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CRYPTO ALPHA
IMPACT OF MARKET INFRASTRUCTURE ON ALPHA GENERATION
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December 2021
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ABSTRACT
In this article, we look at the Cryptocurrency [CC] market structure in more detail and highlight the differences between the traditional financial market. We assess how the performance of trading algorithms differs between Crypto ‘exchanges’. We base this assessment on four exchanges and three common trend following strategies.

In general, we found a difference of at least 22.1 percentage points between best and worst performing ‘exchanges’ whilst running the same algorithm. This difference originates from different prices as well as different trading fees across the exchanges.

The findings implies that a trading bot should use data from multiple exchanges to increase the robustness of the trading signals.

IDIOSYNCRASIES OF CRYPTO MARKET STRUCTURE

In 2008 Satoshi Nakamoto published his white paper describing ‘Bitcoin’. Since then, retail adoption pushed the cryptocurrency market forward. Todate, institutional adoption remains in its infancy due to regulatory limitations and uncertainty.

By now all major currencies are traded on so-called ‘Crypto Exchanges’. Unlike in the traditional financial world, these ‘exchanges’ are not regulated trading venues with institutional infrastructure. Rather they function as a combination of a MTF and broker-dealer operating an OTC market. Furthermore, each ‘exchange’ has its own price determining mechanism leading to no universally reference or closing price. Thereby the market, orderbook, and liquidity is fragmented across venues. In comparison, NASDAQ has almost 100% global market share of traded Apple shares while Coinbase only handled 1.39% of the global Crypto trading volume YTD.

Given this market structure the question arises, if the same trading strategies perform differently on different ‘exchanges’.

SOURCES OF ALPHA GENERATION

TRADING VS INVESTING
When we discuss sources of alpha generation, it is generally helpful to distinguish between trading and investing. The history of distinguishing between traders [speculators] and investors is long and storied in the markets, and it is generally accepted that these are distinct concepts.

Joseph Penso de la Vega was the first writer to articulate the difference in his 1688 book, Confusion of Confusions, the oldest book ever written on the stock exchange business. In this book he outlined three types of people: 1. financial lords [the wealthy investors], 2. the merchants [occasional speculators] and 3. the gamblers [persistent speculators]. Penso de la Vega’s distinction was one of size and success – the rich are the investors. The rest are speculators.

Philip Carret, author of ‘The Art of Speculation’ [1930] put more weight on the motive than the action; in other words, the speculator focuses on the price, while the investor focuses on the business.
John Maynard Keynes, the renowned economist, was even more succinct in his approach, defining speculation as the term for ‘forecasting the psychology of the market’ and investment as ‘the activity of forecasting the prospective yield of assets over their whole life.’ Keynes argued that betting on the economic success of a company is therefore distinct from purely betting on the price of an asset.

Is there a robust set of actions that defines whether something is a trade or an investment or is it the intangible motive of the market participant that defines whether something is a trade or an investment and what about time preferences? In reality, these terms lie on a gradient of multiple axes and different situations will carry aspects of both trading and investing based on the criteria – the two to focus on are MOTIVE and DURATION.

1. MOTIVE

Overall, there seems to be agreement in the financial literature that if someone’s motive for a decision concerns itself with the actual economics of the business and the growth thereof that this is considered investing, whereas basing a decision purely on the expected future price of the asset this is considered trading.

However, both investment and trading have a speculative component: an investment can be thought of as speculating on whether the economics of the business will succeed whilst speculation purely on price can be viewed as an imbalance between supply and demand and not depend on the success of an economic outcome i.e., the economics of the firm. Moreover, any type of speculation is always also a partial bet on human behavior, and humans are reflexive and memetic creatures who often want to replicate social and physical trends.

2. DURATION

In the recent financial literature, long term bets are often associated with investing and short short term bets are often associated with trading. This is often reflected in the framework of betting on short-term opportunities, fads versus betting on real long term secular change. In a similar fashion, the level of conviction in an investment is often higher than the level of conviction in a trade and accordingly the average duration of each ties closely to this. The more highly convicted one is in a thesis, the longer one will generally let it play out and accordingly duration has often become a proxy of conviction.

3. A REMINDER ABOUT INFORMATION

As Grossman-Stiglitz highlighted as far back as 1980, there is also a fundamental conflict between the efficiency with which markets spread information and the incentives to acquire information. This means prices will never reflect the information which is available since if it did, those who spent resources to obtain it would receive no compensation. Which de facto means if you remove the incentive aka cost to hunt for information, you will get bad prices and thus incur risk.

APPLICATION TO CRYPTO — KEY CONSIDERATIONS

In the case of Cryptocurrencies for the above distinction between investing and trading to hold, an additional consideration needs to be taken into account; namely that CCs, like modern day currencies, are not backed by any commodities, ownership rights or other form of collateral.

