



# On Stablecoin Price Processes and Arbitrage

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**Abstract.** This study applies the Caginalp and Balenovic (1999) model for asset flow dynamics to fully collateralized stablecoins. The analysis provides novel insights on how trend-reversion and reactions to peg deviations work together to keep stablecoin prices close to the price they are targeting. A fixed-effects panel regression indicates that the model’s abstraction of trading motivations indeed fits stablecoin price processes well. The results convey first indication that theoretic stablecoin models might benefit from modeling price dynamics to switch between two market regimes: one for day-to-day price formation and limited arbitrage activity; and one for extraordinary market situations.

**Keywords:** Stablecoins · Arbitrage · Price formation

## 1 Introduction

Stablecoins are being increasingly adopted as bridge to trade traditional cryptocurrencies [3, 8, 38, 45], marketed as medium-of-exchange for decentralized finance and smart contracts [39, 40] and have recently been approved by US regulators as payment method for federally chartered banks [1]. Increasing practical relevance fosters the demand for understanding economic properties of such instruments. The majority of projects simply tokenize the asset their tokens are stabilized against (e.g. the USD, EUR or gold) or store a third asset in the respective amount [43]. Assuming that traders trust governance, collateral and technology, and their trust is justified, there is little room for disagreement on the token’s fundamental values. If there were any structured deviation, efficient-market theorists might argue that market participants would seize the resulting opportunity of arbitrage, closing the gap [26].<sup>1</sup> Stablecoin prices would then

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<sup>1</sup> In a strict sense, arbitrage opportunities can be defined as “investment strategy that guarantees a positive payoff in some contingency with no possibility of a negative payoff and with no net investment” [25, p.57]. In this paper the term is used in a wider sense, describing the trader’s perceptions.

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merely reflect the value of the collateral and random noise. If, however, price adjustments are restricted by incomplete arbitrage, interesting patterns might emerge that reflect the trader’s decisions [10, 22]. This paper explores and quantifies such dynamics.

My empiric approach is based on a recent theoretical approach from asset pricing literature proposed first in [18] and refined by [14] which opens up asset pricing to dynamic systems modeling known from thermodynamic physics. In the following, the latter will be called the “Caginalp and Balenovic (1999) asset flow” (*CBAF*) approach. In a nutshell, the authors model price determination by abstracting trading decisions as flows from asset-to-cash and vice versa. As such, traders are abstracted as being driven by price trends and the deviation of the asset’s market price from its fundamental value. Exploring theoretic approaches to the instability of price processes, a first application to the field of cryptocurrencies has been attempted by [12]. Applying the *CBAF* model to stablecoin arbitrage promises to offer a convincing model for the interplay of trend following and peg deviations. In contrast to most models for cryptocurrency pricing, the above model requires few assumptions.<sup>2</sup> Exploring early trading data for 11 fully collateralized stablecoins, this study evaluates the appropriateness of the intuitive trader abstraction adopted by the *CBAF* approach and offers insights into stablecoin price dynamics in general. My empirical setup couples variables approximating trend-following with a measure for peg deviations in a dynamic coin-fixed-effects (coin-FE) panel data regression. The study engages in rigorous robustness checking by testing the models for the influence of seasonal dummies, interaction terms for the direction of trends, sign of peg deviations and different parameters in data preprocessing. I find a striking difference between results being based on data with—and without outlier treatment even for merely truncating price changes exceeding 5 standard deviations. For data including extreme price changes, the *CBAF* model approximates price formation well. Deviations from the peg and trend following are strong determinants of coming price changes. For outlier-free data, however, the effects seem to blend in with other price-determinants (the stablecoin’s token supply and Bitcoin’s price volatility). This result indicates that apart from very few occasions arbitrage activity is weak. This poses the questions, whether costs of arbitrage might be prohibitive high except for extreme but rare market situations. It might be considered to model price formation by switching between two regimes: a first one offering profits for large trades towards the peg, and a second one being characterized by limited levels of arbitrage activity.

