



# Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume

Dirk G. Baur<sup>a,\*</sup>, Daniel Cahill<sup>a</sup>, Keith Godfrey<sup>b</sup>, Zhangxin (Frank) Liu<sup>a</sup>

<sup>a</sup> UWA Business School, The University of Western Australia, 35 Stirling Highway, Crawley, WA, 6009, Australia

<sup>b</sup> University of Alberta, Canada

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## ABSTRACT

There is a large literature that analyzes time-specific anomalies in equity markets such as the Monday effect, the January effect and the Halloween effect. This study reports intra-day time-of-day, day-of-week, and month-of-year effects for Bitcoin returns and trading volume. Using more than 15 million observations from seven global and continuously-traded Bitcoin exchanges, we find time-specific anomalies in returns but no persistent effects across time. In contrast, we find persistent differences in trading activity across all exchanges with lower activity during local evening hours and on weekends. The results suggest that both retail and institutional investors are actively trading Bitcoin.

## 1. Introduction

Bitcoin and the blockchain technology was introduced as a peer-to-peer cash system in 2008 (Nakamoto, 2008). Trading on exchanges commenced a couple of years later and many studies analyze data with sampling periods starting in 2011. Consequently, the literature on Bitcoin is relatively young. Yermack (2013), Kristoufek (2013), Böhme et al. (2015), Dwyer (2015) and Selgin (2015) were among the first to study Bitcoin and its interaction with financial markets. Kristoufek (2013) studies the relationship between search queries and the price of Bitcoin and argues that Bitcoin is driven by short-term investors, speculators, and trend followers and has no intrinsic value. Cheah and Fry (2015) support this idea and find that bubble characteristics exist in Bitcoin arguing that its fundamental price is zero. More recent research has looked at specific features of Bitcoin (e.g. see Klein et al., 2018; Smales, 2019 for the potential safe haven feature of Bitcoin), price clustering (e.g. see Li et al., 2018) and the investibility of Bitcoin (e.g. see Dyhrberg et al., 2018).

The focus of this paper is an investigation of the time-dependent anomalies in Bitcoin return and trading volume. We do not attempt to discuss whether Bitcoin is in a bubble or what its fundamental value should be. We aim to identify specific return and trading volume patterns over an average trading day, over an average week and over an average month. More specifically, we analyze if Bitcoin investors trade differently when major stock exchanges are open compared to when they are closed (e.g. at night or over the weekend) or between June and September during the Northern hemisphere summer months consistent with a “Halloween effect”. To answer these types of questions, we analyze time-of-the-day (ToD), day-of-the-week (DoW) and month-of-the-year (MoY) patterns in Bitcoin returns and trading volume.

\* Corresponding author.

E-mail addresses: [dirk.baur@uwa.edu.au](mailto:dirk.baur@uwa.edu.au) (D.G. Baur), [daniel.cahill@uwa.edu.au](mailto:daniel.cahill@uwa.edu.au) (D. Cahill), [keith1@ualberta.ca](mailto:keith1@ualberta.ca) (K. Godfrey), [frank.liu@uwa.edu.au](mailto:frank.liu@uwa.edu.au) (Z. (Frank) Liu).

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Given the conflict between efficient pricing and the seemingly irrational demand for Bitcoin, in particular during 2017, we look for any consistent patterns in returns and thus profit opportunities that imply that investors have not been exploiting these anomalies rationally. Since Bitcoin is a relatively new and unregulated asset, it is possible that the market has been dominated by retail investors who may not have the capacity to exploit anomalies and thereby eliminate them. The fact that Bitcoin is continuously and globally traded makes an analysis of time-of-day, day-of-week, and month-of-year effects particularly interesting to study as different exchanges may display different effects based on the geographical location of the exchange and the fiat currency with which the Bitcoin is exchanged. For example, Chinese investors trading in yuan may be different than Japanese investors trading in yen who may be different from European investors trading in euro. The fact that Bitcoin is traded in different currencies and in different geographic locations allows a deeper analysis than that for an asset or entire asset class traded in a single currency or on one exchange.”

Our analysis of time-of-day, day-of-week and month-of-year patterns shows evidence of time-specific anomalies such as a lower weekend volume effect and a higher Monday return effect which are consistent with findings reported for currency markets. However, since Bitcoin trading hours resemble traditional currency market trading hours but are distinctively different from non-continuous equity market trading we do not attempt to infer whether Bitcoin behaves more like a currency or an asset. It is also possible that continuous “24/7” trading leads to these anomalies irrespective of the type of asset class.

We find increased trading activity on Bitcoin exchanges at times when European stock exchanges are open and lower trading activity between midnight and the early morning (local time) on most exchanges. We also find that Bitcoin exchanges denominated in US dollars and euro display stronger patterns compared with exchanges denominated in Japanese yen and Chinese yuan. We use heatmaps to illustrate patterns in returns and trading volume both across time and across exchanges. The results support the view that Bitcoin markets are at least weak-form efficient since we do not observe any persistent pattern in returns over across years that could be exploited based on historical information. The findings in volume also suggest that Bitcoin is not traded by retail investors only and that institutional investors play a significant role on US dollar and euro exchanges.

The paper is structured as follows. In [Section 2](#), we briefly review the existing literature and develop our hypotheses. In [Section 3](#), we describe the data and methodology. [Section 4](#) presents the results of the analysis. [Section 5](#) summarizes the findings and provides concluding remarks.

## 2. Literature review

The day-of-the-week effect in stock markets is well documented in the literature but we are not aware of any similar analysis for Bitcoin and other cryptocurrency markets. In equity markets, [French \(1980\)](#) reported higher than average stock returns on the last trading day of the week (Friday) and lower than average on the first trading day (Monday). Studies have identified differences in the day-of-the-week phenomenon depending on geography (see [Gibbons and Hess, 1981](#); [Lakonishok and Levi, 1982](#); [Jaffe and Westerfield, 1985](#)). [Lakonishok and Maberly \(1990\)](#) investigate the trading behaviour between individual and institutional traders to explain day-of-the-week effects on the NYSE. They find that there is lower trading volume on Mondays which coincides with greater retail activity on the same day. Their results suggest that the overall lower trading activity is driven by lower institutional trades. [Chan et al. \(2004\)](#) find that the Monday effect is insignificant in their sample, and suggest that later periods have greater institutional trading. If retail traders dominate the cryptocurrency market, we expect to see greater volume traded outside of typical work hours, as their ability to process information and make investment decisions may be limited during their working hours. In more recent studies on time-dependent anomalies, [Zhang et al. \(2017\)](#) use an international sample to analyze day-of-the-week anomalies in different markets, while ([Birru, 2018](#)) shows predictable variation in cross-sectional returns depending on the day of the week.

[Bollerslev and Domowitz \(1993\)](#) investigate the behaviour in quote arrivals and bid-ask spread on the deutsche mark-dollar exchange and show that market activity is consistent over weekdays, with notable declines in activity over the weekend. [Akram et al. \(2008\)](#) and [Kaul and Sapp \(2009\)](#) also find lower weekend trading volume in the FX market. If Bitcoin behaves like a major currency we should expect to see higher returns at the beginning of the week, and the volume traded should be lower over the weekend compared with weekdays.

## 3. Data

We obtained Bitcoin price and volume data in USD, CNY, JPY, and EUR from [kaggle.com](#), which provides intra-day prices from several exchanges at a 1-min frequency. [Table 1](#) contains the name of each exchange, the currency Bitcoin is traded in, the sample period and the number of observations. The total number of observations over all exchanges exceeds 15 million. The time stamps of the data are converted into universal coordinated time (UTC).

[Table 2](#) presents the summary statistics of the log returns and the log volume (number of bitcoins traded) for 1-min, 1-h, and 1-day intervals for each exchange. The mean and standard deviations of returns and the mean and the standard deviations of trading volume are smallest for the 1-min frequencies and increase monotonically for the lower frequency 1-h and 1-day returns. The Bitstamp exchange displays the largest mean return and Kraken (USD) the smallest mean return.

