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Abstract

Analyzing a set of 200 cryptocurrencies over the period from 2015 to 2019, we document a significant return reversal effect that holds at the daily, weekly, and monthly rebalancing frequencies and is robust to controls for differences in size, turnover, and illiquidity. Moreover, the reversal effect persists during both halves of our sample period and following periods of both high and low market implied volatility. Consistent with the effect being driven by a combination of market inefficiency and compensation for liquidity provision, we find reversals are most pronounced among smaller capitalization and less liquid cryptocurrencies.

Keywords: Cryptocurrency, Short-term reversal, Market efficiency, Market liquidity, Return predictability

JEL Classification: G11, G14

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I. Introduction

Extant literature highlights the phenomenon of return reversals in financial markets. Jegadeesh (1990) provides evidence of significant negative first-order serial correlation in monthly stock returns, and a large body of literature has subsequently explored this phenomenon using different holding periods, methodologies, and asset classes. For instance, Wang and Yu (2004) examine return predictability in U.S. futures markets and document substantial profits to a strategy that goes long futures contracts that underperformed over the past week and short contracts that outperformed – consistent with a strong reversal effect. In contrast, Raza et al. (2014) find evidence of return momentum rather than reversals within a sample of 63 traditional currencies. We extend this line of work by documenting a pervasive return reversal effect within the cryptocurrency market.

Prior research offers two primary explanations for return reversals with both expected to have a pronounced effect on cryptocurrency performance. The first explanation suggests reversals result from investor overreaction and thus indicate market inefficiency (Lehmann, 1990; Cooper, 1999). Alternatively, Campbell et al. (1993) and Hameed and Mian (2015) present evidence that reversals can reflect compensation for liquidity provision, as investors serving as market makers step in to absorb excess selling only at prices low enough to provide an expected return premium. Our results suggest both factors contribute to a large reversal effect across the broader cryptocurrency market, which contains a higher percentage of retail investors and is less liquid compared to traditional asset classes. Our work is closely related to Wei (2018) and Brauneis and Mestel (2018) who also find that return predictability declines with increased cryptocurrency liquidity; however, our approach focuses on the cross-section of returns rather than individual time series for each coin. Consequently, unlike prior studies, we provide evidence that liquidity provision is compensated and contributes to a significant reversal phenomenon.

Our study makes three meaningful contributions to the growing literature on cryptocurrency return predictability (Urquhart, 2016; Bariviera, 2017; Nadarajah and Chu, 2017; Köchling et al., 2019; Vidal-Tomás et al., 2019). First, we document an economically large and statistically significant return reversal effect, which holds for daily, weekly, and monthly rebalancing frequencies. Second, in addition to portfolio-level tests, we utilize cross-sectional regressions to explore the predictive power of past returns while controlling for other individual cryptocurrency characteristics including size, turnover, and illiquidity. To our knowledge, we are the first to conduct predictive cross-sectional regressions for cryptocurrency returns, as the number of cross-sections with available data was previously insufficient to draw meaningful conclusions. Third, we explore the reversal effect across different subsamples and subperiods to provide insight into its key drivers. Altogether, our evidence highlights a widespread return reversal effect that appears strongest among small-cap and illiquid cryptocurrencies.

The rest of the paper is organized as follows. Section II describes our dataset, key variables, and methodology. Section III reports the results of our empirical tests. Section IV concludes.

II. Data and methodology

We obtain data from www.coinmarketcap.com, which reports daily prices based on volume-weighted averages as well as daily volume data aggregated across all exchanges.[1] We collect price and volume data on the 200 largest cryptocurrencies by market cap as of December 28, 2014 and track their performance over the period from January 2015 to June 2019 (see Appendix A for the list of cryptocurrencies). This allows us to form relatively well-diversified portfolios while also excluding the smallest and most volatile coins. Altogether the sample accounts for approximately 99.96% of the total market capitalization among listed cryptocurrencies as of the sample start date. Our outcome variable is the one-period-ahead return on each cryptocurrency, *i*, defined as the percentage change in the closing price, *P*, from period *t* to *t+1*: $R_{i,t+1} = (P_{i,t+1}/P_{i,t} - 1) * 100$. We then define our primary test variable, *REV*, as the return during the prior period, *t*.