The paper is organized as follows: Sect. 2 outlines related work, Sect. 3 introduces the theoretic backgrounds of arbitrage and the *CBAF* model, Sect. 4 discusses data and econometric approach. Sect. 5 describes the results and Sect. 6 concludes the study.

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<sup>2</sup> Compared with, for example, game-theoretic approaches [13] and consumer demand models [2, 4, 7].

## 2 Related Work

Studies investigating the asset class and its manifestations include [19, 23, 41, 43] and [11]. The user perception in the adoption of stablecoins has been studied in [32], while [5] analyzed the suitability of stablecoins as save-haven investment. The relation between cryptocurrency prices and stablecoin trading has been focused on by [3, 8, 45] and [27]. Adopting a risk-oriented approach, [33, 34] and [35] suggest theoretic models to study stability and resilience of stablecoins. While the latter focuses on extreme events, [38] not only offers a theoretic model for day-to-day arbitrage but also provides, to my knowledge, the first extensive empirical analysis of the drivers of stablecoin prices. This paper differs in perspective and econometric approach: Instead of peg deviations, this paper analyzes price processes and tests the *CBAF* model for applicability. While [38] relies on an auto-regressive distributed lag model with a rich database, however, just for *Tether*, this paper adopts a dynamic coin-FE panel data regression on market data for 11 stablecoins.

## 3 Stablecoin Arbitrage and the CBAF Model

Stablecoin arbitrage uses primary and secondary markets [38]. On the primary market, coins are created and redeemed against collateral with the issuer. On the secondary market, stablecoins are traded against fiat and cryptocurrencies. If market prices deviate from the peg, arbitrage traders might decide to either trade against peg deviations directly on the secondary market or involve the stablecoin issuer. In the first case, arbitrage traders simply trade towards the peg. They would buy when prices are below—and sell when prices are above the peg. In the second case, abstracting from technical details,<sup>3</sup> arbitrage traders would purchase coins from the markets and redeem them with the issuer when prices are below the peg. When prices are above the peg, traders would first create coins with the issuer and subsequently sell them on secondary markets.

The *CBAF* approach as presented in [14] models traders as switching from cash to asset or vice versa with a certain probability  $k$ . Variable  $k$  is modeled to include motivations based on past price changes  $\zeta_1$  and the market discount relative to the asset's fundamental value  $\zeta_2$ . These components are modeled using the trader's memory with respect to price trends and deviations from fundamental values ( $c_1$  and  $c_2$ ) and their focus on these two respective components ( $q_1$  and  $q_2$ ). Core component of  $\zeta_1$  is the relative price trend  $f(\tau) = \frac{1}{P(\tau)} \frac{dP(\tau)}{d\tau}$  over period  $\tau$  on time scale  $\tau_0$ .  $\zeta_2$  is constructed around deviations  $g(\tau) = \frac{P_a(\tau) - P(\tau)}{P(\tau)}$  of market price  $P(\tau)$  from fundamental value  $P_a$ . Thus, the two components can be expressed as

$$\zeta_1(t) = q_1 c_1 \int_{-\infty}^t e^{-\frac{(t-\tau)}{c_1}} \cdot f(\tau) d\tau \quad (1)$$

$$\zeta_2(t) = q_2 c_2 \int_{-\infty}^t e^{-\frac{(t-\tau)}{c_2}} \cdot g(\tau) d\tau. \quad (2)$$

<sup>3</sup> Models for more complex stablecoins can be found e.g. in [33] and [34].

