Introduction and Literature Review for Master Thesis U.S.E.

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Do stablecoins fulfill their function?

Empirical analysis of the stable and safe haven properties of stablecoins.

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Table of Contents

Introduction

If you would have asked a trader a decade ago if he had ever heard of Bitcoin, he would have stared at you blankly. Today, however, every trader active on Wall Street – or any big global trading platform for that matter – has heard of the digital currency. Some may even own some.

Bitcoin was 'born' in 2009, when on the third of January the first block of the Bitcoin blockchain was mined (*Genesis Block - Bitcoin Wiki*, 2021). The so-called 'Genesis Block' contained not only cryptographic data but a message: "The Times 03/Jan/2009 Chancellor on brink of second bailout for banks" (*Genesis Block - Bitcoin Wiki*, 2021). This is a direct reference to the headline of The Times that day, a critical piece of journalism on the instability caused by fractional-reserve banking.

Over the last ten years, cryptocurrencies have become increasingly popular, mainly due to their potential to provide their users or investors with very high gains in very short time periods (Kristoufek, 2013). This has sparked a discussion about Bitcoin's categorization. Yermack (2015) argues that Bitcoin is not a medium of exchange, unit of account, or a store of value. Others argue that Bitcoin *is* in fact used as a medium of exchange, albeit mainly for illegal activities such as money laundering (Foley et al., 2019). Harvey rejects this notion and argues that a criminal would always choose cash over Bitcoin, as cash is more anonymous (Harvey, 2014). As Shiller concludes in a New York Times article: "The results of a serious attempt to assess the value of Bitcoin can only be ambiguous."(Shiller, 2017) The ambiguity around the value of Bitcoin brings a lot of volatility along with it.

At its core, Bitcoin can be categorized as a fiat currency with no intrinsic value (Fatás, 2019). Bitcoin's value is based on the market' expectations of its future price. Those expectations can change quickly. What separates Bitcoin from other fiat currencies is the absence of a stabilizing mechanism. The volatility of Bitcoin relative to the dollar is higher than the volatility between the major G10 currencies (Osterrieder & Lorenz, 2016; Yermack, 2015). Initially, investors and traders could only escape the volatility through traditional fiat currencies on regulated exchanges (Cermak et al., 2021). Then stablecoins entered the field.

Stablecoins were created as an instrument for traders to escape the volatility of cryptocurrencies, such as Bitcoin and Ethereum, whilst staying in the crypto sphere. This category of cryptocurrencies is a bearer monetary asset designed to mimic the price of fiat currencies by utilizing a stabilization mechanism. A Stablecoins is designed to be a cryptocurrency that fulfills the three functions of money that Bitcoin cannot: a means of payment unit, unit of account, and a store of value (Fatás, 2019). They also have some institutional features. As mentioned earlier, stablecoins allow the user to stay in the crypto space and transfer stablecoins with ease across different exchanges and the blockchain. This is important, as some crypto exchanges have yet to add a fiat-on-ramp feature and only accept fiat currency in the form of stablecoins (Lyons & Viswanath-Natraj, 2020). Another institutional feature is added intermediation costs. Some crypto exchanges have longer processing lags for dollar withdrawals and fees are often imposed for large withdrawal quantities (Lyons & Viswanath-Natraj, 2020).

Therefore, it is no surprise that stablecoins became extremely popular due to their usability and the benefits they pose to crypto traders, investors and users. Between mid-February 2020 and January this year, the total supply of issued stablecoins grew from $5.7bln to $37.9bln (*CoinGecko*, 2021). This was caused by several catalysts. Notable catalysts include Bitcoin losing its lead as base currency in spot trading, the growth of stablecoin-collateralized derivatives, the rise of Decentralized Finance (DeFi), yield farming, and an increased demand for cryptocurrencies in general (Cermak et al., 2021). Other noteworthy statistics from 2019 up to 2020 that The Block, a large analysis and research brand in the crypto space, revealed: stablecoin volume grew to more than a trillion dollars (320% growth), there were more than a million passive users (260% growth), around 230 thousand daily active users (260% growth) and there were on average 500 thousand daily transactions (500% growth). In a year's time the velocity of stablecoins, a measurement of the rate at which the supply is exchanged, reached 8. This means stablecoins changed hands eight times, indicating that the available supply on-chain is becoming more active. To conclude this section on the rise of stablecoins, it should be pointed out that Visa is testing the ability of settling transactions on-chain using the major stablecoin USDC (Zacks, 2021). This demonstrates that using crypto is becoming more and more mainstream.

The purpose of this paper is to contribute to existing research on stablecoins and safe haven properties. As mentioned before, stablecoins' main purpose is to escape the volatility in the crypto markets and thus possibly pose a safe haven for users who want to do so. Stablecoins entered the crypto markets in 2018 and are still fairly new, even though they have become extremely popular this past year. Due to their infancy, research on stablecoins lags behind their growth. The central research question addressed in this paper is: *Can stablecoins act as a consistent and stable escape vehicle for investors from volatile crypto assets?* For crypto users, the answer to this question is decisive. Stablecoins have the potential to be one of the first real safe haven assets in the crypto space, because of the various stabilization mechanisms in place to keep the currency pegged to a set value. (This is explained in further detail in a later section.)

The paper is a replication and an extension of the research done by Baur and Hoang on whether or not stablecoins are viable as a safe haven in the crypto market for investors (Baur & Hoang, 2021). In their paper, they use a standard econometric model that tests the safe haven property of a currency against a base currency. Baur and Hoang collected one minute, hourly and daily price quotes for the six largest stablecoins in market capitalization at that time (USDT, USDC, TUSD, PAX, Dai and GUSD). The investigated period spans from December 2018 to mid-July 2019, 225 days in total. The main goal of their research is to analyze stablecoins on stability and if they can function as safe haven against extreme negative Bitcoin returns. On the lower timeframes Baur and Hoang find little evidence of the safe haven property of stablecoins. The coefficients on the lower timeframes are small and they expect them to become larger over time as investors delay their reaction to see if the negative returns become more extreme on the longer timeframes. It turns out that on longer timeframes the coefficients are indeed larger. The paper concludes that some stablecoins have a relatively strong "safe haven" property as they negatively correlate with extreme negative Bitcoin price changes. However, they also conclude that stablecoins do not live up to their name as the value is not consistently and reliably stable over time. Baur and Hoang conclude that most of the stablecoins cannot be considered a safe haven apart from USDT, which offers protection to extreme negative Bitcoin price changes.