**Table 1**

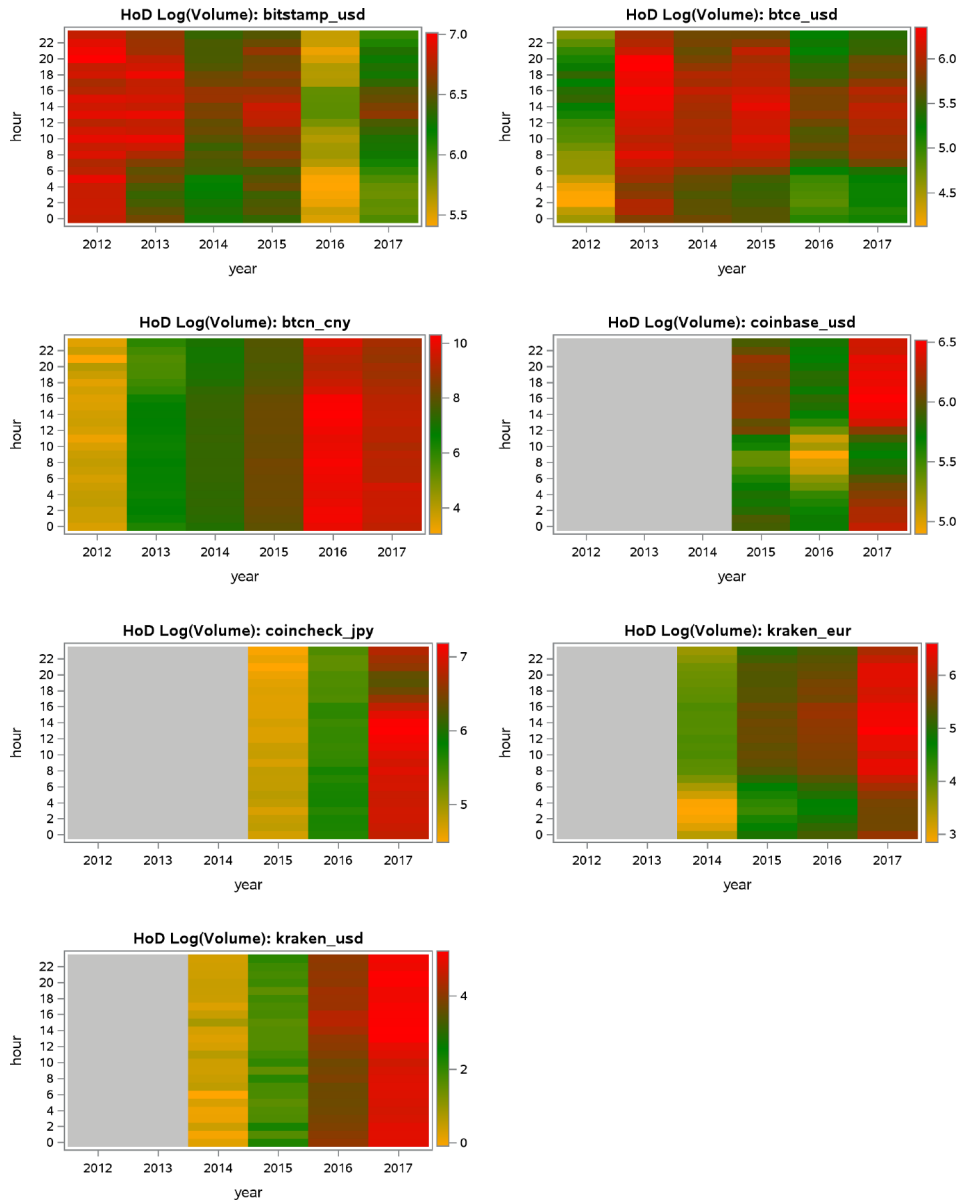
**Summary of data sets.** This table displays the exchanges, denominated currency, and data range. The frequency of the data is per minute, and it extends from 2011 to 2017.

Exchange	Currency	Start date	End date	Obs.
BitStamp	USD	31 Dec 2011	20 Oct 2017	3,045,857
BTCE	USD	31 Dec 2011	31 May 2017	2,751,594
CoinBase	USD	1 Dec 2014	20 Oct 2017	1,459,076
Kraken	USD	7 Jan 2014	31 May 2017	1,706,404
BTCN	CNY	31 Dec 2011	31 May 2017	2,746,814
Coincheck	JPY	31 Oct 2014	20 Oct 2017	1,562,030
Kraken	EUR	8 Jan 2014	31 May 2017	1,716,589

**Table 2**

**Summary statistics for Bitcoin returns and trading volume.** This table shows the descriptive statistics for log returns and log volume (Bitcoin traded) for each exchange at 1-min, 1-h, and 1-day frequency.

Type	Exchange	Mean	Std Dev	Max	Min	Freq
Return	Bitstamp_USD	0.0002%	0.54%	5.96%	−5.97%	1-min
	BTCE_USD	0.0002%	0.26%	1.02%	−1.18%	1-min
	BTCN_CNY	0.0002%	0.38%	3.79%	−3.79%	1-min
	Coinbase_USD	0.0002%	1.24%	9.67%	−9.89%	1-min
	Coincheck_JPY	0.0002%	0.16%	4.34%	−3.20%	1-min
	Kraken_EUR	0.0001%	0.15%	1.36%	−2.20%	1-min
	Kraken_USD	0.0001%	0.20%	1.99%	−2.66%	1-min
	Bitstamp_USD	0.0140%	1.22%	29.9%	−34.7%	1-h
	BTCE_USD	0.0134%	1.21%	37.6%	−47.4%	1-h
	BTCN_CNY	0.0136%	1.19%	34.6%	−38.3%	1-h
	Coinbase_USD	0.0114%	1.11%	47.0%	−56.5%	1-h
	Coincheck_JPY	0.0114%	0.87%	17.9%	−26.6%	1-h
	Kraken_EUR	0.0039%	0.75%	14.7%	−20.2%	1-h
	Kraken_USD	0.0031%	1.15%	22.9%	−25.3%	1-h
	Bitstamp_USD	0.3366%	4.83%	33.7%	−66.4%	1-day
	BTCE_USD	0.3197%	4.72%	34.6%	−69.9%	1-day
	BTCN_CNY	0.3259%	4.99%	60.2%	−45.1%	1-day
	Coinbase_USD	0.2730%	4.61%	53.2%	−77.3%	1-day
	Coincheck_JPY	0.2743%	3.89%	29.1%	−31.9%	1-day
	Kraken_EUR	0.0940%	3.37%	16.0%	−23.5%	1-day
	Kraken_USD	0.0745%	3.84%	22.4%	−29.2%	1-day
Volume	Bitstamp_USD	11.1	36.4	5,853.9	0.00E+00	1-min
	BTCE_USD	7.6	23.7	999.0	0.00E+00	1-min
	BTCN_CNY	143.1	747.0	81,908.0	0.00E+00	1-min
	Coinbase_USD	6.2	15.3	1,563.3	1.00E-08	1-min
	Coincheck_JPY	6.9	17.7	1,205.1	1.00E-08	1-min
	Kraken_EUR	5.4	13.7	1,012.7	1.00E-06	1-min
	Kraken_USD	3.5	9.4	661.5	1.00E-07	1-min
	Bitstamp_USD	667.6	1,057.9	48,212.1	9.27E-02	1-h
	BTCE_USD	314.4	562.2	15,899.0	0.00E+00	1-h
	BTCN_CNY	5,910.7	27,352.0	845,694.0	1.00E-03	1-h
	coinbase_USD	374.1	551.1	31,505.5	1.11E-03	1-h
	Coincheck_JPY	413.1	740.9	15,042.1	1.09E-03	1-h
	Kraken_EUR	197.4	318.4	9,455.5	2.80E-04	1-h
	Kraken_USD	53.4	111.2	3,545.3	1.53E-05	1-h
	Bitstamp_USD	16,004.6	13,135.9	150,486.9	0.1	1-day
	BTCE_USD	7,400.1	9,065.8	145,635.6	6.7	1-day
	BTCN_CNY	130,788.5	484,467.7	5,914,403.3	27.3	1-day
	Coinbase_USD	8,965.0	7,705.8	165,763.0	1.7	1-day
	Coincheck_JPY	9,906.2	14,116.7	169,159.4	10.2	1-day
	Kraken_EUR	4,719.9	5,291.2	39,758.9	24.5	1-day
	Kraken_USD	846.7	1,626.0	14,233.5	3.81E-05	1-day