Limiting  $k$  to values between 0 and 1,  $k$  is constructed as  $k = \frac{1}{2} + \frac{\tanh(\frac{\zeta_1 + \zeta_2}{2})}{2}$ . For  $\zeta_1$  and  $\zeta_2$  equal to zero, the probability of flows from cash to asset and vice versa are thus equally likely. Demand  $D$  and supply  $S$  of the asset are modeled using  $k$  and the fraction already invested into the asset  $B$ . Their relation can be expressed as  $D = k(1 - B)$  and  $S = (1 - k)B$  and thus  $\frac{D}{S} = \frac{k}{1-k} \frac{1-B}{B}$ . Prices  $P$  are assumed to change logarithmic with excess demand, leading to

$$\frac{1}{P} \frac{dP}{dt} = \delta \cdot \log\left(\frac{D}{S} - 1\right) = \delta \cdot \log\left(\frac{k}{1-k} \frac{1-B}{B}\right) \quad (3)$$

with  $\delta$  representing an amplitude that scales with time. For a deeper discussion of the model and its applications see [14, 16, 17, 44] and [12]. While this paper will not be offering estimates for the individual parameters, the study gathers evidence supporting the basic intuition of the model: Under the efficient market hypothesis, fluctuations of  $P(t)$  around the peg, assumed to equal  $P_a$ , would merely be random.<sup>4</sup> Obviously, in this case, neither of the two components ought to be reflected in market data of stablecoins. If, however, evidence of  $\zeta_1$  or  $\zeta_2$  is present, it is of considerable interest to understand how the two components are jointly driving stablecoin prices.

## 4 Data and Econometric Approach

The following paragraphs will discuss data preprocessing and the economic approach for testing the applicability of the *CBAF* model.

Data was gathered from [www.coingecko.com](http://www.coingecko.com). Similar to [www.coinmarketcap.de](http://www.coinmarketcap.de) the data provider currently crawls 382 cryptocurrency exchanges but offers hourly data over a well-documented API for free.<sup>5</sup> The full dataset comprises 19 cryptocurrencies. The sample includes projects that are listed at [www.coingecko.com](http://www.coingecko.com), promise stability of their exchange rates in their whitepapers and collateralize their tokens to at least 100%. The study considers designs that use the asset-pegged-to as collateral but also includes tokens that use a third asset, often a crypto-asset, in a quantity reflecting at least full collateralization. Some of the 19 cryptocurrencies are quite young and immature. Shallow markets with low volumes and few trades per measurement period might in part be driven by market microstructure effects which could lead to biased regressions. To reduce noise, this study thus excludes months for that the stablecoin shows a market capitalization of under USD 10 m or daily trading volumes of under USD 1 m. Coins have been dropped completely if the remaining dataset included less than  $24 \cdot 31$  hourly observations. This restricted the dataset to 11 stablecoins with 767 to 16970 trading hours leading to 101,243 observations in total. Table 6 of Appendix 7.3 in the full paper shows that the results hold as well if market capitalization thresholds of USD 100 m and USD 5 m—and thresholds for

<sup>4</sup> This study assumes that traders rightfully trust in the peg as a correct estimate of the tokens fundamental value. This fails when doubts about the stablecoins collateral or security arise.

<sup>5</sup> As of 2020-08-17.

daily trading volumes of USD 50m and USD 50k are chosen. To understand the effect of extreme values on the estimated models, price changes diverging over 5 standard deviations (SD) from the mean have been truncated. Table 1 in Appendix B gives an overview over cutoff points and the relative and absolute number of classified outliers. The threshold was chosen deliberately high to correct only the most extreme values. Such might have a disproportionate effect on ordinary-least-squares (OLS) regression results [6]. To make the estimated coefficients comparable, all variables apart from the dummies have been standardized based on Z-scores  $X^{stand} = \frac{X - \mu(X)}{\sigma(X)}$ , with mean  $\mu(\cdot)$  and standard deviation  $\sigma(\cdot)$ . To verify the applicability of the *CBAF* model, a linear panel regression in conjunction with squared and cubed trend variables to model nonlinear relationships has been applied to exchange-traded funds [17] and stocks [15]. Now this framework is applied to stablecoins by adjusting it slightly to the characteristics of the dataset and adding a variety of robustness checks. Traditional linear modeling might fail to pick up the complex relations in price formation. In contrast to linear models, polynomials allow for very strong negative (positive) past returns to induce positive (negative) bounce-back effects. Mixing up relations between strong and weak price changes, simple auto-regressive price regressions abstaining from the above step might miss potential information on prices. As a remedy, following [15] and [17], this study includes variables to the power into a fixed-effects panel data approach.<sup>6</sup> To capture price trends, in accordance to [15], this paper uses a simple weighted aggregation of past price changes. The prior might be expressed using prices  $P$  and smoothing factor  $s$  over a look-back window  $d$  as