It is an extension on *A crypto safe haven* by Baur and Hoang as it uses more recent data and different stablecoins. Additionally, the same test is performed on the collateral that backs the stablecoins to see if there is a difference between stablecoins and what they represent on the blockchain. In the past year, the crypto space and stablecoins have changed drastically. For investors it is important to know how these changes have affected the findings of Baur and Hoang on the safe haven properties of stablecoins.

Literature Review

This section will provide an overview of the topics that will act as the foundation for this research paper. First, an overview of the relevant insights from research into safe havens will be offered. The second section covers stablecoins, clarifying the different types of stablecoins, their stabilizing mechanisms and their risks. The literature review concludes with empirical articles on the stability of stablecoins.

Safe havens

The insights on safe havens offered here have primarily been drawn from research on gold and/or Bitcoin as a safe haven. Gold has historically proven to be a strong and viable safe haven. Meanwhile, literature on Bitcoin as possible safe haven is also relevant, as it is within the crypto sphere and thus closely related to stablecoins.

The safe haven property of an asset is an important topic in literature on diversification and flight-to-quality. Investors seek diversification to reduce the risk of suffering heavy losses. In the same vein, they may seek a safe haven in response to severe market shocks suffered over a short period (Forbes & Rigobon, 2002). It is important to distinguish a safe haven form a hedge or a diversifier. Crucially, a safe haven asset is defined as an asset that is uncorrelated or negatively correlated with another asset in times of market stress or turmoil. A hedge, meanwhile, is only negatively correlated, and a diversifier is positively correlated (Baur & Lucey, 2010).

In order to identify the safe haven property an econometric model is used that was constructed by Baur and McDermott, allows for the distinction of a weak and strong safe haven (Baur & McDermott, 2010). It is the same model Baur and Hoang used for their analysis on stablecoins. The distinction between a weak and strong safe haven is important, because positive returns of an asset during times of financial turmoil can enhance the stability of the market by reducing overall losses. The distinction also adds more depth to the knowledge and understanding of safe havens. A strong safe haven is defined as an asset that is negatively correlated with another asset in certain periods only. Subsequently, a weak safe haven is uncorrelated with the other asset. A good safe haven also enjoys high liquidity, so it is relatively easy for an investor to liquidate his/her portion of assets to this safe haven asset.

Baur and McDermott find evidence that investors react to short-lived and extreme negative shocks by buying gold. The purchase of gold in the immediate aftermath of an extreme negative market shock can be seen as a flight by investors to a safe haven. More recently, however, the efficiency of gold as safe haven after the financial crisis of 2008 has been questioned, because the interest rate reached the zero lower bound and the financialization of gold intensified (Bekiros et al., 2017; Klein, 2017). Gold had no longer the ultimate safe haven image it once had. Enter Bitcoin, presumably ‘digital gold’.

Bitcoin was supposedly created as a reaction to the financial crisis. Due to its characteristics it has been argued that Bitcoin is a shelter from sovereign risk and the fragility of the global financial system (Bouri, Molnár, et al., 2017). The digital currency is a good diversifier, due to its insulation from financial and economic variables and its weak relationship with other financial assets (Bouri, Jalkh, et al., 2017; Kristoufek, 2015). This has been empirically confirmed through standard models based on regressions augmented by dummy variables capturing extreme negative returns in global and regional stock indices, as well through an analysis of the joint dynamics of Bitcoin and different financial assets through a multivariate GARCH model (Bouri, Molnár, et al., 2017; Guesmi et al., 2019). However, an analysis using the general econometric model from Baur and McDermott pointed out that the role of Bitcoin as a safe haven against negative market movements in the world stock index is ambiguous, due to the exchange rates, the volatility of the asset, the high transaction fees and times, and the liquidity of the currency in general (Shahzad et al., 2019; Smales, 2019). It is safe to say that Bitcoin has to mature as an asset and that it cannot be considered as a safe haven asset.

Stablecoins: what they are and how they work

It can be concluded from the literature on safe haven assets that there is a distinction to be made between a weak and strong safe haven. As stated before, this paper questions whether stablecoins are a viable safe haven for investors in the crypto markets. Before delving into the data and method section it is important to explain in more detail what stablecoins are and how they work.

To define a stablecoin in the simplest terms: a stablecoin is a representation of fiat currency that lives on the blockchain. Stablecoins have three main attributes that differentiate them from one another: peg, collateral and collateral amount (Jeger et al., 2020).

The pegged value of a stablecoin is the first major aspect. The majority of stablecoins are pegged to the dollar, but some are pegged to other fiat-currencies such as the euro, the south Korean won, or even to gold.

Stablecoins achieve their value through collateralization. Collateral choices are fiat currencies, commodities, other cryptocurrencies, or a mix of these three. There is also a difference between on-chain and off-chain collateral: this will be explained later on.

Lastly, there are some differences in collateral amount between stablecoins. If the stablecoin is fully collateralized, it means that the issuer of the stablecoin is in possession of reserves that are equal to, or surpass, the market cap of said stablecoin. In the case of partial collateralization, there is a chance that the issuer is unable to redeem all coin holders. This negatively affects the stability of the coin. In the case of uncollateralized stablecoins, there is a different system in place to compensate holders for their risk, for example a fixed income system (Jeger et al., 2020).

These attributes vary for the three main types of stablecoins: Tokenized funds, collateralized stablecoins (whether on-chain or off-chain), and algorithmic stablecoins. Tokenized funds are defined as units of monetary value stored electronically on the blockchain. They represent already existing currency units, hence their name. A user can transfer funds to the issuer, who then mints/creates an equal number of tokenized units and send those back. These can then be spent on the blockchain as any other cryptocurrency. The same goes for redeeming tokenized funds. The user sends the tokenized units to the account of the issuer or to a smart contract. The tokenized funds will be burned/destroyed and an equal amount in capital is returned to the user (Bullmann et al., 2019). An example of this type of stablecoin is Tether, which will be discussed in greater detail in Data & Methods.

The second type of stablecoin is collateralized stablecoins. This type of stablecoins is backed by collateral that can fluctuate over time. *Off-chain* collateralized stablecoins are very similar to tokenized funds, where the issuer is in custody of the collateral amount. The process of minting and burning stablecoins is the exact same as for the process of tokenized funds (Bullmann et al., 2019). In case of *on-chain* collateralization, users send cryptocurrencies to a smart contract that will act as collateral. Against that collateral, the user can then mint stablecoins and use them as they please. This scheme can best be defined as a loan. In order to unlock their collateral, the user has to repay the amount of stablecoins, often with interest (Bullmann et al., 2019). The most well-known on-chain collateralized stablecoin is Dai, which, again, will be explained in greater detail in Data & Methods.