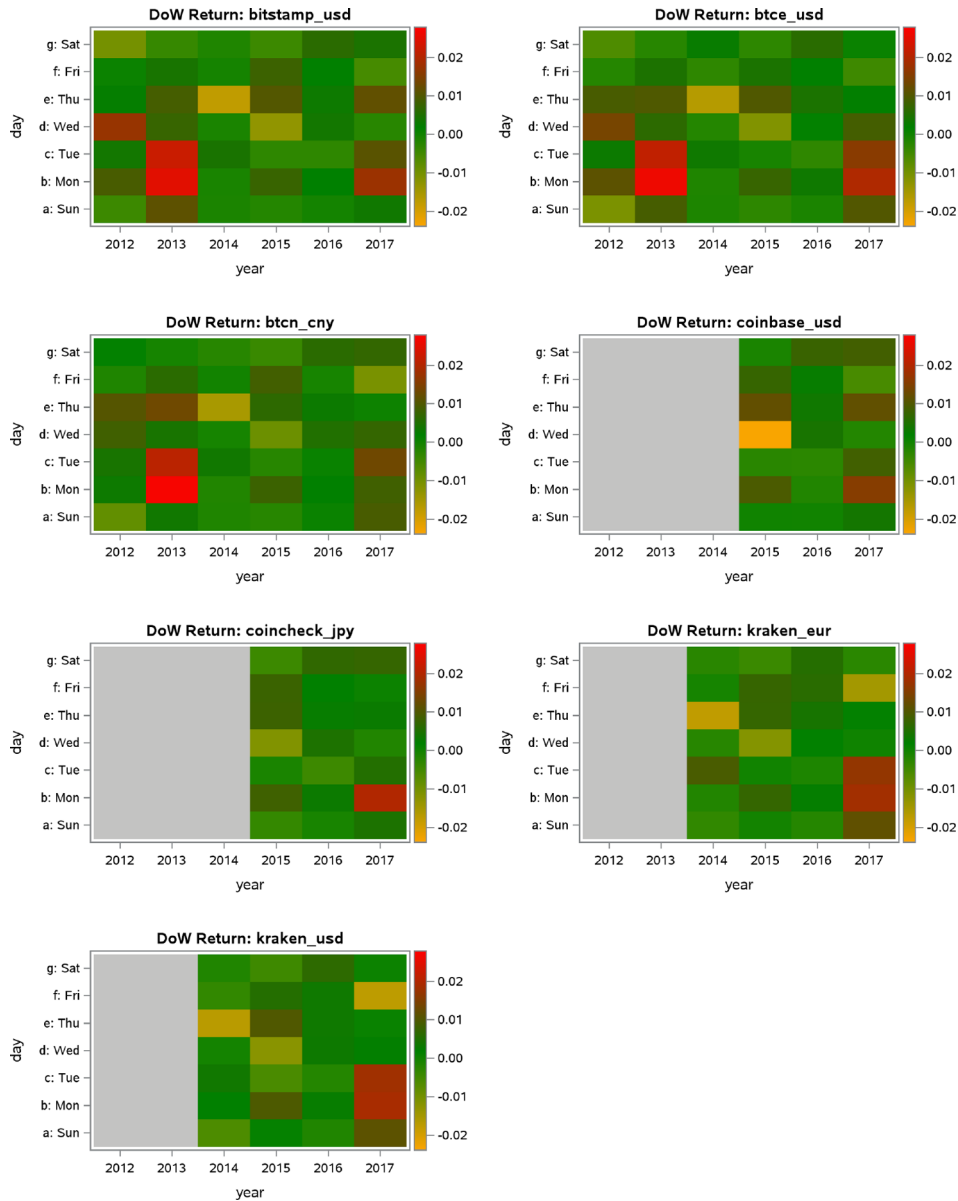


**Fig. 1. Log volume time of day (ToD).** Heatmaps of ToD volume (number of Bitcoins) traded for seven exchanges: Bitstamp (USD); BTCE (USD); BTCN (CNY); Coinbase (USD); Coincheck (JPY); Kraken (EUR); and Kraken (USD). The denominated currency for each exchange is given in parentheses. The time standard is Universal Coordinated Time (UTC). 0 corresponds to the first hour of the day (12am), 1 is the second hour of the day (1am), and so on. The colour scheme displays greater trading volume in areas marked red, and lower trading volume marked yellow. Volume is the hourly average log volume for each hour during the year traded. The volume scale is given to the right of the heatmap for each exchange. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

#### 4. Empirical analysis

We use heatmaps to analyze specific time-of-day (ToD), day-of-week (DoW) and month-of-year (MoY) anomalies in returns and trading volume. The heatmaps illustrate similarities and differences in returns and trading volume across time and across exchanges and help to identify both consistent and transient patterns.<sup>1</sup> If anomalies are persistent across time we infer that investors are not aware of such anomalies or do not have the capacity to profit from them. In contrast, if anomalies are transient we assume that

<sup>1</sup> The hour (time of day), day (day of week) or month (month of year) is plotted on the y-axis, whereas the year is plotted on the x-axis. The colour scheme of each box in the heatmap represents the magnitude of the corresponding variable in each Figure. Generally speaking, the warmer the colour (more red) the larger the magnitude.