$$T_t = \frac{1}{\sum_{k=1}^d e^{sk}} \sum_{k=1}^d \left( \frac{P_{t-k+1} - P_{t-k}}{P_{t-k}} \cdot e^{sk} \right). \quad (4)$$

The smoothing term ensures that older observations of variable changes are entering the sum with lower weights ( $s = -0.25$  and  $d = 10$ ). Trends in prices have been shown to explain variation in future returns for cryptocurrencies in [20, 30] and [28]. To calculate the distance  $D$  of market price  $P$  from the peg  $P_a$ , simply  $D_t = P_t - P_{a,t}$  is formed. As control variables the token supply and Bitcoin's price-volatility are used. Controlling for the volatility of the second and third largest traditional cryptocurrencies by trading volume (*Ether* and *Ripple*) or for the *Ethereum Gas* price turned out to yield insignificant coefficients. Regressions are formed denominating cryptocurrency price changes as  $\Delta P$ , the trend as  $T$  and peg deviations as  $D$ . Moreover  $\Delta S$  and  $\Delta V^{BTC}$  are the first differences of token supply and Bitcoin's price-volatility respectively. Dummy variables include seasonal ones ( $Z_t^{\text{hour}}$ ,  $Z_t^{\text{day}}$ ,  $Z_t^{\text{month}}$ ) and others that account for the sign of the peg deviation ( $Z_t^{D>0}$ ) and the direction of the trend ( $Z_t^{T>0}$ ). The unobserved coin effect is denominated as  $a_i$  while  $b_t$  gives the unobserved

<sup>6</sup> Robustness against multicollinearity among the regressors is ensured by checking the respective Variance Inflation Factors (VIF) (compare Appendix 7.2 Table 3 of the full paper).

time effect and the remaining residual errors are given as  $u_{it}$ . A parsimonious base-line regression can thus be based on unobserved-effects equation

$$\begin{aligned} \Delta P_{i,t+1} = & \beta_2 T_{i,t} + \beta_3 T_{i,t}^2 + \beta_4 T_{i,t}^3 + \beta_5 D_{i,t} + \beta_3 D_{i,t}^2 + \beta_4 D_{i,t}^3 \\ & + \beta_5 \Delta S_{i,t} + \beta_6 \Delta V^{\text{BTC}} + a_i + b_t + u_{it}, \end{aligned} \quad (5)$$

while the full general regression is based on

$$\begin{aligned} \Delta P_{i,t+1} = & \beta_2 T_{i,t} + \beta_3 T_{i,t}^2 + \beta_4 T_{i,t}^3 + \beta_5 D_{i,t} + \beta_6 D_{i,t}^2 + \beta_7 D_{i,t}^3 \\ & + \beta_8 \Delta S_{i,t} + \beta_9 \Delta V_{i,t}^{\text{BTC}} + Z_t^{\text{hour}} + Z_t^{\text{day}} + Z_t^{\text{month}} + \beta_{10} T_{i,t} \cdot Z_t^{T>0} \\ & + \beta_{11} T_{i,t} \cdot Z_t^{D>0} + \beta_{12} D_{i,t} \cdot Z_t^{D>0} + \beta_{13} D_{i,t} \cdot Z_t^{T>0} + a_i + b_t + u_{it}, \end{aligned} \quad (6)$$

where  $t$  is the time- and  $i$  the coin index.