The third and final type of stablecoin is the algorithmic stablecoin. This type has yet to be proven viable, as most of the algorithmic stablecoins persistently trade below their peg. There is no collateralization in place to ensure the pegged value of these stablecoins. Instead, they rely on stabilization through interest rates or by inflating and deflating balances proportionally to the price (Bullmann et al., 2019). CoinGecko, a cryptocurrency tracking platform, indicates that all current algorithmic stablecoins are not trading on, or near, peg. As such, these coins will be excluded from this research, as they add no value to the question whether stablecoins are viable safe havens or not.

The main component of the stabilization mechanism of a stablecoin is collateralization. There are, however, some more factors at play that determine how stable the coin is over time. For instance, the issuers of tokenized funds and off-chain stablecoins must remain trusted and credible. Whenever users lose trust in the ability of the issuer to redeem funds to them, it causes the stablecoin to trade below peg, as was the case for Tether (USDT) in 2018 (Cermak et al., 2021). Another mechanism is the reliance of these coins on the open market for stabilization. When the coin is trading of above or below its peg, arbitrageurs come in and buy/sell until the coin is trading at its pegged value again. Thirdly, mechanisms incorporated within the smart contract, such as the accumulation of fees, staking of stablecoins, redemption limits and penalty fees, help stabilize the coin even further (Bullmann et al., 2019). Stabilizing mechanisms are briefly mentioned here, but will not be included in the analysis, as they are beyond the scope of this paper.

Empirical research into the stability of stablecoins

This section will discuss the empirical research that has been done to analyze the stability of stablecoins.

First of all, evidence has been found that for Tether, issuances play only a small role in the stabilization of the coin (Lyons & Viswanath-Natraj, 2020). More important are the stabilizing forces on the demand side. Lyons and Viswanath-Natraj combined data of wallets interacting with the Tether Treasury (the smart contract for minting and burning USDT) and data of trades to create net flows. They found that once Tether was deployed on the Ethereum blockchain, more wallets interacted with the Tether Treasury (Lyons & Viswanath-Natraj, 2020). A decline in size of price deviation off peg was detected. Arbitrage spreads became lower and there was a decreased average size of arbitrage trades. It could be concluded that arbitrage flows to the secondary market stabilized the price of USDT.

Another paper draws the same conclusion; there is an importance to be placed on the open market to reinstitute par value by providing arbitrage opportunities (Bullmann et al., 2019). Jeger et al. introduce a stablecoin exchange rate. This measures the stablecoins' price volatility independently of their pegs during the COVID-19 crash in 2020. The exchange rate defines the rate at which the stablecoin could be redeemed (Jeger et al., 2020). In their paper Jeger et al. analyze the instability of stablecoins by applying the EWMA to the exchange rate log-returns. The conclusion: during the COVID-crash USD pegged stablecoins performed the best. The two largest fiat collateralized stablecoins provided liquidity and stability during the crash. Jeger et al. also stated that on-chain stablecoins displayed many flaws during the crisis as Dai traded long off its peg. Following the crisis, users of MakerDAO voted for additional mechanisms to ensure stability for Dai.

For a stablecoin to live up to its name and function as a safe haven in the crypto markets, it needs to meet the following requirements. High volatility means large price swings and high deviation means that it constantly trades off peg. A 'stable' stablecoin therefore has both low volatility and low deviation. Additionally, in order to be a safe haven, the stablecoin has to be uncorrelated or negatively correlated with Bitcoin during extreme negative market shocks (Baur & Hoang, 2021).

Data & Methods

This study uses an econometric model that originates from a paper by Baur and Lucy (2010) on the role of gold as safe haven asset against losses in financial markets. This model was well received in standard safe haven literature as it examines the expected reaction of the potential safe haven asset conditional on extreme negative returns of the base asset. The model allows for the identification of weak and strong safe haven assets, as it shows a positive asymmetric connectedness is a sufficient, but not a necessary condition. In equation form:

$$r_{stablecoin,j} = \alpha_0 + \beta_0 r_{BTC} + \sum_{i=1}^{3}(\alpha_i Dq_i + \beta_i r_{BTC} Dq_i) + \varepsilon_j.$$

The dependent variable $r_{stablecoin,j}$ is the log return of stablecoin j, r_{BTC} is the log return of Bitcoin. The second part of the equation contains the dummy variable Dq_i which takes on the value 1 if r_{BTC} is below the 10%, 5%, and 1% for i =1,2,3, and it takes on 0 otherwise. The quantiles vary with the return frequency and are smaller in absolute terms for the 1-minute returns than for the hourly returns which are smaller than the daily returns (Baur & Hoang, 2021). The quantiles indicate where a specified proportion of the data lies. The quantiles are used in this model to determine whether the random data sample is a good fit of the population or not.

Stablecoins are, by design, pegged to the value of a fiat currency. They are expected to hold their value, i.e. remain stable. Therefore, stablecoins are expected not to react to extreme negative Bitcoin returns. No reaction translates to betas of zero in the safe haven model. If this is the case, the stablecoin is said to be stable and a weak safe haven, as it does not co-move with Bitcoin in times of extreme volatility. Alternatively, a stablecoin is an unstable but sufficient safe haven if the token reacts positively to extreme negative Bitcoin returns. This is when the betas are significant and negative. Finally, if a stablecoin reacts negatively to extreme negative Bitcoin returns, the token is said to be neither a safe haven nor a stable stablecoin. This is signified by betas that are significant and positive.

This paper is a replication of the research done by Baur and Hoang on the safe haven property of stablecoins in the crypto markets. During the time period they investigated, the market capitalization of Tether, the largest stablecoin in their dataset, grew from $2bln to $3.5bln. At the time of writing, the market cap of Tether alone is $54bln and the total market cap of all stablecoins is $91bln. Clearly, the market has grown significantly. Therefore, it is important to replicate the research done by Baur and Hoang on the safe haven properties of stablecoins.