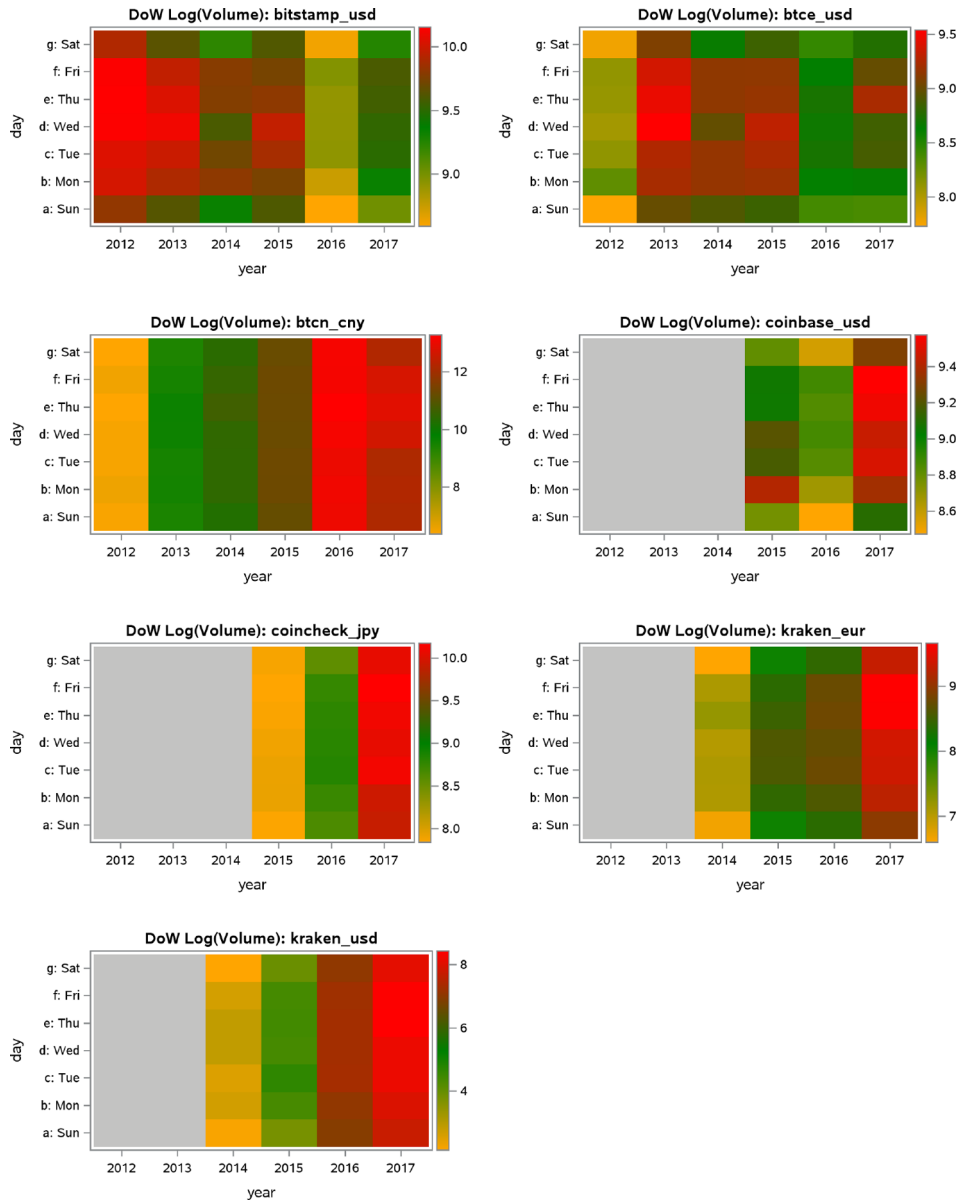
**Fig. 2. Return day of week (DoW).** Heatmaps of DoW returns for seven exchanges: Bitstamp (USD); BTCE (USD); BTCN (CNY); Coinbase (USD); Coincheck (JPY); Kraken (EUR); and Kraken (USD). The denominated currency for each exchange is given in parentheses. The time standard is Universal Coordinated Time (UTC). The colour scheme displays greater return in areas marked red, and lower return marked yellow. Return is the daily average log return for each day during the week for each year traded. The return scale is given to the right of the heatmap for each exchange. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

investors trade on anomalies and eliminate them. We also use statistical tests to evaluate the significance of the differences in returns and volume during the day, week, and month.

#### 4.1. Time-of-day (ToD) effects

This section discusses the time-of-day return and volume heatmaps. The returns do not show any clear or persistent patterns across years which suggests that transient ToD return effects across exchanges are either driven by specific events or quickly detected by investors and arbitrated away. For example, the effect found in Bitstamp (USD) in the 9th hour (see Fig. 4 in the Appendix) appears to be driven by high returns in 2012 and 2013.

In contrast, the volume time-of-day effects exhibit more variation within a day and across years Fig. 1. For example, some exchanges are more active during specific periods of the day, which often coincides with trading in stock exchanges and periods when



**Fig. 3. Log volume day of week (DoW).** Heatmaps of DoW volume (number of Bitcoins) traded for seven exchanges: Bitstamp (USD); BTCE (USD); BTCN (CNY); Coinbase (USD); Coincheck (JPY); Kraken (EUR); and Kraken (USD). The denominated currency for each exchange is given in parentheses. The time standard is Universal Coordinated Time (UTC). The colour scheme displays greater volume in areas marked red, and lower volume marked yellow. Volume is the daily average log volume for each day during the week for each year traded. The volume scale is given to the right of the heatmap for each exchange. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

potential investors are more likely to be awake. Such periods are 0800–1600 h UTC at Bitcoin exchange in US dollars, 1200–2400 h UTC at Coinbase in USD and 0800–2400 h UTC at Kraken in EUR

The pattern for the Japanese and Chinese exchanges indicate relatively constant trading activity throughout the day. The average investor appears to have no preferred time to trade in contrast to the average investor trading in US dollars and euro. This finding supports the idea that these markets are dominated by retail investors and is consistent with anecdotal and empirical evidence (e.g. see [Bloomberg, 2017](#); [Financial Times, 2017](#) and [Hirose et al., 2009](#)).

#### 4.2. Day-of-week (DoW) effects

The heatmaps for the day-of-week effects are presented in [Fig. 2](#) for returns and in [Fig. 3](#) for volume. The returns show no

**Table 3**  
**Mean difference in returns by day-of-week.** This table shows the differences in the means of the log returns at 1-min, 1-h, and 1-day frequencies for each day of the week. The t-statistics are in parentheses and \*, \*\*, \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