While two-way fixed-effects regression are applied to eliminate time and entity effects in the original framework [15, 17], recent research indicates that this approach might lead to mostly uninterpretable coefficients [29, 36] and biased inferences in most general applications [31]. This study thus settles on eliminating  $a_i$  by coin-fixed-effects but models common time effects by including seasonal dummies and control variables. Treatment of the Nickel bias and other issues related to panel data regressions with long time series dimensions (e.g. heteroskedasticity, non-stationarity and serial correlation) are treated in line with state-of-the-art approaches. For more information refer to Appendix A.

## 5 Results

Table 1 supplies estimates of the coefficients given in Eq. 4. As suggested by the applied asset pricing theory, not only current deviations from the peg but also price trends show significant relations with the coming hour's price change. Also, the adopted nonlinear regression framework has proven useful. Most of the variables that are raised to the second and third power show high significance and our models explain roughly 20% of the variance in the one-hour-ahead price changes.

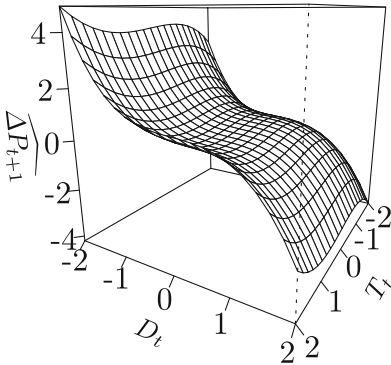
<sup>7</sup> However, coefficient estimates vary with the way outliers are treated. For the model based on data for which no outlier treatment has been implemented (compare Column 1 Table 1), the polynomial of significant coefficients for the estimated price change is  $\widehat{\Delta P}_{t+1} = -0.160D_t + 0.085D_t^2 - 0.417D_t^3$ . This polynomial is displayed in Fig. 1, which relates peg deviations and trends to the coming hours price change. Even relative small peg deviations are associated with moderate price changes. Large peg deviations, however, precede extreme price changes forcefully driving prices back to the peg. The coefficients related to price trends display nonlinearity as well and form  $\widehat{\Delta P}_{t+1} = -0.266D_t + 0.178D_t^3$ . Weak price trends seem to be reverted, while stronger ones lead to trend following. In other

<sup>7</sup> Price changes are famously noisy [9]. Regressing daily order flows on price changes for *Tether* [38] arrive at R-squares up to 13%.

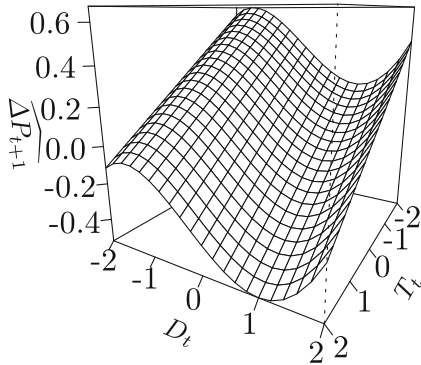
**Table 1.** Coin-FE regression based on Eq. 4.

	Dependent variable:	
	$\Delta P_{t+1}$	
	(1)	(2)
$D_t$	-0.160*** (0.008)	-0.259*** (0.008)
$D_t^2$	0.085*** (0.027)	0.046*** (0.006)
$D_t^3$	-0.417*** (0.046)	0.056** (0.023)
$T_t$	-0.266*** (0.009)	-0.184*** (0.005)
$T_t^2$	-0.009 (0.023)	-0.005 (0.008)
$T_t^3$	0.178*** (0.053)	-0.011 (0.037)
$\Delta S_t$	0.208*** (0.077)	0.394*** (0.144)
$\Delta V_t^{BTC}$	-0.070 (0.050)	-0.308*** (0.089)
Observations	101,243	101,243
R <sup>2</sup>	0.200	0.198
Adjusted R <sup>2</sup>	0.200	0.198
F Statistic	3,162.209***	3,123.468***
(df = 8; 101224)		

Note: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$   
 Variable denominations are given in Sect. 4 under Eq. 4.  
 Column (1) for untreated- and column (2) for outlier free data. Standard errors given in brackets.