The Keynesian perspective would likely consider investing in CCs a technical misnomer as there is, in the
traditional sense, no real economics to speak of and CCs would thus be viewed as purely a compelling bet with sufficient upside to warrant the transaction. Conversely, buyers of CCs intending to hold them over a long period, and despite the fact that the motive may resemble a trade, the conviction level in this case may reach that of an investment. Therefore, in this context it seems that CCs resemble a high-conviction trade given the success of CCs is measured in terms of price for the most part.

Although some of the differences may seem philosophical, understanding the qualities of both approaches provides a useful reference point and associated trade offs.

For example, on the understanding that TRADING is a short term, price based game, one can start to develop general rules and an appropriate trading strategy. Furthermore and from a short term perspective, it’s always more valuable to ask the question of the perception of the fundamentals rather than the actual fundamentals, as perception drives price in the short term more than true fundamentals do. When looking at a trade in the crypto space, one should focus on the criteria that directly impact price instead of those that tangentially do.

Conversely, when INVESTING, it’s preferable to ignore the short term perceptions of the market and focus on the larger picture of how the path will actually unfold. One should spend much more time building conviction in an investment than a trade, given the duration is likely to be longer; in particular with more time devoted to understanding the value accrual mechanisms, the potential for product fit, and the long term perception of the market.

For the purposes of this study, we focus on the execution of short-term price focused CCs trading strategies across 4 CCs exchanges to establish the impact of infrastructure or distinct platforms running the same identical trading algorithm on various exchanges.
TRADING STRATEGIES

The bulk of trading strategies can be traced back to either a TREND FOLLOWING or MEAN REVERSION model. Both of these approaches can be deployed over short and long time periods. Furthermore, indicators and strategies can be combined in a number of different ways to run a specific [systematic] quantitative model [i.e., a stochastic oscillator can be used to identify reversals in the price of a mean reversion strategy or it can be used to determine time periods of statistically significant momentum in a trend following strategy]. Accordingly, the demarcation between the two strategies is somewhat arbitrary and both strategies can be successful although the economic return can vary significantly. The table below provides an indication of the key differences between the two paradigms.

For the purpose of this study, we will focus solely on algorithms where the performance assessment is undertaken using common trend following strategies, namely:

1. EMA – EXPONENTIAL MOVING AVERAGE
2. RSI – RELATIVE STRENGTH INDEX
3. MACD – MOVING AVERAGE CONVERGENCE DIVERGENCE

<table>
<thead>
<tr>
<th>METRIC</th>
<th>TREND FOLLOWING</th>
<th>MEAN REVERSION</th>
</tr>
</thead>
<tbody>
<tr>
<td>P/L</td>
<td>many small losses, few large profits</td>
<td>many small profits, few large losses</td>
</tr>
<tr>
<td>PROBABILITY RATIO</td>
<td>approx 30% of trades profitable</td>
<td>approx 80% of trades profitable</td>
</tr>
<tr>
<td>RISK OVER TIME</td>
<td>risk increases over duration of trend</td>
<td>risk increases as entry threshold decreases</td>
</tr>
<tr>
<td>CORRELATION</td>
<td>macro trends tend to be correlated</td>
<td>mean reversion tends to be uncorrelated</td>
</tr>
<tr>
<td>TIME</td>
<td>works best over long time periods</td>
<td>works best over short time periods</td>
</tr>
<tr>
<td>COSTS</td>
<td>costs less important</td>
<td>cost can be important</td>
</tr>
<tr>
<td>STOP/ LOSS</td>
<td>stop/ loss may prevent fat tail gains</td>
<td>large stop loss provisions should be used</td>
</tr>
<tr>
<td>HARVEST</td>
<td>profit taking may prevent fat tail gains</td>
<td>profit taking is essential</td>
</tr>
<tr>
<td>VOLATILITY</td>
<td>low volatility can be an advantage</td>
<td>low volatility should be avoided</td>
</tr>
</tbody>
</table>


METHODOLOGY

We use data from four known and established ‘exchanges’ to identify the role of crypto market infrastructure on investment and trading performance using three different trend following strategies. The following exchanges have been included in this study Bitstamp, Coinbase, FTX and Kraken. For the analysis we have masked the names and randomly assigned each of the exchanges a letter, henceforth referring to them as EXCHANGE A, B, C and D.

The dataset comprises daily OHLCV data for Bitcoin covering the period from 22/09/2019 to 20/09/2021 from each of the four exchanges. We run our backtests via the APEX:E3 analytics and backtesting platform. APEX:E3 offers a cloud based institutional data and analytics platform. Users and organisations can access data, analytics and backtesting functionality using a low code API.