Stablecoins with safe haven properties are an important tool for investors to utilize during extreme negative Bitcoin returns. The analysis of this study shows which of the largest stablecoins in the market have those properties. To discern this, price quotes of three different time frames of the four largest stablecoins of the past six months have been retrieved and regressed against Bitcoin returns. The stablecoins of interest prove to be Tether (USDT), USD Coin (USDC), Binance USD and Dai (Dai). These have been gathered through the APIs of crypto exchanges. USDT, USDC and BUSD are issued by a company and are entirely backed by dollars (Grant Thornton, 2021; Moore Cayman, 2021; withum, 2021). Lately, there has been some controversy regarding the collateral of Tether (S, 2021). To conduct this research it is assumed that these three stablecoins are entirely backed by dollars. Dai is an on-chain collateralized stablecoin. On the MakerDAO platform users can deposit crypto assets as collateral and mint Dai. The intraday price quotations of Tether in dollars was retrieved from the API of Bitfinex. This crypto exchange has high liquidity and high volume for the USDT/USD pair. The price quotations of Dai, USDC and BUSD against USDT were taken from Binance.

The investigated period is 151 days, spanning from November 2020 up to April this year. The intervals are 15 minutes, 1 hour, and daily. As stated above, the betas are expected to be zero for stablecoins to be proven truly unstable. If the betas are non-zero, the expectation is that the betas are larger on the higher timeframes. After all, investors and traders will wait out a crash on the lower timeframe to see if it persists on the longer timeframe before 'tethering': going from crypto to stablecoins. In the analysis multiple timeframes are analyzed in order to validate the safe haven property of a stablecoin.

The second part of the analysis is the same safe haven test, performed now on the collateral of the stablecoins. In equation form:

$$r_{stablecoin} = \alpha_0 + \beta_0 r_{Collateral} + \sum_{i=1}^{3}(\alpha_i Dq_i + \beta_i r_{Collateral} Dq_i) + \varepsilon_j \ .$$

The dependent variable $r_{stablecoin,j}$ is the log return of stablecoin j, $r_{Collateral}$ is the log return of the underlying collateral of the stablecoin. The first beta represents normal conditions, and the dummy variables represents extreme negative returns on the collateral. Stablecoins are expected to co-move 1 on 1 with the collateralized assets to maintain the value of the dollar. Therefore, the beta for normal market conditions is expected to be equal to one. The betas for extreme negative market returns are expected to be non-significant. Any discrepancy in the betas would signal that there is a difference between stablecoins and what they represent. Due to their unique features and function on the blockchain, stablecoins might add more value than the dollar, i.e., the beta would be negative. However, they might also be worth less, as the tokens merely are a representation of a dollar on the blockchain. In this case, the beta would be positive.

Descriptive statistics

The descriptive statistics of the hourly log returns for the stablecoins and Bitcoin can be found in Table 1. Already from the data can be seen that stablecoins clearly are a different type of cryptocurrency compared to Bitcoin. The mean log returns of stablecoins are extremely close to zero indicating that they are somewhat stable. On the other hand, Bitcoin has a mean log return of 0.029% consistent with a daily mean return of 0.696%. However, the minimum and maximum returns of the stablecoins are much larger showing that the average return is misleading. In *A crypto safe haven* Baur and Hoang draw the same conclusion with minimum and maximum returns for stablecoins ranging up to 60% for USDC. In the dataset used for this paper the minimum and maximum returns are way smaller with the highest value of 1.2% for Dai. Perhaps indicating that the stablecoins have become much more stable and reliable. Though, still indicating stablecoins are not stable at all. Additionally, through an augmented Dicky-Fuller all the variables are proven to be stationary.

Figure 1 supplements the descriptive statistics with plots of daily returns for the four stablecoins. It shows how stablecoins can deviate from their peg of $1 over time.

Table 1

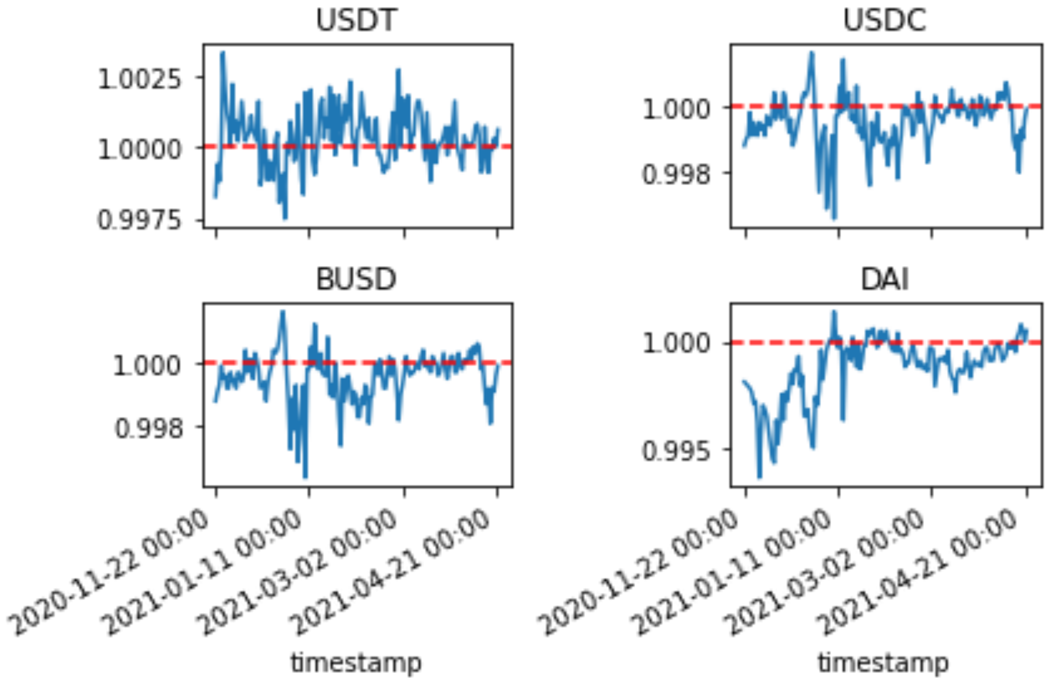
Descriptive Statistics. This table presents the descriptive statistics of hourly returns of stablecoins (USDT, USDC, BUSD, and DAI) and Bitcoin.

	Mean (%)	Median (%)	Std.Dev (%)	Min (%)	Max (%)	Obs	ADF statistic
USDT	0.000057	0.000000	0.045807	-0.332612	0.262707	3625	-16.860***
USDC	0.000014	0.000000	0.029582	-0.441280	0.311105	3616	-32.631***
BUSD	0.000008	0.000000	0.027495	-0.602291	0.512178	3616	-29.383***
DAI	0.000075	0.000000	0.049996	-0.867991	1.249135	3616	-22.027***
BTC	0.029358	0.033330	1.004280	-6.808419	11.497451	3625	-14.331***

Note: *p<0.1; **p<0.05; ***p<0.01.