We control for size, turnover, and illiquidity given evidence of their associations with cryptocurrency performance (Wei, 2018; Bouri et al., 2019b; Li et al., 2019). We define *SIZE* as the market capitalization of each cryptocurrency and *TURN* as the daily trading volume divided by

[1] Details available at: https://coinmarketcap.com/methodology/#market-data.

market cap summed over all days in the portfolio formation period.[2] Following Amihud (2002), we compute our measure of illiquidity, *ILLIQ*, as follows,

$$ILLIQ_{i,t} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{VOL_{itd}} * 100 \quad (1)$$

where D represents the total number of days in period t and is used to average the absolute value of daily returns relative to the corresponding daily trading volumes. We multiply this variable by 100 for scaling consistency. To mitigate the effect of outliers in our cross-sectional tests, we winsorize the regression explanatory variables at their respective 1st and 99th percentiles.[3] Our final sample contains 199 unique cryptocurrencies with 6,782 coin-month, 29,952 coin-week, and 261,377 coin-day observations in our respective tests.

We first use standard portfolio sorts to explore whether cryptocurrencies with low returns in the prior period (i.e. losers) tend to outperform those with high returns (i.e. winners). For each rebalancing frequency, we sort all cryptocurrencies into five equally-weighted quintile portfolios based on their period t return, *REV*, and we track their performance over the subsequent period. We also construct a loser-minus-winner portfolio that measures the difference in performance.

To evaluate the strength of the return reversal effect while controlling for differences in other cryptocurrency characteristics previously shown to influence returns, however, we estimate cross-sectional Fama and MacBeth (1973) regressions. Our primary specification is shown below in equation 2.

$$R_{i,t+1} = \beta_0 + \beta_1 REV_{i,t} + \beta_2 log(SIZE_{i,t}) + \beta_3 TURN_{i,t} + \beta_4 ILLIQ_{i,t} + e_{i,t+1} \quad (2)$$

We predict a negative β_1 coefficient, which implies that cryptocurrencies exhibit return reversals

[2]To limit possible microstructure effects we remove observations with monthly turnover of less than 1% or corresponding rates for our daily and weekly tests. The results are robust to imposing no turnover requirement or higher requirements.

[3]We exclude the cryptocurrency Vertacoin (VTA) from our analysis, as it represents an extreme outlier with a monthly time series standard deviation of at least 20 times more than any other coin; however, our results are robust to its inclusion.

even after controlling for other relevant characteristics. Subsequently, we explore the reversal effect within various subsamples to assess its primary determinants.

III. Results

Table 1 presents the results from the portfolio sorts. Panel A reveals a large and pervasive reversal effect in cryptocurrency returns, as past losers earn significantly higher average returns than past winners at the daily, weekly, and monthly rebalancing frequencies. The loser-minus-winner return spread is highly significant and increases with the length of the portfolio holding period with values of 7.37% (t = 24.23), 10.03% (t = 7.03), and 28.22% (t = 3.28) at the daily, weekly, and monthly rebalancing frequencies, respectively. Moreover, although the reversal effect is most concentrated at the daily frequency, the magnitude of the daily return spread is roughly one-quarter of the monthly return spread suggesting that any short-run effects cannot explain the longer-horizon results.[4]

Panel B presents additional performance statistics based on the time series of monthly returns, with other holding periods omitted in the interest of space, and Panels C and D report the mean and median characteristic values for the individual cryptocurrencies in each portfolio. The loser-minus-winner return difference is positive in 44 out of 54 months (81.48%) with the month-by-month return spread illustrated graphically in Figure 1.

Table 2 presents the results from our predictive cross-sectional regressions with t-statistics computed using Newey-West standard errors that are robust to heteroscedasticity and autocorrelation. For each holding period, the *REV* variable enters with a negative coefficient that is significant at the one percent level – both with and without controls for size, turnover, and illiquidity. This result is consistent with our portfolio-level analysis and suggests past losers (winners) tend to have higher (lower) subsequent returns even after accounting for important differences in other characteristics known to contribute to differences in performance.