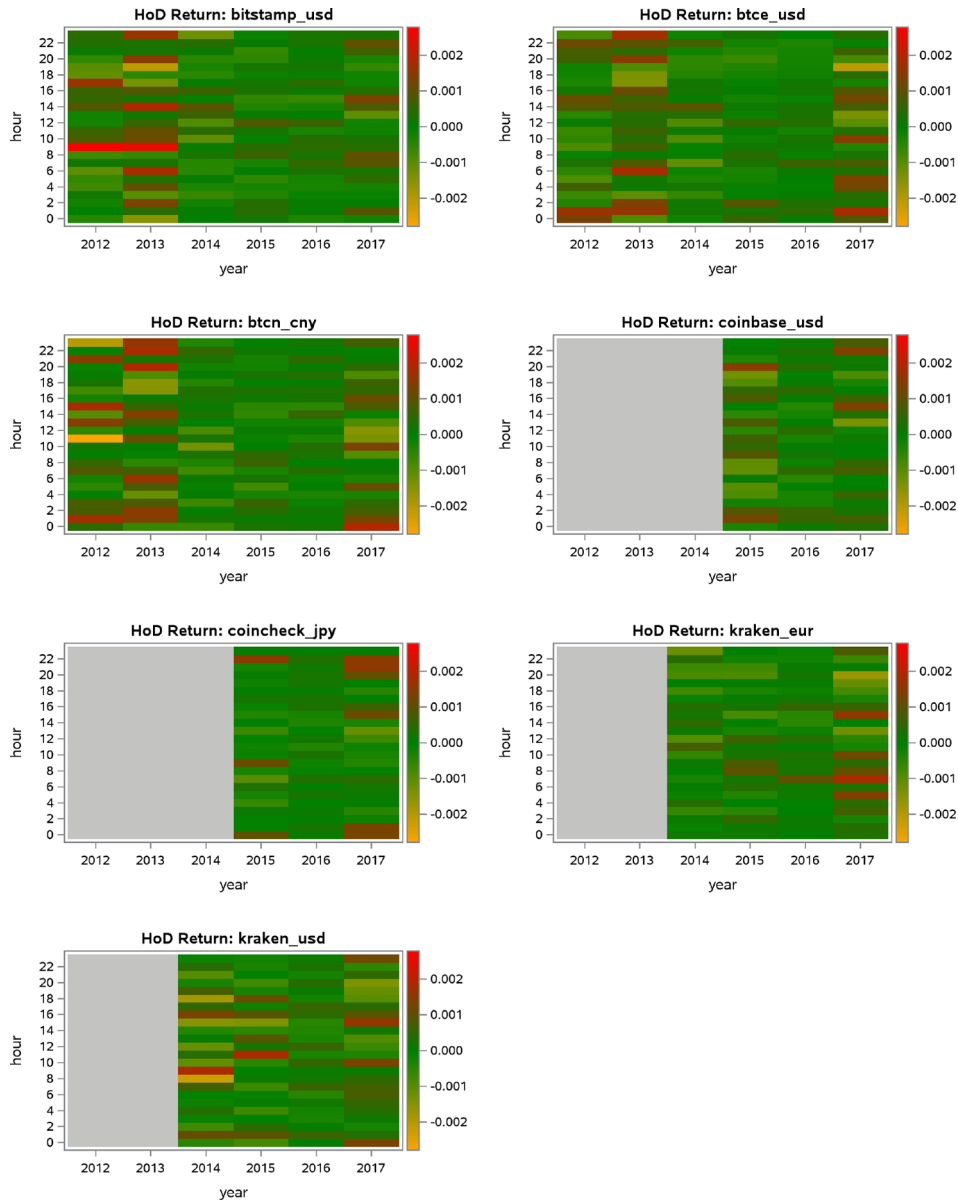
Return Freq	Day	Bitstamp_USD	BTCE_USD	BTCN_CNY	Coinbase_USD	Coincheck_JPY	Kraken_EUR	Kraken_USD
		Mean	Mean	Mean	Mean	Mean	Mean	Mean
		t-value	t-value	t-value	t-value	t-value	t-value	t-value
1-min	Sun	0.0001%	0.0000%	0.0000%	0.0001%	0.0000%	0.0000%	0.0000%
	Mon	0.0007%	0.0007%	0.0006%	0.0005%	0.0007%	0.0003%	0.0005%
	Tue	0.0004%	0.0004%	0.0005%	0.0001%	0.0000%	0.0003%	0.0001%
	Wed	0.0002%	0.0002%	0.0002%	−0.0005%	−0.0002%	−0.0002%	−0.0002%
	Thu	0.0002%	0.0002%	0.0003%	0.0006%	0.0003%	−0.0001%	0.0000%
	Fri	0.0001%	0.0001%	0.0001%	0.0001%	0.0003%	0.0001%	0.0000%
	Sat	−0.0001%	0.0000%	0.0001%	0.0004%	0.0002%	0.0000%	0.0000%
1-h	Sun	0.0057%	−0.0019%	−0.0018%	0.0061%	0.0005%	0.0008%	−0.0002%
	Mon	0.0418%	0.0427%	0.0338%	0.0311%	0.0415%	0.0204%	0.0287%
	Tue	0.0254%	0.0241%	0.0273%	0.0038%	−0.0003%	0.0205%	0.0057%
	Wed	0.0104%	0.0100%	0.0095%	−0.0293%	−0.0107%	−0.0146%	−0.0100%
	Thu	0.0126%	0.0147%	0.0151%	0.0376%	0.0200%	−0.0065%	−0.0028%
	Fri	0.0083%	0.0050%	0.0075%	0.0087%	0.0160%	0.0089%	0.0011%
	Sat	−0.0060%	−0.0007%	0.0039%	0.0217%	0.0131%	−0.0021%	0.0014%
1-day	Sun	0.1376%	−0.0453%	−0.0437%	0.1465%	0.0112%	0.0190%	−0.0055%
	Mon	1.0008%	1.0199%	0.8062%	0.7453%	0.9967%	0.4893%	0.6856%
	Tue	0.6099%	0.5795%	0.6540%	0.0919%	−0.0081%	0.4917%	0.1363%
	Wed	0.2496%	0.2375%	0.2268%	−0.31%	−0.2564%	−0.3480%	−0.2394%
	Thu	0.3023%	0.3517%	0.3623%	0.9022%	0.4797%	−0.1560%	−0.0667%
	Fri	0.1988%	0.1186%	0.1788%	0.2063%	0.3814%	0.2131%	−0.0253%
	Sat	−0.1436%	−0.0160%	0.0925%	0.5209%	0.3132%	−0.0497%	0.0320%

Table 4

Mean difference in Bitcoin volume by day-of-week. This table shows the differences in the means of the log volume (number of Bitcoins traded) at 1-min, 1-h, and 1-day frequencies for each day of the week. The t-statistics are in parentheses and \*, \*\*, \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Volume	Day	Bitstamp_ USD	BTCE_USD	BTCN_CNY	Coinbase_ USD	Coincheck_ JPY	Kraken_ EUR	Kraken_ USD
Freq		Mean	Mean	Mean	Mean	Mean	Mean	Mean
		t-value	t-value	t-value	t-value	t-value	t-value	t-value
1-min	Sun	8.65	6.21	130.44	4.59	6.10	4.35	2.81
	Mon	11.22	7.76	133.89	6.82	6.41	4.96	3.06
	Tue	11.93	7.94	126.32	6.76	7.37	5.60	3.50
	Wed	12.54	8.48	148.44	6.82	7.05	5.67	3.61
	Thu	12.41	8.45	168.09	6.65	7.19	6.08	3.85
	Fri	12.18	7.98	150.74	6.84	7.50	6.03	3.78
	Sat	8.97	6.14	143.21	5.15	6.58	4.95	3.49
1-h	Sun	518.79	244.31	5,283.06	275.28	365.87	140.86	40.35
	Mon	673.32	326.23	5,492.73	409.07	384.38	189.89	45.87
	Tue	715.90	336.56	5,229.93	405.58	442.25	218.32	56.56
	Wed	752.41	358.02	6,156.32	408.98	423.14	217.32	56.86
	Thu	744.31	356.09	6,995.32	398.86	431.52	233.65	62.09
	Fri	730.91	335.72	6,355.90	410.46	449.89	224.39	61.09
	Sat	538.36	244.38	5,855.26	308.80	394.83	157.88	50.12
1-day	Sun	12,451.00	5,731.02	115,899.48	6,606.61	8,780.77	3,367.49	603.83
	Mon	16,128.63	7,698.17	121,778.83	9,817.57	9,225.10	4,537.39	736.34
	Tue	17,181.60	7,945.15	116,184.58	9,725.54	10,614.12	5,221.70	924.62
	Wed	18,057.87	8,350.29	136,113.16	9,815.57	10,155.38	5,167.28	907.08
	Thu	17,863.55	8,396.27	156,203.30	9,561.74	10,356.37	5,602.18	1,009.16
	Fri	17,435.71	7,931.42	140,479.21	9,786.02	10,727.02	5,380.17	992.05
	Sat	12,920.68	5,763.86	128,966.98	7,400.41	9,475.94	3,775.17	757.06