Figure 1

Daily prices of USDT, USDC, BUSD and DAI.



Analysis

The following section discusses the results of the regression regarding the safe haven property of stablecoins. To test whether or not a stablecoin can be considered as a safe haven, the following econometric model is used, as in the paper by Baur and Hoang (2021):

$$r_{stablecoin,j} = \alpha_0 + \beta_0 r_{BTC} + \sum_{i=1}^{3}(\alpha_i Dq_i + \beta_i r_{BTC} Dq_i) + \varepsilon_j.$$

This equation allows for the identification of one asset (dependent variable) as a safe haven to the base asset (independent variable). The asset in question is considered a strong safe haven when it correlates negatively with the base asset during periods of market distress. In this case, the coefficients of the interaction term would be negative. The asset in question is considered a weak safe haven when it is uncorrelated with the base asset.

In the following paragraphs, the results of the econometric model applied to different time frames. The expectation is that the betas will be zeros, because stablecoins are supposed to be stable. The tables containing all the results are displayed in Appendix 1. The main findings of this section are displayed in Table 2.

Table 2

Main findings of the safe haven test on multiple time frequencies.

	USDT (1-hour)	USDT (daily)	DAI (15-minute)
Intercept	-0.001	0.004	0.000
	(0.001)	(0.008)	(0.000)
r_{BTC}	0.006***	-0.006	-0.009***
	(0.002)	(0.003)	(0.001)
$r_{BTC}Dq_{1\%}$	-0.058***	0.117**	0.040*
	(0.020)	(0.047)	(0.022)
$r_{BTC}Dq_{5\%}$	0.017	-0.064	0.011
	(0.030)	(0.103)	(0.020)
$r_{BTC}Dq_{10\%}$	-0.008	-0.027	-0.007
	(0.024)	(0.090)	(0.017)

Note: *p<0.1; **p<0.05; ***p<0.01. Model: $r_{stablecoin,j} = \alpha_0 + \beta_0 r_{BTC} + \sum_{i=1}^{3}(\alpha_i Dq_i + \beta_i r_{BTC} Dq_i) + \varepsilon_j$.

Results across time frames

Table 3 displays the results of the regression analysis on the 15-minute time frame. The coefficients of average returns on Bitcoin are statistically significant and negative for both Dai and USDC on the 1% and 5% level respectively. This implies that these stablecoins are a hedge against Bitcoin, as they do not co-move with Bitcoin price movements. For all four stablecoins, the coefficient with the average returns on Bitcoin is very close to zero, proving that stablecoins are in fact relatively stable: on average, they do not change in value. Again, it must be noted that only the coefficients of Dai and USDC are significant. Additionally, the coefficient of the interaction term of Dai with the most extreme negative Bitcoin returns: the 1% quantile is significant on the 10% level and positive. It can be concluded that on the 15-minute timeframe, Dai is not a safe haven for investors during extreme negative market conditions, because Dai correlates positively with negative Bitcoin returns. It can be argued that users of MakerDAO are burning Dai to free up their collateralized crypto assets to prevent liquidation. Lastly, the coefficients of the interaction terms with the quantiles are very small for all four stablecoins. This means that the tokens barely react to extreme negative Bitcoin returns. Therefore, it can be said that there is weak evidence for the stable property of stablecoins on the 15-minute timeframe.

Table 4 displays the results of the regression on the 1-hour time. The coefficients on all the variables are slightly higher than those of the 15-minute timeframe. It can be reasoned that this is because investors wait out the initial breakdown on the lower time frames and see if it persists on the longer time frame. The coefficients of r_{BTC} for USDC, BUSD and Dai are negative and statistically significant. This implies that these stablecoins are a hedge against Bitcoin. The coefficient of r_{BTC} USDT is positive and statistically significant, implying Tether is correlated with Bitcoin during normal market conditions. For all the stablecoins, the coefficients on the interaction term of r_{BTC} and the quantiles representing extreme negative Bitcoin returns are not statistically significant except for $r_{BTC} * Dq_3$ in the model for USDT. In this case, the coefficient is negative and statistically significant on the 1% level, meaning that USDT shows signs of having the safe haven property for the most extreme Bitcoin returns on the 1-hour timeframe. Meanwhile the coefficients are not equal to zero, meaning that the stablecoins in question are not stable.

The table with the regression using daily returns (Table 5) contains no statistically significant coefficients for normal market conditions. Despite not being statistically significant, the coefficients are near-zero and thus exhibit weak evidence for the stable property of the stablecoins. The only statistically significant coefficient in the table is in the model of USDT. It is the coefficient for the interaction term of the 1% quantile. This number is positive, implying that USDT co-moves with Bitcoin during the most extreme negative Bitcoin returns on the daily time frame. Therefore, there is strong evidence that USDT does not have the safe haven property on the daily timeframe. As all the coefficients for normal market conditions are near-zero for all stablecoins, but not statistically significant, it can be said that there is weak evidence for the stable property of stablecoins.

As the results in the tables have shown, there is weak evidence of the safe haven property of stablecoins, as they are uncorrelated with Bitcoin. Only in the case of the most extreme negative Bitcoin returns on the 1-hour timeframe for USDT is a coefficient negative and significant, thus showing signs of stronger evidence for the safe haven property. This implies that on the 1-hour timeframe during the most extreme negative Bitcoin returns, traders and investors are selling crypto assets for

Tether to reduce losses. USDT can therefore be considered as a safe haven for investors on the 1-hour timeframe. Additionally, on the daily timeframe the coefficient of the interaction term of the 1% quantile is positive for USDT. From the 1-hour to the daily timeframe, this coefficient flipped positive. This means that on the daily, Tether is correlated with Bitcoin returns and investors are selling Tether. This suggests that on the lower timeframe, investors see Tether as a safe haven; but then on the daily timeframe, they are actually selling their Tether, most likely for other crypto assets. In all the models, the coefficients of the independent variables exhibit near-zero values, but they are almost never statistically significant. Therefore, there is no strong evidence of the stable property for all stablecoins.