BACKTESTING

For the backtest we run each strategy in its standard configuration and calculate the required parameters from the closing prices in the dataset. In more detail, we define the following parameters for the calculation:

1 Popular Investment Strategies: 1. Value Investing is based on a mean reversion strategy whereby one buys something that is undervalued by the market and waits until the market has brought it back to the long term price aka the mean before selling. 2. Global Macro is based on a trend short/medium long term following model. 3. Statistical Arbitrage is a mean reverting strategy i.e., when a historical correlation deviates from the long term mean.
EMA – EXPONENTIAL MOVING AVERAGE

The EMA is generally widely used in forex trading. For this, one overlays short term EMA with a long term EMA. The trading bot then enters the market when the short term EMA crosses the long term EMA from below and exits if it crosses from above. The most commonly used EMA model uses a 50/200 day timeframe to calculate the short/long term EMA. However, given the highly volatile crypt market, using these parameters do not lead to any trades being executed. Therefore, we reduce the parameter by a factor of 10 in our model and use a 5/20 EMA Model.

RSI – RELATIVE STRENGTH INDEX

The RSI is a widely used indicator to assess if a market is temporarily overbought or oversold. Generally it is accepted that a RSI above 70 indicates overbought and a RSI below 30 relates to oversold. However, sudden and sharp price moves can cause false signals. In our RSI trading strategy, we use the standard 14 day period to calculate the RSI and enter the market when it is oversold and exit when it is overbought.

MACD – MOVING AVERAGE CONVERGENCE DIVERGENCE

The MACD strategy is one of the most popular technical trading indicators. The MACD basically calculates the difference between a long term EMA and a short term EMA. The difference makes up the MACD. The MACD can then be converted into a signal using a 9 day EMA on the MACD itself. Whenever the MACD moves above the signal line, our trading bot enters the market and when it moves below the single line exits. For the calculation of the MACD we use the following time periods: short period = 12 days, long period = 26 days and signal period = 9 days.
To ensure no unfair advantage of our backtesting algorithms, we execute all trades at a time $T+1$, where $T$ refers to the time an entry or exit condition is met. Additionally, we also incorporated the trading fees from each of the respective ‘exchanges’ and ensured that we reduce the fees in accordance with the 30 day volume deductions on each exchange. Our initial investment is USD100,000. We do not model any slippage as it is almost impossible to model slippage without any orderbook data.

**RESULTS**

From our backtests, we can extract two learnings. First, we can compare our trading strategies to a long term buy-and-hold investment. Secondly, we can compare the relative performance of our strategies between exchanges.

**TRADING VS INVESTING**

As described in the introduction, there is a fundamental difference between trading and investing. As it happens, our analysis clearly shows the difference between the two. All three strategies outperformed a buy and hold strategy in the short term. However, in the long run, only the EMA strategy outperforms the buy and hold strategy.

This remains the case, if we assume no trading fees. Thereby one can see how short-term price games can generate short-term alpha. However, in the long run achieving the same performance as a buy and hold investor becomes more and more difficult. Furthermore, we should point out that the RSI algorithm was out of the market between April 2020 to June 2021. This means that due to the continued growth of the market, our RSI indicator never indicated an oversold market and the algorithm missed out on the large gains that occurred during this period; a general limitation of a RSI strategy.
CROSS EXCHANGE COMPARISON

As the price differences between the exchanges are minimized by arbitrageurs and as only two trades need to be executed, the buy and hold strategy roughly performed similarly across all exchanges. However, when trading the small price differences and different exchange fees can add up quite a lot. For each strategy, we identified a difference of at least 22.1 percentage points between best and worst performing exchange.

Further, we noticed that a difference in performance still exists if we set trading fees to zero and that not always the same exchange performed best. These two facts clearly indicate that the gap is not solely explainable by the different fee structure of the exchanges. Rather the difference originates from a combination of the different prices, trading fees and signal point on each exchange.

While it is difficult to see from the graphs, it is not always at the same point in time that the algorithms always entered or exited the market. This is explainable by the fact that sometimes, the difference in prices is just above the trading signal on one exchange while it remains below on another one. To avoid having false signals before executing a trade, one could leverage the CC market structure and implement a consensus algorithm. Thereby one could ensure that the majority of exchanges produce the same signal within a given timeframe. This should minimize false signals of a single exchange and help to avoid a labor intensive manual checking of the signals. Note, for an EMA strategy, all trades are executed at the same point in time, meaning that the averaging across a given time frame reduces the dependency on the price fluctuation between the exchanges.