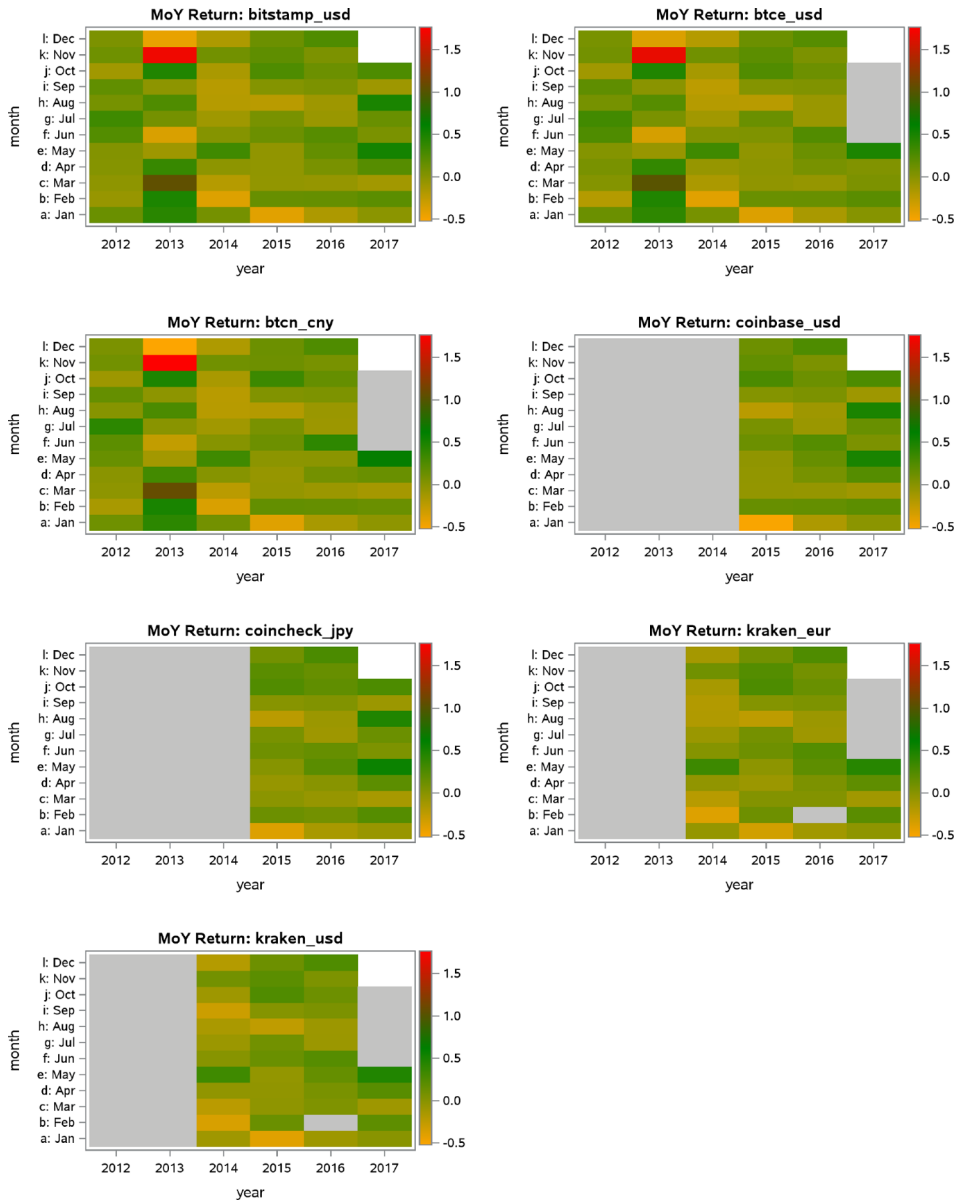




**Fig. 4. Return time of day (ToD).** Heatmaps of ToD returns for seven exchanges: Bitstamp (USD); BTCE (USD); BTCN (CNY); Coinbase (USD); Coincheck (JPY); Kraken (EUR); and Kraken (USD). The denominating currency for each exchange is given in parentheses. The time standard is Universal Coordinated Time (UTC). 0 corresponds to the first hour of the day (12am), 1 is the second hour of the day (1am), and so on. The colour scheme displays greater return in areas marked red, and lower returns marked yellow. Return is the average hourly return for each hour during the year traded. The return scale is given to the right of the heatmap for each exchange. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

consistent pattern on any day across years or over two subsequent years. Mondays and to a lesser extent Tuesdays are the only days that show higher than average returns in 2013 and 2017 across exchanges.

In contrast, Fig. 3 displays a noticeably higher trading volume on weekdays, reflected in the darker shades between Monday and Friday for most exchanges except the Chinese and the Japanese exchanges. The lower weekend trading volume effect is consistent across the sample period for four out of seven exchanges. Since retail investors can be assumed to trade every day or do not decrease their trading on weekends, the results support the hypothesis that the global Bitcoin market is not dominated by retail investors and that institutional investors also play a role.



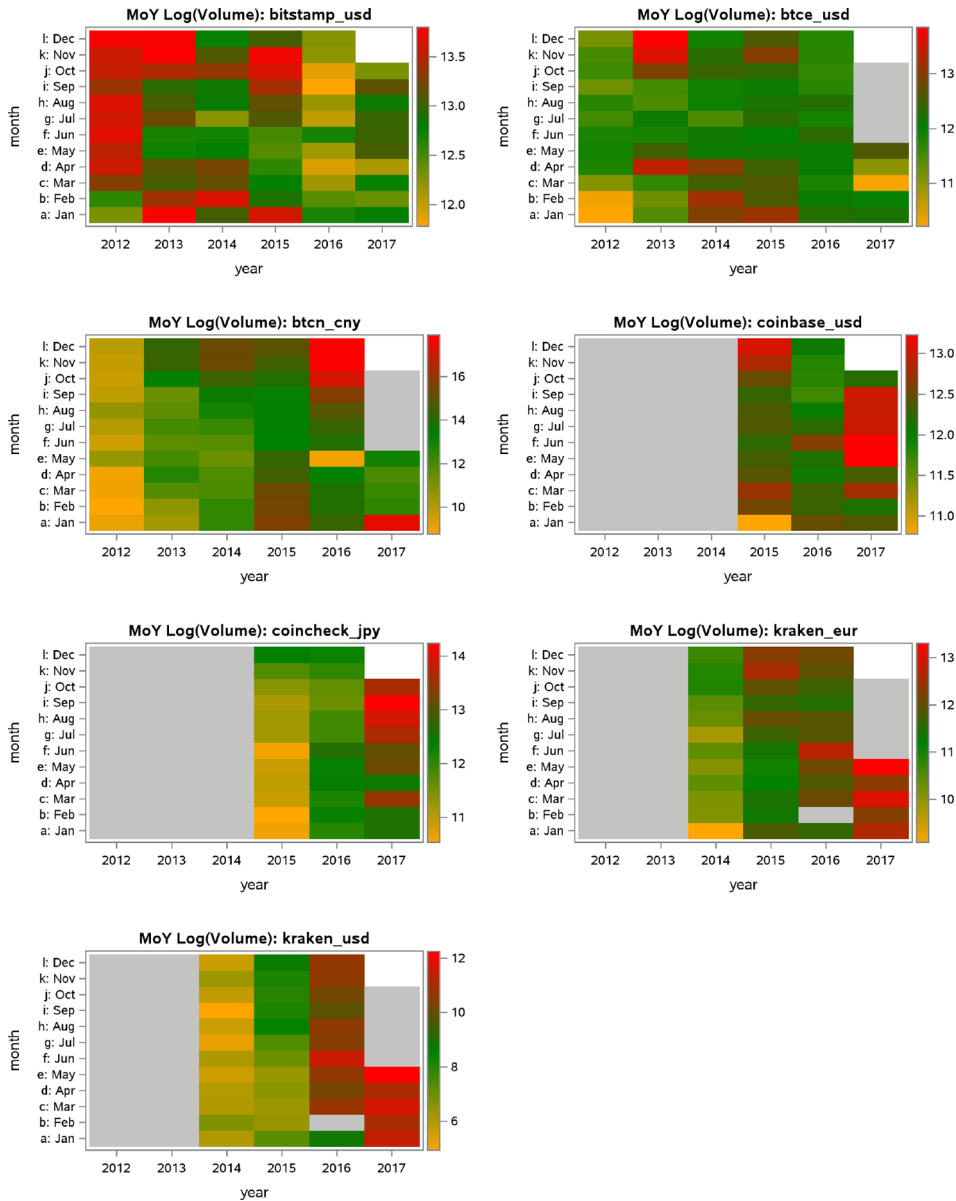
**Fig. 5. Return month of year (MoY).** Heatmaps for MoY returns for seven exchanges: Bitstamp (USD); BTCE (USD); BTCN (CNY); Coinbase (USD); Coincheck (JPY); Kraken (EUR); and Kraken (USD). The denominating currency for each exchange is given in parentheses. The time standard is Universal Coordinated Time (UTC). The colour scheme displays greater return in areas marked red, and lower return marked yellow. Return is the monthly average log return for each month during the year for each year traded. The return scale is given to the right of the heatmap for each exchange. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

#### 4.3. Month-of-year (MoY) effects

The heatmaps for the month-of-year effects (see Figs. 5 and 6 in the Appendix) do not display any clear patterns in MoY returns across time and Bitcoin exchanges. However, there is some evidence for lower trading volume in Northern hemisphere summer months for Bitstamp and BTCE consistent with the findings reported in Hong and Yu (2009) for equity markets. If market participants are on holiday, there is less trading volume. The heatmaps also indicate increased trading activity in selected years and exchanges in January but the evidence is inconsistent and thus too weak to identify a “January effect”.