Testing stablecoins' value against their collateral

This section embodies the second part of the analysis, in which the value of stablecoins is tested against their collateral. This is done by applying the same econometric model as is used in the first part of the analysis, but now regressing the log return of the stablecoin against the log return of the underlying collateral. As explained earlier, the underlying collateral for Tether, USDC and BUSD is assumed to be the dollar. For these stablecoins we take the BTC/USD pair and inverse it so Bitcoin is used as reference asset. Dai is another story, as a user can collateralize a wide variety of crypto assets in order to mint Dai. According to the website *daistats.com*, a community site that tracks different metrics of Dai, the most used cryptos as collateral are, at the time of writing, wBTC (~5.9%), ETH (~38.9%) and USDC (~56.2%). Of course, these numbers fluctuate from day to day. Unfortunately, it was very hard to find a source that had any history information on this metric. To still perform this part of the analysis for Dai, the current distribution of collateralized crypto assets, reported above, is assumed to be constant over time and is used to create a portfolio log return on which the log return of Dai is regressed.

To reiterate, we use a variation of the model used in part I: $r_{stablecoin} = \alpha_0 + \beta_0 r_{Collateral} + \sum_{i=1}^{3}(\alpha_i Dq_i + \beta_i r_{Collateral} Dq_i) + \varepsilon_j$. The coefficient for average market returns in the case of USDT, USDC and BUSD are expected to be equal to 1, as the stablecoins comove 1 on 1 with the collateralized dollars. In the case of Dai, it is expected to be close to one, but not exactly equal to one, as it consists of more assets and it is assumed that the distribution does not vary over time. The coefficients of the interaction term of the dummy variable for extreme negative market conditions and the log return of the collateral the expectation is that those are equal to or near zero. The stablecoin should comove with the underlying collateral. If this coefficient turns out to be negative, then the stablecoin does not react as strong as the underlying collateral to extreme negative market conditions. The stablecoin would withstand the crash better than their collateral. In case of a positive coefficient, the stablecoin has a stronger reaction than the underlying collateral to extreme negative market conditions.

The results of the regression on the 15-minute timeframe are displayed in Table 6. The coefficient of the log return of dollar collateral for the three dollar-collateralized stablecoins are statistically significant on the 1% level and very close to 1 as expected. As expected, the coefficient of the log return of crypto collateral is not equal to one, most likely caused by the assumption of the distribution. The value of the coefficient is slightly lower than 1 and statistically significant, meaning that the returns of Dai do not co-move exactly with the underlying collateral.

On the 1-hour timeframe, similar results are computed (Table 7). All the log returns of the collateral are statistically significant on the 1% level and equal or close to 1 except for Dai. Furthermore, the coefficient of the interaction term of the log return of crypto collateral and the 5% quantile is statistically significant on the 10% level and negative. This signals that the reaction of Dai on extreme negative market returns is not as strong as that of the underlying collateral.

Finally, we turn to the daily results, which can be found in Table 8. Again, all the coefficients are very close to 1, as expected, and statistically significant on the 1% level – with the exception, again, of Dai, which has a coefficient of 0.929, slightly below 1. The interaction term with the 1% quantile of the log return of the collateral for USDT and USDC is statistically significant on the 5% and 10% level respectively. The coefficients are also negative, indicating that the stablecoins do not react as severely as their underlying collateral to extreme negative returns. There is also the statistically significant coefficient for the interaction term with the 5% quantile for the model of USDC on the 10% level. In this case, the coefficient is positive, indicating that the log returns of the stablecoin respond more strongly than the underlying collateral.

This part of the analysis has demonstrated that stablecoins move in step with the underlying collateral as the beta for normal market conditions is equal to one and the betas for extreme negative returns are non-significant. This is at least the for the dollar collateralized stablecoins USDT, USDC and BUSD. As noted, the model for Dai is not accurate enough, due to the absence of historical data on the distribution of the collateral that backs the stablecoin.

There is no evidence that stablecoins add more value or remove value on the blockchain as opposed to their underlying collateral. It must be noted that USDT and USDC show evidence of some deviation on the daily timeframe with negative coefficients for the 1% quantiles and a positive coefficient for USDT for the 5% quantile. In conclusion, dollar collateralized stablecoins are merely a representation of the underlying collateral on the blockchain and there is little evidence that these tokens add any additional value.

Conclusion

Stablecoins fulfill a very important role in the cryptocurrency landscape. Often backed by on- or off-chain collateral, this category of tokens offers traders and crypto users the option to convert their crypto holdings to fiat without leaving the blockchain. Put simply, most stablecoins are digital representations of the dollar. Stablecoins can also be pegged to the value of other assets, but the ones used in this paper were all pegged to the dollar. Not only are stablecoins used to escape volatility in the crypto markets, they fulfill the important functions of money that were absent on the blockchain before their emergence: a means of payment unit, a unit of account, and a store of value.

Through the regression of an econometric model, this paper analyzed the safe haven and stable properties of USDT, USDC, BUSD, and Dai. The log returns of the stablecoins were regressed on the log return of Bitcoin and dummy variables representing extreme negative Bitcoin returns. This was done to test the behavior of the stablecoins during severe market breakdowns and to analyze whether investors and traders used the stablecoins as safe havens.

The regression results reject this thesis. There is no strong evidence of the safe haven property for any of the analyzed stablecoins. On the 1-hour timeframe, Tether shows a sign of the safe haven property in the form of a negative and significant coefficient for the 1% quantile, the most extreme negative Bitcoin returns. On the daily timeframe this coefficient turns positive, meaning that Tether co-moves with Bitcoin. This suggests that on short timeframes, investors see USDT as safe haven and sell their crypto assets for the stablecoin. However, on the longer timeframe, Tether correlates positively with Bitcoin, meaning the token is sold, most likely for other crypto assets.

However, there is evidence for the weak safe haven property of stablecoins, as they are uncorrelated to Bitcoin.

By design, stablecoins are meant to be pegged to the value of the dollar. The betas therefore were expected to equal zero, as the tokens are expected to contain the stable property and maintain their value. This would prove that stablecoins are numb to Bitcoin price changes even during extreme negative Bitcoin returns. As can be seen from the regression results, the betas are non-zero, rendering stables to be not stable and even reacting to extreme negative Bitcoin returns.

The findings in this paper are largely in line with the research done by Baur and Hoang (2021) . In their paper, they also find that stablecoins are not stable and do react to extreme negative Bitcoin returns. The only coin showing a sign of the strong safe haven property was USDT, which was also the case in this paper. Baur and Hoang concluded that although stablecoins do not fulfill the stable property, the tokens are uncorrelated enough with Bitcoin to provide investors with a strong safe haven to reduce their overall risk to the market.