[4]To ensure our results are not driven by outliers, we recompute average long-short portfolio returns when excluding observations in excess of 2.24 standard deviations from the mean as recommended by Aguinis et al. (2013). The loser-minus-winner return spread remains highly significant at 6.78% (t = 37.70), 8.69% (t = 9.60), and 15.72% (t = 3.54) for daily, weekly, and monthly frequencies, respectively.

Table 1
Portfolios sorted on past returns.

Portfolio:	1 (Loser)	2	3	4	5 (Winner)	1-5
Panel A: Average portfolio returns						
Daily holding period	6.25***	1.36***	0.90***	0.86***	-1.11***	7.37***
t-statistic	(22.05)	(7.70)	(6.88)	(4.28)	(-5.59)	(24.23)
Weekly holding period	12.57***	4.86***	3.55***	3.89***	2.55**	10.03***
t-statistic	(7.40)	(3.15)	(3.35)	(3.81)	(2.07)	(7.03)
Monthly holding period	39.72***	16.87**	18.81**	20.55**	11.49**	28.22***
t-statistic	(3.64)	(2.35)	(2.65)	(2.42)	(2.05)	(3.28)
Panel B: Monthly portfolio performance statistics						
Median	19.63	-0.77	6.67	6.01	-0.89	15.39
Maximum	443.57	264.82	275.26	329.63	159.06	346.93
Minimum	-41.28	-43.28	-41.10	-36.84	-47.90	-61.35
Std.Dev.	80.26	52.79	52.23	62.46	41.11	63.14
Skewness	2.88	2.55	2.60	3.01	1.26	3.05
Kurtosis	13.63	11.19	12.25	13.87	4.68	14.51
Pct. > 0	68.52	50.00	55.56	61.11	44.44	81.48
Panel C: Average monthly cryptocurrency characteristics						
REV	-38.12	-12.21	4.30	26.91	107.96	
Log(SIZE)	13.11	14.21	14.38	14.41	14.12	
TURN	0.62	0.51	0.58	0.70	0.86	
ILLIQ	11.72	5.45	4.09	6.83	12.60	
Panel D: Median monthly cryptocurrency characteristics						
REV	-34.36	-11.80	4.22	25.25	81.66	
Log(SIZE)	13.04	13.98	14.11	14.11	13.83	
TURN	0.28	0.24	0.29	0.29	0.34	
ILLIQ	0.11	0.02	0.01	0.02	0.05	

Note: Panels A and B report portfolio performance statistics, while Panels C and D report mean and median cryptocurrency characteristics. ***, **, *and* * denote significance at the 10%, 5%, and 1% level, respectively.

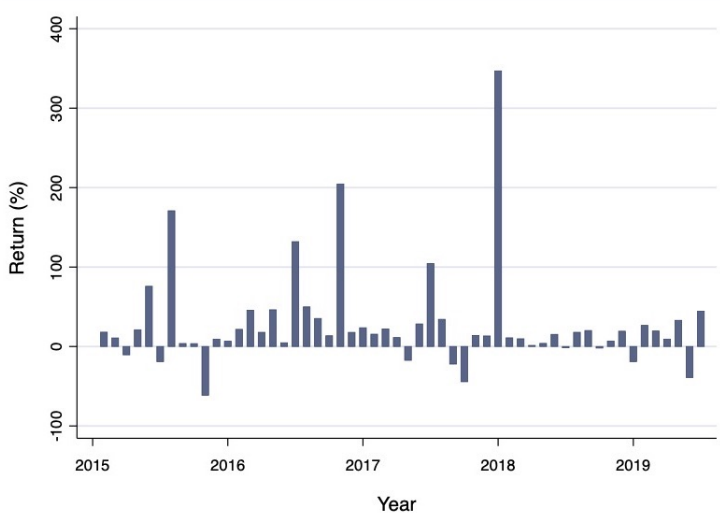

Fig. 1. Monthly return spread between past losers and winners.

Table 2
Cross-sectional return prediction regressions.