#### 4.4. Means test

This section reports the statistical differences-of-means tests. Consistent with the heatmaps there is no apparent pattern or



**Fig. 6. Log volume month of year (MoY).** Heatmaps of MoY volume (number of Bitcoins) traded for seven exchanges: Bitstamp (USD); BTCE (USD); BTCN (CNY); Coinbase (USD); Coincheck (JPY); Kraken (EUR); and Kraken (USD). The denominating currency for each exchange is given in parentheses. The time standard is Universal Coordinated Time (UTC). The colour scheme displays greater volume in areas marked red, and lower volume marked yellow. Volume is the monthly average log volume for each month during the year for each year traded. The volume scale is given to the right of the heatmap for each exchange. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

anomaly in returns across the sample period on any exchange and a clear pattern in lower and higher trading activity for specific hours of the day depending on the exchange. Trading volume is generally lower during evening hours or non-peak hours (which varies across exchanges due to their different geographical locations) and higher at times when the stock exchange is open. For brevity here, the results are reported in the Appendix in [Tables 5 and 6](#).

[Tables 3 and 4](#) present the results for day of the week returns and trading volume for 1-min, 1-h and daily frequencies. At the 1-h and 1-day frequencies we observe a Monday effect across most exchanges, where the difference in the average return on Monday is significantly greater than any of the other days of the week. In addition to the higher returns on Mondays, Bitstamp (USD) and BTCE (USD) show significantly lower returns on Saturday at the 5% and 10% levels respectively.

Whilst these results are in contrast to the findings for equity markets by [French \(1980\)](#), the higher than average returns on Mondays are consistent with the results for currency markets ([McFarland et al., 1982](#)). The statistical tests for differences in trading

**Table 5**  
**Mean difference in bitcoin returns by time-of-day.** This table shows the differences in the means of the log returns at different hours of the day. The time standard is Universal Coordinated Time (UTC) which corresponds to GMT. Hour 00 corresponds to the return during the first hour of the day (from 12am to 1am), H01 is the second hour (1am to 2am), and so on. The t-statistics are in parentheses and \*, \*\*, \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Hour (UTC)	Bistamp_USD		BTCE_USD		BTCN_CNY		Coinbase_USD		Coincheck_JPY		Kraken_EUR		Kraken_USD	
	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value
H00	-0.037%	(-2.14)**	0.025%	(0.46)	0.012%	(-0.06)	0.005%	(-0.18)	0.078%	(2.19)**	0.016%	(0.61)	-0.017%	(-0.59)
H01	0.030%	(0.63)	0.091%	(2.70)***	0.080%	(2.03)**	0.088%	(1.38)	0.045%	(1.18)	0.010%	(0.28)	0.085%	(2.86)***
H02	0.026%	(0.47)	0.050%	(1.38)	0.061%	(1.75)*	0.061%	(1.91)*	-0.004%	(-0.56)	0.020%	(0.85)	-0.007%	(-0.42)
H03	-0.033%	(-1.78)*	-0.038%	(-1.49)	0.032%	(0.67)	-0.011%	(-0.71)	-0.003%	(-0.52)	-0.022%	(-1.47)	-0.008%	(-0.43)
H04	-0.011%	(-1.15)	0.025%	(0.48)	-0.031%	(-1.86)*	-0.021%	(-1.01)	-0.019%	(-1.29)	0.017%	(0.72)	-0.011%	(-0.49)
H05	-0.008%	(-1.05)	-0.014%	(-1.14)	0.003%	(-0.46)	-0.035%	(-1.96)*	0.004%	(-0.31)	0.009%	(0.26)	0.011%	(0.31)
H06	0.018%	(0.16)	0.024%	(0.43)	0.031%	(0.72)	-0.011%	(-0.89)	0.021%	(0.32)	0.024%	(1.02)	-0.005%	(-0.30)
H07	0.020%	(0.25)	0.025%	(0.43)	0.020%	(0.25)	0.003%	(-0.28)	-0.009%	(-0.60)	0.052%	(2.09)**	0.027%	(0.65)
H08	0.012%	(-0.07)	0.007%	(-0.23)	0.008%	(-0.21)	-0.024%	(-0.60)	-0.012%	(-0.93)	0.052%	(2.18)**	-0.048%	(-1.24)
H09	0.114%	(3.94)***	0.001%	(-0.45)	0.012%	(-0.05)	0.041%	(0.81)	0.025%	(0.50)	0.041%	(1.63)	0.058%	(1.64)
H10	0.028%	(0.48)	-0.007%	(-0.78)	-0.001%	(-0.54)	0.022%	(0.39)	0.000%	(-0.50)	0.017%	(0.49)	-0.011%	(-0.36)
H11	0.035%	(0.82)	0.005%	(-0.36)	-0.043%	(-2.41)**	0.019%	(0.33)	-0.022%	(-1.20)	0.027%	(1.00)	0.060%	(1.63)
H12	0.015%	(0.04)	0.005%	(-0.33)	-0.031%	(-1.75)*	-0.004%	(-0.41)	-0.012%	(-0.82)	-0.002%	(-0.28)	-0.017%	(-0.62)
H13	0.000%	(-0.54)	0.003%	(-0.37)	0.029%	(0.62)	-0.008%	(-0.53)	-0.005%	(-2.50)**	-0.021%	(-1.19)	0.014%	(0.29)
H14	0.068%	(2.17)**	0.065%	(1.65)*	0.015%	(0.06)	-0.014%	(-0.81)	-0.019%	(-1.30)	0.000%	(-0.19)	-0.033%	(-1.10)
H15	0.013%	(-0.02)	0.038%	(0.97)	0.039%	(1.05)	0.026%	(0.58)	0.013%	(0.05)	-0.008%	(-0.55)	-0.075%	(-2.10)**
H16	0.051%	(1.52)	0.041%	(1.04)	0.020%	(0.25)	0.052%	(1.58)	0.026%	(0.49)	0.042%	(1.77)*	0.094%	(3.09)***
H17	0.018%	(0.11)	-0.028%	(-1.39)	-0.020%	(-1.25)	0.037%	(1.02)	0.019%	(0.28)	0.001%	(-0.15)	0.033%	(0.86)
H18	-0.040%	(-1.72)*	-0.041%	(-1.94)*	-0.025%	(-1.47)	-0.037%	(-1.82)*	-0.008%	(-1.03)	-0.041%	(-2.14)**	-0.034%	(-1.13)
H19	-0.056%	(-2.61)***	-0.050%	(-2.34)**	-0.009%	(-1.01)	-0.068%	(-1.67)*	0.003%	(-0.40)	-0.008%	(-0.57)	0.004%	(0.03)
H20	0.000%	(-0.52)	0.012%	(-0.03)	0.034%	(0.76)	0.071%	(1.35)	0.043%	(1.53)	-0.063%	(-3.48)***	-0.033%	(-1.10)
H21	0.010%	(-0.17)	0.013%	(-0.01)	0.045%	(0.99)	0.000%	(-0.40)	0.044%	(1.27)	-0.037%	(-1.68)*	-0.028%	(-0.86)
H22	0.040%	(1.12)	0.046%	(1.35)	0.049%	(1.45)	0.056%	(1.61)	0.111%	(3.21)***	-0.005%	(-0.40)	0.007%	(0.12)
H23	0.023%	(0.36)	0.023%	(0.36)	-0.005%	(-0.69)	0.027%	(0.58)	0.007%	(-0.16)	-0.026%	(-1.52)	0.011%	(0.27)