**Fig. 1.** Coefficient interplay for untreated data



**Fig. 2.** Coefficient interplay for outlier-free data

words, series of consecutive strong price changes of the same direction are prolonged. This might be a result of consecutive hours of price jumps after large deviations. In comparison to price trends, but also all other tested variables, the joint influence of the coefficients for peg deviations seems to be the largest by far. Their influence is roughly symmetric for positive and negative price deviations. For the model based on data for which price changes in excess of 5 SD have been truncated (Column 2 of Table 1), the joint estimated effect of price trends and peg

deviations on coming price changes is displayed in Fig. 2. For peg deviations, the polynomial of significant coefficients is  $\overline{\Delta P}_{t+1} = -0.259D_t + 0.046D_t^2 + 0.056D_t^3$  with roots roughly at  $-2.6$ ,  $0$  and  $1.8$ . The effect of smaller peg deviations is in line with expectations: The relation of peg deviations and the coming price change is positive for  $-2.6 \leq D \leq 0$  and negative for  $0 \leq D \leq 1.8$  and would thus lead to mean-reverting prices. For positive deviations  $D > 1.8$  and negative deviations  $D < -2.6$ , however, signs turn and peg deviations are associated with price changes leading away from the peg. The reason for this seemingly counter-intuitive result might be that the majority (95.37%) of observed price changes lie within the 2 SD displayed in Figs. 1 and 2. Rather than avoiding rare but large errors from outliers, the coefficients seem to be optimized to fit smaller fluctuations around the peg. Not only the results for peg deviations—but also price trends differ. The latter, estimated based on outlier free data, show a linear, negative relation to coming price changes. In other words, series of price changes of equal sign revert soon. The size of the coefficients for trend and peg deviations are relatively low, though. For instance, a peg deviation of 2 SD in negative direction is associated merely with an increase in prices of 0.1 SD. A negative price trend of 1 SD is associated with an increase of prices of around 0.2 SD. Arbitrage is estimated to have a very limited effect in the outlier-free dataset. With coefficients of 0.394 and  $-0.308$  respectively, the change in token supply and the change in the Bitcoin’s price volatility seem to be equally important price determinants, at least. This contrast is surprising, given that they are caused by the truncation of merely 363 of 101243 observations. Table 2 of Appendix B gives coefficients for the same model but complemented by dummy representations accounting for hours, weekdays, months as well as interaction terms for the sign of the peg deviation and the direction of the price trend. The results differ only negligibly.

## 6 Conclusion

The stark contrast of the importance of peg deviations in the fitted models with—and without outlier treatment is striking. For data including extreme price changes, peg deviations and trend dynamics seem to approximate price formation well. For stablecoins, the intuitive *CBAF* approach to model trader behavior might thus be seen as a good approximation for the determinants of price changes. For outlier-free data, however, the effects seem to blend in with other price-determinants. The above results pose the question of whether stablecoin markets might not best be modeled as switching between a first regime characterized by limited arbitrage, and a second one setting in when markets promise sufficient profits for large trades towards the peg. While the most obvious candidate for explaining such results might be costs of arbitrage, at least short-term variation of the *Ethereum Gas* price turned out to yield insignificant coefficients when adopted as control variable. Future research might employ cointegration analysis capable of unvailing also longterm relationships.



## A Robustness

The dataset applied in this study combines 11 timeseries of differing lengths and might thus be described as an unbalanced timeseries panel. While a large  $T$  dimension is generally beneficial, simple panel data approaches might be misspecified. A first issue is serial correlation. In most financial time series prior realizations affect coming ones. Including lagged data might thus be useful to capture serial correlation in the data - this is usually referred to as dynamic panel modeling. Instead of including lagged data explicitly, in this study, the trend variable is carrying auto-regressive information. Using simple fixed-effects models jointly with lagged variables, however, induces the so-called Nickell bias as the lagged variable causes endogeneity in the regressors [42]. As argued by [21, p.163], including fixed-effects into dynamic specifications of panel data regressions, even for simple OLS estimates, can mitigate the issue to some degree. Their coefficients, however, are still seriously biased for small  $T$ . In our case, including coin-fixed-effects and considering that  $T$  is very large, Nickell's bias should be negligible.<sup>8</sup> There are other issues known from time-series analysis, though. [46] warned about relying on the above for inference for non-stationary data (which might lead to spurious regression results) and suggested to check the error term for heteroskedasticity, serial correlation and nonnormality. To counter this problem, this study ensures stationarity using the Levin-Lin-Chu unit root test [37]. As the test does not reject the presence of a unit root for token supply and volatility, we take first differences of these variables.