Dependent Variable: $Return_{i,t+1}$						
	Int	*REV*	*Log(SIZE)*	*TURN*	*ILLIQ*	R^2
Panel A: Daily holding period						
Daily coefficient	1.70***	-0.27***				0.086
t-statistic	(9.51)	(-17.72)				
Daily coefficient	7.15***	-0.27***	-0.42***	2.40	3.30	0.177
t-statistic	(13.22)	(-26.38)	(-13.10)	(1.20)	(1.31)	
Panel B: Weekly holding period						
Weekly coefficient	5.97***	-0.17***				0.044
t-statistic	(3.56)	(-7.04)				
Weekly coefficient	15.33***	-0.13***	-0.77***	-0.31	2.44	0.107
t-statistic	(4.71)	(-7.97)	(-4.58)	(-0.30)	(1.54)	
Panel C: Monthly holding period						
Monthly coefficient	24.05**	-0.12***				0.026
t-statistic	(2.52)	(-3.77)				
Monthly coefficient	38.91**	-0.12***	-1.39**	0.58	1.69	0.081
t-statistic	(2.60)	(-4.53)	(-2.38)	(0.26)	(1.04)	

Note: This table presents the results of Fama-MacBeth regressions estimated over the full sample period from January 2015 to June 2019. ***, **, *and* * denote significance at the 10%, 5%, and 1% level, respectively.

In Table 3, we explore the drivers of the reversal effect using a series of subsample tests. Han et al. (2018) show that investor inattention and behavioral biases have greater impact on smaller traditional currencies in emerging markets, and liquidity effects may also contribute to return reversals (Hameed and Mian, 2015). Thus, we examine the effects of both size and liquidity on return reversals in cryptocurrency markets. To better isolate their effects, we first partition the sample into two groups by market capitalization. We then double sort each set of cryptocurrencies into two portfolios by *ILLIQ* and quintile portfolios by *REV* with the results for small-cap and large-cap cryptocurrencies presented in Panels A and B, respectively. Daily holding periods indicate a significant reversal effect among all subgroups. The reversal effect remains significant with weekly holding periods among large-cap coins with low liquidity as well as small-cap coins with both high and low liquidity, suggesting both size and liquidity contribute to the effect. Lastly, we find return reversals remain significant even with monthly holding periods among both small and large illiquid coins.[5] Altogether, the evidence suggests that in addition to behavioral factors, compensation for liquidity provision helps to explain the reversal effect as investors earn substantially higher aver-

[5]The monthly loser-minus-winner return spread is also economically large among small, liquid cryptocurrencies at 12.15% (t=1.45), but the lack of statistical significance may partially reflect the reduced power of subsample tests.

Table 3
Subsample analyses.