**Table 6**  
**Mean difference in bitcoin volume traded by time-of-day.** This table shows the differences in the means of the log volume (number of Bitcoins) traded at different hours of the day. The time standard is Universal Coordinated Time (UTC) which corresponds to GMT. Hour 00 corresponds to the return during the first hour of the day (from 12am to 1am), H01 is the second hour (1am to 2am), and so on. The t-statistics are in parentheses and \*, \*\*, \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Hour (UTC)	Bitstamp_USD Mean	t-value	BTCE_USD Mean	t-value	BTGN_CNY Mean	t-value	Coinbase_USD Mean	t-value	Coincheck_JPY Mean	t-value	Kraken_EUR Mean	t-value	Kraken_USD Mean	t-value
H00	570.01	(-5.15)***	233.56	(-8.71)***	5,883.38	(-0.04)	403.19	(2.56)**	418.29	(0.24)	144.84	(-7.22)***	56.60	(0.84)
H01	579.49	(-4.09)***	238.05	(-5.82)***	6,652.39	(1.06)	396.88	(2.01)**	435.54	(1.14)	117.15	(-13.62)***	52.99	(-0.13)
H02	562.21	(-4.32)***	229.96	(-6.51)***	6,657.17	(1.16)	373.77	(-0.03)	444.71	(1.40)	103.90	(-15.43)***	52.69	(-0.20)
H03	543.34	(-6.57)***	214.86	(-9.67)***	6,207.58	(0.49)	351.67	(-2.14)**	433.95	(0.98)	91.21	(-22.11)***	47.82	(-1.70)**
H04	563.39	(-5.08)***	214.30	(-9.67)***	5,784.43	(-0.23)	339.38	(-3.13)***	441.31	(1.31)	94.71	(-18.78)***	45.42	(-2.41)**
H05	591.06	(-2.27)**	231.39	(-7.88)***	6,312.05	(0.57)	308.03	(-6.65)***	439.75	(1.29)	114.59	(-13.67)***	45.22	(-2.47)**
H06	584.67	(-3.69)***	268.74	(-3.82)***	6,148.18	(0.39)	278.58	(-9.49)***	452.06	(1.71)*	138.56	(-8.12)***	44.91	(-2.12)**
H07	620.58	(-2.12)**	318.98	(0.31)	6,505.27	(0.79)	241.23	(-15.78)***	442.61	(1.28)	179.51	(-2.41)**	44.21	(-2.60)***
H08	687.63	(0.90)	352.97	(2.57)**	6,896.92	(1.32)	226.96	(-18.41)***	473.07	(2.24)**	230.11	(3.66)***	45.83	(-2.35)**
H09	675.39	(0.40)	347.16	(2.57)**	6,464.00	(0.86)	210.31	(-17.73)***	433.17	(0.90)	240.98	(4.54)***	42.03	(-3.55)***
H10	726.98	(2.63)***	348.43	(2.54)**	5,880.27	(-0.05)	254.99	(-4.57)***	452.67	(1.46)	238.21	(4.93)***	38.89	(-5.60)***
H11	721.94	(2.50)**	346.36	(2.35)**	5,730.58	(-0.31)	272.36	(-3.50)***	477.34	(2.30)**	245.97	(5.16)***	46.55	(-2.03)**
H12	729.91	(2.83)***	358.77	(3.30)***	6,359.86	(0.67)	363.06	(-0.35)	489.61	(2.56)**	256.20	(6.21)***	49.44	(-1.18)
H13	814.51	(5.37)***	375.22	(4.97)***	7,037.32	(1.59)	406.29	(1.17)	510.11	(3.34)***	272.02	(6.13)***	57.36	(0.92)
H14	778.38	(5.45)***	395.65	(6.41)***	7,548.83	(2.08)**	455.59	(3.33)***	500.79	(2.94)**	270.27	(7.14)***	64.96	(2.69)***
H15	786.26	(5.42)***	397.10	(6.80)***	7,261.58	(1.67)*	472.84	(4.53)***	462.01	(1.91)*	269.07	(6.88)***	68.08	(3.69)***
H16	744.10	(4.07)***	406.25	(7.44)***	7,132.27	(1.60)	480.26	(8.29)***	405.55	(-0.35)	270.08	(7.18)***	69.38	(3.53)***
H17	683.76	(0.84)	357.94	(3.62)***	5,183.11	(-1.35)	457.65	(6.76)***	332.92	(-4.36)***	224.23	(3.02)***	58.94	(1.40)
H18	725.68	(2.56)**	365.06	(3.41)***	4,446.88	(-3.13)***	468.82	(7.46)***	296.35	(-7.30)***	225.26	(2.99)***	58.85	(1.42)
H19	685.43	(0.89)	355.23	(2.80)***	4,052.53	(-4.50)***	465.92	(6.74)***	274.80	(-9.42)***	224.65	(2.48)**	57.82	(1.08)
H20	695.71	(1.07)	330.38	(1.19)	3,722.67	(-5.72)***	452.49	(6.64)***	279.69	(-9.75)***	219.26	(2.29)**	58.20	(1.21)
H21	687.62	(0.83)	302.03	(-1.03)	3,776.15	(-5.42)***	458.56	(5.93)***	315.44	(-5.52)***	216.96	(1.63)	59.02	(1.04)
H22	652.85	(-0.66)	280.85	(-2.82)***	4,064.56	(-4.44)***	422.66	(3.80)***	337.08	(-4.38)***	186.32	(-1.19)	54.72	(0.34)
H23	612.42	(-2.85)***	259.77	(-5.21)***	4,841.43	(-2.14)**	417.02	(3.31)***	366.66	(-2.25)**	160.50	(-4.18)***	58.21	(1.00)

volumes show significantly lower trading volumes on weekends compared with the weekdays. This finding is consistent with the heatmaps and Bollerslev and Domowitz (1993) who show a decline in trading activity in currency markets during the weekend.

Our findings are inconsistent with the notion that retail traders increase their trading activity on weekends, which suggests that institutional traders play a bigger role than is generally acknowledged.

The statistical tests of the means of the time-of-day, day-of-week, and month-of-year also confirm the results visible in the heat maps.

## 5. Summary and concluding remarks

This paper studies the temporal effects in Bitcoin returns and trading volume across seven global exchanges using high-frequency data and more than 15 million observations. The paper is motivated by the question whether Bitcoin markets exhibit any of the time-dependent patterns documented in equity markets and currency markets. We hypothesize that the presence of specific patterns indicate whether the market is dominated by retail investors or institutional investors.

We demonstrate that there are no persistent anomalies in the time-of-day, day-of-week, and month-of-year returns. This supports the hypothesis that investors exploit anomalies and thereby reduce their strength or even eliminate them. The fact that anomalies arise and subsequently disappear indicates that anomalies are not arbitrated away immediately or in the short run but only over longer horizons. This conclusion is consistent with large arbitrage profits as reported in Makarov and Schoar (2018).

Heatmaps show that higher returns observed on Mondays are due to returns in particular years rather than being consistently high relative to the other days of the week. In contrast, there is strong evidence for persistent variations in trading volume over each day and each week with lower trading volumes at evening or non-peak hours and on Saturdays and Sundays. This weekend effect in trading volume is also found in currency markets and suggests the presence of institutional traders assuming that retail investors would also trade on weekends and not significantly reduce their trading activities. The results also show that the patterns found for trading in US dollars and in euros are weak or non-existent for Chinese and Japanese exchanges indicating that retail investors play a bigger role in these markets.

## Appendix

This Appendix provides additional heatmaps and tables for the time-of-day and month-of-year effects in Bitcoin returns and volumes at seven exchanges. Fig. 4 presents the time-of-day effects in Bitcoin returns. Figs. 5 and 6 present the monthly effects in the return and trading volume. Tables 5 and 6 present the statistical significance of the means tests of the time-of-day effects in returns and volume.

## Supplementary material

Supplementary material associated with this article can be found, in the online version, at [10.1016/j.frl.2019.04.023](https://doi.org/10.1016/j.frl.2019.04.023).

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