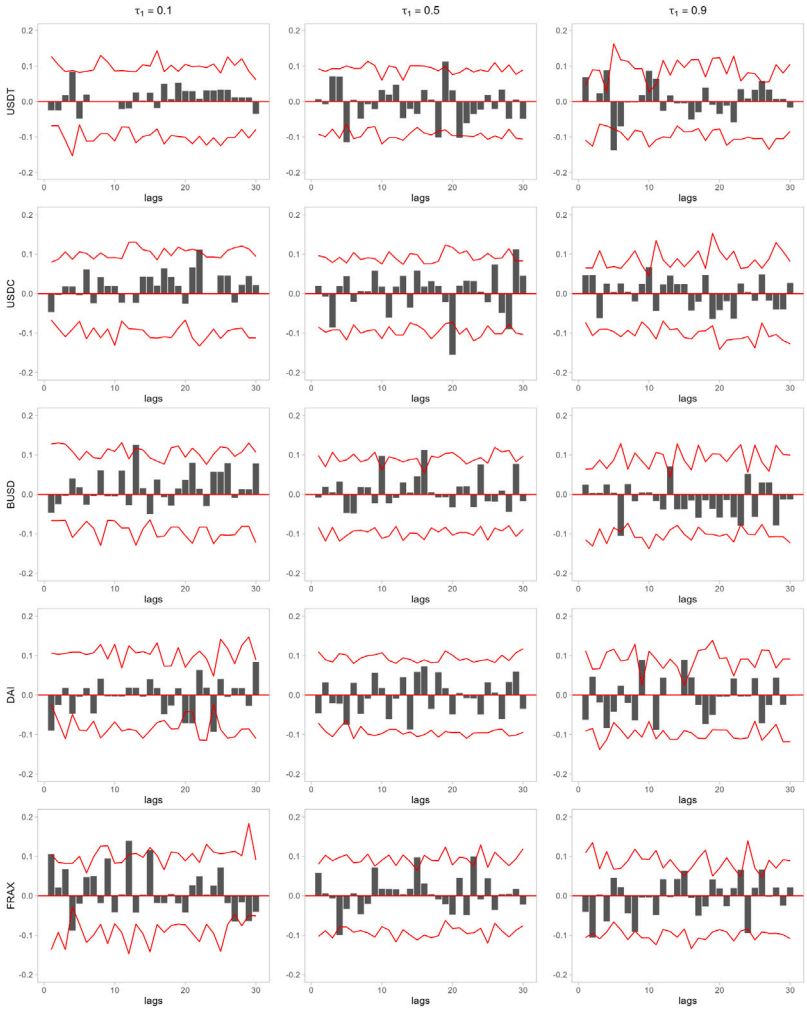


Fig. 7. Directional predictability from the lower tail of the intermediary squared leverage (HKML) to the stablecoins
Notes: The graph plots the cross-quantilograms for the periods of 1 to 30 lags and different quantiles given by $\tau_1 = (0.1, 0.5, 0.9)$ and for the 90th percentile deviations of the stablecoins. The gray bar graphs represent the directional predictability of the τ_1 percentile index (columns) and the respective cryptocurrency deviation lag (rows). The red lines are the bootstrapped confidence intervals constructed using the stationary bootstrap method of Politis and Romano (1994) and the automatic block length selection of Politis and White (2004) and Patton et al. (2009) with 1000 bootstrap repetitions.
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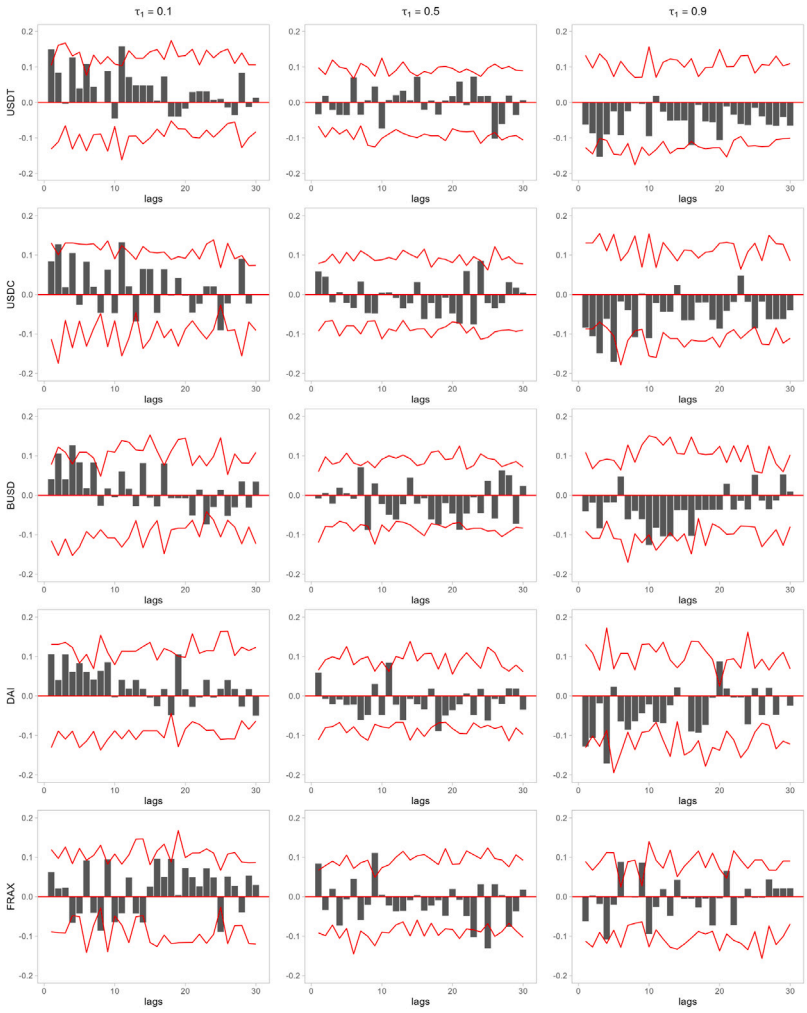


Fig. 8. Directional predictability from the lower tail of the illiquidity index (ILISTL) to the stablecoins.
Notes: The graph plots the cross-quantilograms for the periods of 1 to 30 lags and different quantiles given by $\tau_1 = (0.1, 0.5, 0.9)$ and for the 90th percentile deviations of the stablecoins. The gray bar graphs represent the directional predictability of the τ_1 percentile index (columns) and the respective cryptocurrency deviation lag (rows). The red lines are the bootstrapped confidence intervals constructed using the stationary bootstrap method of Politis and Romano (1994) and the automatic block length selection of Politis and White (2004) and Patton et al. (2009) with 1000 bootstrap repetitions.
Source: Author's Calculations.

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