Portfolio:	1 (Loser)	2	3	4	5 (Winner)	1-5
Panel A: Small-cap only liquidity subsamples						
Daily – Low Liquidity	17.20***	4.50***	3.40***	1.46***	-1.43**	18.63***
	(17.68)	(9.53)	(5.59)	(5.12)	(-2.12)	(15.77)
Daily – High Liquidity	3.58***	1.25***	0.89***	0.56***	-0.89***	4.48***
	(12.68)	(7.94)	(5.26)	(3.07)	(-4.05)	(14.17)
Weekly – Low Liquidity	37.69***	9.39***	11.05**	5.38***	1.38	36.31***
	(5.95)	(5.00)	(2.46)	(3.44)	(0.73)	(5.86)
Weekly – High Liquidity	10.20***	5.16***	2.76**	3.72***	2.23	7.97***
	(6.23)	(3.40)	(2.50)	(3.02)	(1.57)	(4.69)
Monthly – Low Liquidity	84.66***	21.88**	25.44**	18.56**	20.61**	64.05**
	(3.52)	(2.60)	(2.59)	(2.09)	(2.18)	(2.65)
Monthly – High Liquidity	23.33**	19.39**	21.60**	22.16**	11.18	12.15
	(2.38)	(2.10)	(2.19)	(2.47)	(1.52)	(1.45)
Panel B: Large-cap only liquidity subsamples						
Daily – Low Liquidity	4.56***	0.93***	0.56***	0.26	-1.13***	5.69***
	(6.99)	(6.22)	(3.78)	(1.53)	(-2.82)	(7.69)
Daily – High Liquidity	0.67***	0.42***	0.31***	0.27**	0.23	0.44***
	(5.05)	(3.32)	(2.59)	(2.03)	(1.40)	(2.96)
Weekly – Low Liquidity	12.93***	3.47***	1.90*	4.36***	1.93	11.00***
	(2.93)	(3.04)	(1.92)	(3.04)	(1.20)	(2.65)
Weekly – High Liquidity	1.45	2.13**	3.26***	3.63***	3.03***	-1.58
	(1.49)	(2.04)	(2.88)	(3.12)	(2.60)	(-1.61)
Monthly – Low Liquidity	25.73**	17.58**	11.68*	19.56**	6.65	19.08**
	(2.59)	(2.01)	(1.97)	(2.32)	(1.20)	(2.39)
Monthly – High Liquidity	21.46	14.34	12.78*	12.63**	20.21**	1.25
	(1.50)	(1.59)	(1.78)	(2.20)	(2.51)	(0.10)
Panel C: Implied market volatility						
Daily – Low VIX	7.11***	1.72***	1.33***	1.34***	-0.44	7.55***
	(15.64)	(5.94)	(6.98)	(5.13)	(-1.39)	(15.47)
Daily – High VIX	5.33***	0.96***	0.43**	0.34	-1.84***	7.17***
	(16.45)	(5.07)	(2.44)	(1.10)	(-7.88)	(20.55)
Weekly – Low VIX	16.78***	8.72***	6.64***	7.24***	5.97***	10.82***
	(5.90)	(3.16)	(3.84)	(4.48)	(2.92)	(4.46)
Weekly – High VIX	8.06***	0.73	0.24	0.29	-1.11	9.18***
	(4.83)	(0.66)	(0.21)	(0.26)	(-0.91)	(6.48)
Monthly – Low VIX	50.62**	28.56**	33.00**	40.26**	19.39*	31.22**
	(2.54)	(2.24)	(2.62)	(2.59)	(2.04)	(2.06)
Monthly – High VIX	28.82***	5.18	4.63	0.83	3.59	25.22***
	(3.25)	(0.84)	(0.82)	(0.18)	(0.63)	(2.98)
Panel D: Subperiod analysis						
Daily – First half	6.39***	1.51***	0.86***	0.35**	-1.57***	7.96***
	(20.28)	(5.41)	(5.61)	(2.28)	(-6.85)	(22.54)
Daily – Second half	6.12***	1.21***	0.93***	1.37***	-0.65**	6.77***
	(12.96)	(5.57)	(4.42)	(3.70)	(-2.01)	(13.70)
Weekly – First half	10.69***	2.35***	2.32***	3.41***	3.11**	7.58***
	(6.86)	(2.63)	(2.64)	(3.38)	(2.29)	(4.40)
Weekly – Second half	14.46***	7.37**	4.78**	4.36**	1.98	12.47***
	(4.79)	(2.51)	(2.48)	(2.46)	(0.96)	(5.52)
Monthly – First half	41.29***	12.26**	14.33**	10.78**	8.31	32.98***
	(3.77)	(2.28)	(2.55)	(2.05)	(1.59)	(3.07)
Monthly – Second half	38.14*	21.48	23.30*	30.31*	14.68	23.46*
	(1.99)	(1.60)	(1.77)	(1.88)	(1.47)	(1.73)

Note: This table presents the results of subsample analyses. Panels A and B include only cryptocurrencies with below and above median market capitalization, respectively, which are double sorted by Amihud illiquidity and prior returns. Panels C and D present subperiod results by dividing the full sample period based on the CBOE Volatility Index (VIX) and calendar time, respectively. ***, **, *and* * denote significance at the 10%, 5%, and 1% level.

age returns when buying previously underperforming cryptocurrencies, particularly in less liquid markets.