In the second part of the analysis, the same econometric model was used to investigate whether stablecoins moved in step with their collateral or if the tokens added more value on the blockchain. USDT, USDC and BUSD are completely backed by dollars, whereas Dai is backed by deposited and locked crypto assets in smart contracts. The dollar-collateralized stablecoins co-move exactly with their collateral, as the beta on average log returns is equal or very close to one and the betas on the interaction terms are equal or close to zero. Exceptions were USDT and USDC on the daily timeframe, which were negative for the 1% quantile. This would indicate that these coins react less strongly than their underlying collateral to extreme negative returns. In the case of Dai it was hard to find historic data on the distribution of the collateral. It was assumed that the most recent distribution was present through the whole dataset which probably led to inaccurate numbers. Nonetheless, the regression yielded betas close to one on all timeframes.

Further research to the safe haven property of stablecoins could include other large cryptocurrencies such as Ethereum or Binance Coin as base asset in the regression analysis. It would be interesting to see how stablecoins behave in relation to crypto assets other than Bitcoin to see if they yield the same results. Additionally, the safe haven test could be performed on a crypto index, such as CRIX, and see how stablecoins behaves during extreme negative crypto market returns. Furthermore, Terra USD (UST) was excluded in this paper. This token is very new compared to the other four currencies but has already reached the top five stablecoins in market capitalization (*CoinGecko*, 2021; Kwon, 2020). The same safe haven test could be applied to UST to test the safe haven property of this coin.

The stablecoins are also regressed against their collateral. Unsurprisingly, they follow the returns of the collateral in lockstep. The purpose of this test was to see if stablecoins follow the value of the underlying collateral during extreme negative returns, or if they deviate. Were they to behave differently then stablecoins could add more value as an asset in the crypto space. This was not the ideal test to the stability of stablecoins. Additionally, the different price stabilizing mechanisms for the stablecoins could be investigated to see how effective they bring the tokens back to peg. For USDT, USDC and BUSD this could result in an analysis of in-, and outflows to the respective smart contracts that facilitate arbitrage. In the case of MakerDAO this would mean an analysis of the different interest fees set on the different crypto assets that an user can deposit as collateral.

To conclude, the stablecoins investigated in this paper were pegged to the dollar but are not constantly equal to the value of the dollar. The tokens are bound to supply and demand and therefore experience price movements. It can be said that stablecoins lack a real stable property. However, this category of cryptocurrency does offer investors in the space something they had no access to: an easy way to convert from crypto to dollars. As the regression results have shown the analyzed stablecoins are no strong safe havens, but due to their uncorrelation with Bitcoin they can be considered weak safe havens. The tokens can be utilized by traders and investors as instruments to escape volatility and reduce risk during extreme negative market returns.

Appendix 1: Regression results of safe haven test on different time frames

Table 3

Regression results of the safe haven test with 15-minute data frequency.

	Model 1	Model 2	Model 3	Model 4
Intercept	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
r_{BTC}	0.000	-0.002^{**}	-0.001	-0.009^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
$r_{BTC}Dq_{1\%}$	-0.014	0.010	0.006	0.040^{*}
	(0.010)	(0.013)	(0.016)	(0.022)
$r_{BTC}Dq_{5\%}$	0.012	-0.007	-0.003	0.011
	(0.014)	(0.011)	(0.008)	(0.020)
$r_{BTC}Dq_{10\%}$	-0.004	0.007	0.001	-0.007
	(0.013)	(0.010)	(0.007)	(0.017)
Observations	14,500	14,456	14,456	14,456
R^2	0.001	0.004	0.002	0.016
Adjusted R^2	0.000	0.003	0.002	0.015
Residual Std. Error	0.024 (df=14492)	0.018 (df=14448)	0.014 (df=14448)	0.038 (df=14448)
F Statistic	0.392 (df=7; 14492)	3.133^{***} (df=7; 14448)	1.628 (df=7; 14448)	17.917^{***} (df=7; 14448)

Note: *p<0.1; **p<0.05; ***p<0.01. Model: $r_{stablecoin,j} = \alpha_0 + \beta_0 r_{BTC} + \sum_{i=1}^{3}(\alpha_i Dq_i + \beta_i\, r_{BTC} Dq_i) + \varepsilon_j$.

Table 4

Regression results of the safe haven test with 1-hour data frequency.

	Model 1	Model 2	Model 3	Model 4
Intercept	-0.001	0.001	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.001)
r_{BTC}	0.006***	-0.007***	-0.005***	-0.005***
	(0.002)	(0.001)	(0.001)	(0.002)
$r_{BTC}Dq_{1\%}$	-0.058***	0.037	0.050	0.025
	(0.020)	(0.029)	(0.038)	(0.023)
$r_{BTC}Dq_{5\%}$	0.017	0.006	-0.010	-0.038
	(0.030)	(0.014)	(0.014)	(0.066)
$r_{BTC}Dq_{10\%}$	-0.008	-0.007	0.003	0.057
	(0.024)	(0.012)	(0.012)	(0.066)
Observations	3,625	3,616	3,616	3,616
R^2	0.021	0.057	0.052	0.023
Adjusted R^2	0.019	0.055	0.050	0.021
Residual Std. Error	0.045 (df=3617)	0.029 (df=3608)	0.027 (df=3608)	0.049 (df=3608)
F Statistic	4.316*** (df=7; 3617)	17.882*** (df=7; 3608)	9.521*** (df=7; 3608)	4.994*** (df=7; 3608)

Note: *p<0.1; **p<0.05; ***p<0.01. Model: $r_{stablecoin,j} = \alpha_0 + \beta_0 r_{BTC} + \sum_{i=1}^{3}(\alpha_i Dq_i + \beta_i r_{BTC} Dq_i) + \varepsilon_j$.

Table 5

Regression results of the safe haven test with daily data frequency.