As discussed earlier, we apply coin-FE panel regressions based on simple OLS-estimation. As a consequence, several assumptions are to be ensured. Residuals ought to display a mean of zero and be free of heteroscedasticity, cross-sectional, and serial correlation. Breusch-Pagan Lagrange Multiplier tests and Pesaran cross-sectional dependence tests are used to test for cross-sectional dependence in the residuals. Additionally, Student's t-tests have been applied to check the residuals for a mean of zero. Breusch-Godfrey/Wooldridge tests have been applied to test for serial correlation. Breusch-Pagan tests are used for detecting heteroskedasticity. While a deviation from zero for the residuals is strongly rejected, unfortunately, the remaining tests reveal heteroscedasticity, serial, and also cross-sectional correlation. In other words, residuals are showing variance clusters and are depending on their own- and even lags across coins. As a consequence, the simple OLS estimator is biased. To still draw robust inferences from the estimated model, spacial correlation consistent (SCC) estimators introduced in [24] are used. The approach adapts Newey-West estimators to the panel setting and leads to robust standard errors even in the presence of heteroscedasticity and cross-sectional and serial correlation.

For tables and further details on the above robustness checks, please refer to the full paper.

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<sup>8</sup> In fact, following [46], the bias for the fixed-effects estimator approaches zero with rate  $1/T$ .

## B Tables

**Table 1.** Outliers.

Cutoff (in Std. Dev.)	Outliers as defined by cutoff in percent	
	N	%
1	18839	18.6
2	4686	4.63
3	1563	1.54
4	683	0.67
5	363	0.36

Fraction of data classified as outliers.

**Table 2.** Coin-FE regression.

	<i>Dependent variable: <math>\Delta P_{t+1}</math></i>	
	(1)	(2)
$D_t$	-0.111*** (0.010)	-0.230*** (0.014)
$D_t^2$	0.089*** (0.027)	0.047*** (0.007)
$D_t^3$	-0.472*** (0.047)	0.032 (0.025)
$T_t$	-0.248*** (0.012)	-0.180*** (0.009)
$T_t^2$	-0.010 (0.023)	-0.006 (0.009)
$T_t^3$	0.162*** (0.054)	-0.015 (0.038)
$\Delta S_t$	0.202*** (0.074)	0.392*** (0.142)
$\Delta V_t^{\text{BTC}}$	-0.063 (0.051)	-0.304*** (0.089)
$Z_t^{\text{hour}}$	-0.0003 (0.0003)	-0.0003 (0.001)
$Z_t^{\text{day}}$	-0.0002 (0.0003)	-0.001 (0.001)
$Z_t^{\text{month}}$	-0.003*** (0.0003)	-0.006*** (0.001)
$D \cdot Z_t^{D>0}$	-0.018*** (0.002)	-0.006 (0.009)
$D \cdot Z_t^{T>0}$	-0.003** (0.001)	-0.011 (0.007)
$T \cdot Z_t^{D>0}$	0.003*** (0.001)	-0.005 (0.008)
$T \cdot Z_t^{T>0}$	0.0001 (0.001)	0.009 (0.007)
Adjusted R <sup>2</sup>	0.208	0.199
F Statistic	1,769.824***	1,681.830***
(df = 15; 101217)		

Note: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

This table gives the results of a coin-FE regression for the full model specified in Eq. 4. Column (1) for untreated- and column (2) for outlier free data. Coefficient's standard errors given in brackets.

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