Nagel (2012) argues that return reversal strategy profits among stocks are highly correlated with the CBOE Volatility Index (VIX), as it reflects the extent of turmoil in financial markets and should be related to the liquidity premium. Panel C divides our sample into periods when the VIX was above and below its sample median to test for a similar effect in cryptocurrency markets. Finally, because average cryptocurrency liquidity has increased over time as markets have matured, Panel D divides our sample period into halves by calendar time. The results in Panels C and D indicate no meaningful effect on return reversals.[6] Given the lack of a significant decline in return predictability, previously documented behavioral factors likely still contribute to the reversal effect such as overreaction (Jegadeesh and Titman, 1995), speculative bubbles (Cheah and Fry, 2015), and herding behavior (Bouri et al., 2019a).

IV. Conclusion

We explore a panel dataset featuring 200 cryptocurrencies that began trading before 2015 and provide evidence of a significant reversal effect in cryptocurrency returns. Past losers outperform past winners in the following period by economically large and statistically significant margins and with notable regularity. This result holds for daily, weekly, and monthly holding periods, and cross-sectional regressions yield similar evidence when controlling for differences in market capitalization, turnover, and illiquidity. Our subsample analyses indicate the effect likely reflects a combination of both compensation for liquidity provision and market inefficiency, as return reversals are most pronounced among small-cap and illiquid coins but are only significant at shorter holding periods for the largest capitalization and most liquid coins. Given our results, it appears that the broader cryptocurrency market still exhibits significant return predictability and that greater market depth is needed to help stabilize prices.

[6] In unreported tests, we also partition the sample using the Global and U.S. Economic Policy Uncertainty (EPU) Indexes and find similar results with a large and significant reversal effect following periods of both high and low uncertainty.

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Appendix A

Table A1
Cryptocurrencies ranked by market capitalization as of December 28, 2014.

Rank: 1–25	26–50	51–75	76–100	101–125	126–150	151–175	176–200
BTC	NXTV	UTC	NOO	DVC	BBR	NOXT	XMG
XRP	BCN	MONA	MAX	BTM	MLS	HTML5	CKC
XPY	QRK	SDC	VTC	XST	NAUT	NAV	RBY
LTC	NOTE	XDN	CURE	XDP	PINK	EAC	EXCL
BTS	DEX	NXTcoinsco	OPAL	ZCC	DEM	FIBRE	DIME
MAID	XUSD	GRCX	HYPER	XCR	FRC	BLU	COL
XLM	FTC	NVC	EMC	BOST	HZ	CBX	NXTI
DOGE	PANGEA	XC	APC	VASH	BOOM	GAIA	TIT
NXT	BITUSD	URO	FLDC	GSX	NET	UNC	SSD
PPC	RDD	BILS	BITS*	START	HYP	TAG	CAP
XCP	XPM	UNO	BAY	MMNXT	DORCS	JPC	SRC
DASH	MTC	QORA	ARCH	MOON	HRNXT	RIC	CHASH
NMC	ETC	VRC	SYS	DMD	HRL	XAI	CRYPT
FC2	NXTTY	I0C	GLC	USDE	KARMA	VIOR	EFL
NSR	JLH	ZET	BITCNY	DGB	CLR	BYC	MMC
UNITY	VIA	SKYNET	MRKT	XWT	SUPER	AUR	XQN
YBC	IXC	CNMT	ATOMIC	CCN	QSLV	TEK	IOC
XMR	PND	ANC	NODE	TRC	XWC	AM	TES
BANX	JINN	FAIR	MINT	SYNC	PTC	BITS**	XVG
USNBT	NXTprivacy	XTC	POT	XCH	FLT	CZC	NAS
SJCX	PTS	DICE	DGC	LXC	BEAR	ABY	GHC
BLK	IFC	CANN	FIMK	NEM	EMC2	MAZA	SEED
SWARM	CLAM	NLG	SLR	NOBL	TIPS	LTCD	VTA
BTCD	MEC	Privatebet	MGW	ZEIT	XMY	CARBON	AC
OMNI	WDC	BURST	SPR	HBN	TIX	RIN	ECC

Note: This table presents the symbols of the top 200 cryptocurrencies by market capitalization (from top to bottom) as of December 28, 2014. BITS* is used to denote Bitswift while BITS** denotes Bitstar, since both share the same listed abbreviation.