	Model 1	Model 2	Model 3	Model 4
Intercept	0.004	-0.000	0.001	-0.000
	(0.008)	(0.005)	(0.005)	(0.005)
r_{BTC}	-0.006	-0.001	-0.002	0.001
	(0.003)	(0.002)	(0.002)	(0.002)
$r_{BTC}Dq_{1\%}$	0.117**	-0.020	-0.012	-0.042
	(0.047)	(0.032)	(0.027)	(0.050)
$r_{BTC}Dq_{5\%}$	-0.064	-0.046	-0.044	-0.052
	(0.103)	(0.061)	(0.060)	(0.081)
$r_{BTC}Dq_{10\%}$	-0.027	0.051	0.040	0.103
	(0.090)	(0.050)	(0.052)	(0.064)
Observations	151	151	151	151
R^2	0.086	0.096	0.101	0.050
Adjusted R^2	0.041	0.052	0.057	0.004
Residual Std. Error	0.108 (df=143)	0.069 (df=143)	0.071 (df=143)	0.081 (df=143)
F Statistic	290.034*** (df=7; 143)	94.250*** (df=7; 143)	155.062*** (df=7; 143)	53.013*** (df=7; 143)

Note: *p<0.1; **p<0.05; ***p<0.01. Model: $r_{stablecoin,j} = \alpha_0 + \beta_0 r_{BTC} + \sum_{i=1}^{3}(\alpha_i Dq_i + \beta_i r_{BTC} Dq_i) + \varepsilon_j$.

Appendix 2: Regression results of the collateral test on different time frames

Table 6

Regression results of the collateral test with 15-minute data frequency.

	Model 1	Model 2	Model 3	Model 4
Intercept	0.000	-0.000	0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)
$r_{Portfolio}$				0.914***
				(0.009)
$r_{Portfolio}Dq_{1\%}$				-0.039
				(0.093)
$r_{Portfolio}Dq_{5\%}$				-0.012
				(0.098)
$r_{Portfolio}Dq_{10\%}$				0.054
				(0.086)
$r_{Collateral}$	0.997***	1.000***	0.998***	
	(0.003)	(0.003)	(0.003)	
$r_{Collateral}Dq_{1\%}$	0.002	0.020	0.019	
	(0.032)	(0.036)	(0.033)	
$r_{Collateral}Dq_{5\%}$	-0.014	-0.056	-0.003	
	(0.041)	(0.045)	(0.040)	
$r_{Collateral}Dq_{10\%}$	0.014	0.039	0.003	
	(0.036)	(0.040)	(0.035)	
Observations	14,456	14,456	14,456	14,456
R^2	0.987	0.983	0.987	0.882
Adjusted R^2	0.987	0.983	0.987	0.882
Residual Std. Error	0.062 (df=14448)	0.070 (df=14448)	0.061 (df=14448)	0.187 (df=14448)
F Statistic	43415.608*** (df=7; 14448)	30820.123*** (df=7; 14448)	39664.073*** (df=7; 14448)	4280.916*** (df=7; 14448)

Note: *p<0.1; **p<0.05; ***p<0.01. Model: $r_{stablecoin} = \alpha_0 + \beta_0 r_{Collateral} + \sum_{i=1}^{3}(\alpha_i Dq_i + \beta_i r_{Collateral} Dq_i) + \varepsilon_j$.

Table 7

Regression results of the collateral test with 1-hour data frequency.

	Model 1	Model 2	Model 3	Model 4
Intercept	-0.001	-0.001	-0.000	-0.005
	(0.001)	(0.001)	(0.001)	(0.005)
$r_{Portfolio}$				0.924^{***}
				(0.017)
$r_{Portfolio} Dq_{1\%}$				0.115
				(0.149)
$r_{Portfolio} Dq_{5\%}$				-0.270^{*}
				(0.159)
$r_{Portfolio} Dq_{10\%}$				0.204
				(0.134)
$r_{Collateral}$	0.999^{***}	1.007^{***}	1.003^{***}	
	(0.003)	(0.004)	(0.004)	
$r_{Collateral} Dq_{1\%}$	-0.072	-0.041	-0.063	
	(0.051)	(0.051)	(0.049)	
$r_{Collateral} Dq_{5\%}$	0.274^{*}	0.211	0.228	
	(0.151)	(0.157)	(0.154)	
$r_{Collateral} Dq_{10\%}$	-0.245	-0.222	-0.210	
	(0.152)	(0.157)	(0.154)	
Observations	3,616	3,616	3,616	3,616
R^2	0.992	0.991	0.992	0.904
Adjusted R^2	0.992	0.991	0.992	0.903
Residual Std. Error	0.088 (df=3608)	0.095 (df=3608)	0.089 (df=3608)	0.313 (df=3608)
F Statistic	21913.094^{***} (df=7; 3608)	17427.264^{***} (df=7; 3608)	19273.445^{***} (df=7; 3608)	1816.707^{***} (df=7; 3608)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Model: $r_{stablecoin} = \alpha_0 + \beta_0 r_{Collateral} + \sum_{i=1}^{3}(\alpha_i Dq_i + \beta_i r_{Collateral} Dq_i) + \varepsilon_j$.

Table 8

Regression results of the collateral test with daily data frequency.

	Model 1	Model 2	Model 3	Model 4
Intercept	0.013	0.011	0.012	-0.137
	(0.008)	(0.008)	(0.008)	(0.116)
$r_{Portfolio}$				0.929***
				(0.056)
$r_{Portfolio}Dq_{1\%}$				-0.016
				(0.212)
$r_{Portfolio}Dq_{5\%}$				-1.230
				(1.043)
$r_{Portfolio}Dq_{10\%}$				0.970
				(1.023)
$r_{Collateral}$	1.001***	1.004***	1.006***	
	(0.003)	(0.003)	(0.003)	
$r_{Collateral}Dq_{1\%}$	-0.136**	-0.154*	-0.140	
	(0.062)	(0.093)	(0.099)	
$r_{Collateral}Dq_{5\%}$	0.084	0.214*	0.140	
	(0.121)	(0.118)	(0.131)	
$r_{Collateral}Dq_{10\%}$	0.028	-0.105	-0.049	
	(0.105)	(0.081)	(0.089)	
Observations	151	151	151	151
R^2	0.999	0.999	0.999	0.878
Adjusted R^2	0.999	0.999	0.999	0.872
Residual Std. Error	0.123 (df=143)	0.119 (df=143)	0.118 (df=143)	1.549 (df=143)
F Statistic	14251.358*** (df=7; 143)	16969.760*** (df=7; 143)	15759.845*** (df=7; 143)	171.264*** (df=7; 143)

Note: *p<0.1; **p<0.05; ***p<0.01. Model: $r_{stablecoin} = \alpha_0 + \beta_0 r_{Collateral} + \sum_{i=1}^{3}(\alpha_i Dq_i + \beta_i r_{Collateral} Dq_i) + \varepsilon_j$.

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