<table>
<thead>
<tr>
<th>EXCHANGE</th>
<th>Buy ‘n Hold</th>
<th>EMA</th>
<th>RSI</th>
<th>MACD</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Return as % of initial investment</td>
<td>481.8%</td>
<td>617.7%</td>
<td>118.0%</td>
</tr>
<tr>
<td></td>
<td>Number of trades</td>
<td>2</td>
<td>22</td>
<td>20</td>
</tr>
<tr>
<td>B</td>
<td>Return as % of initial investment</td>
<td>481.5%</td>
<td>711.0%</td>
<td>120.8%</td>
</tr>
<tr>
<td></td>
<td>Number of trades</td>
<td>2</td>
<td>22</td>
<td>20</td>
</tr>
<tr>
<td>C</td>
<td>Return as % of initial investment</td>
<td>482.0%</td>
<td>672.3%</td>
<td>140.8%</td>
</tr>
<tr>
<td></td>
<td>Number of trades</td>
<td>2</td>
<td>22</td>
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</tr>
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CONCLUSIONS

As our results indicate, the same algorithms yield quite different results across different exchanges. Due to different prices on different venues, the signal strength to enter and exit is not always achieved at the same point in time. Furthermore, differences in trading fees further increase the discrepancy between the ‘exchanges’.

These facts imply that a trader should carefully assess which venues he chooses for his trading strategy/ bot. He should pay special attention to the trading fees as well as uptime, data fees and security. Furthermore, complementing your trading bot with data from other exchanges, seems like a reasonable approach given the crypto market structure. Additionally, this might help to avoid trading on false signals.

In further research the difference between DEX and CEX should be incorporated into the trading models. Furthermore, one should include mean reversion algorithms as well as potential AI based model calibration tools.
About the authors

Dr Peter T. Golder joined SIX Digital Exchange [SDX] in June 2020 and serves as its Chief Commercial Officer with a mandate to define and execute innovative and commercially viable business models to establish SDX as a leader in global institutional Digital Assets and Crypto markets. Peter is a Board member of the Global Blockchain Business Council [GBBC] and the Ethereum Enterprise Alliance [EEA]. In addition, he serves on the InterWork Alliance [IWA] Leadership Council and is an advisor to the FinTech Council of the International Capital Markets Association [ICMA]. Peter regularly publishes on industry matters and is a frequent speaker at [Digital Asset and Crypto] industry events. Peter is a passionate financial services entrepreneur, executive and investor with over 25 years of international capital markets and investment banking experience. Peter is an advocate of the power of data and technology to enable the creation of innovative/disruptive business models to build a more trusted, sustainable and effective financial services ecosystem.

Prior to SDX, Peter was the Founder and CEO of Euroclear Information Solutions, where he was responsible for establishing the Groups data and analytics business across a global post trade platform with over €30 trillion of Assets under Administration. Peter also served as a senior executive adviser to venture capital/private equity firms and numerous award-winning FinTech, distributed ledger and Crypto firms.

Joël L. Glässer is a business analyst focused on using his analytic skills to transform data into insights. He combines a strong technical background, with mathematical skills and financial markets expertise. Joel holds a master degree from ETH Zurich in Management, Technology, and Economics and has gained work experience in national as well as international financial institutions.

Usman Khan is a serial technology entrepreneur, co-founding and advising a number of successful startups. He is focused on developing institutional grade technology solutions that can help bridge traditional and digital asset finance.
About SIX and SIX Digital Exchange

SIX is a major Financial Market Infrastructure [FMI] provider that operates exchanges and Centralized Securities Depositories [CSD] in Switzerland and, via the acquisition of the BME in 2020, also in Spain. SIX runs the payments system in Switzerland and operates payment infrastructure on behalf of the Swiss National Bank. SIX also manages a financial information business focused on providing data products and services to financial institutions globally.

SIX is building new digital market infrastructure in its fully owned subsidiary SIX Digital Exchange [SDX].

SDX has obtained FINMA licenses for its Exchange and Central Securities Depository [CSD] and plans to offer issuance, listing, trading, settlement, servicing, and custody of digital assets. SDX is also a global leader in the development of Central Bank Digital Currency [CBDC] via its partnership with the Swiss National Bank and the Bank for International Settlements. SDX has partnered with SBI Digital Asset Holdings from Japan to set up a similar digital market infrastructure offering in Singapore.

SDX Vision

- a trusted global integrated institutional liquidity network and ecosystem
- for the issuance, trading & settlement, transfer, custody of digital assets
- in both public and private markets as well as regulated digital securities and crypto assets
- underpinned by a data collection and distribution layer advanced analytics capabilities

ABOUT APEX:E3

APEX:E3 offers a cloud-based institutional grade Digital Asset analytics platform. Users and organizations can access formatted data, analytics and backtesting functionality using a powerful low code API. Email usman@apexe3.com for more information.
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