TMAX Strategy and Lottery-like Demand in the Cryptocurrency and Mutual Funds Market

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TMAX STRATEGY AND LOTTERY-LIKE DEMAND IN THE CRYPTOCURRENCY AND MUTUAL FUNDS MARKET

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Abstract

This Master's thesis explores the profitability of the novel TMAX Strategy by Lin et al. (2021) in the cryptocurrency and mutual funds market. In the cryptocurrency market, this investment strategy generates statistically significant average raw losses of 4.38% per week under equal weights and 6.01% under value weights. The research thereby provides empirical evidence of a 'TMAX momentum' effect in the cryptocurrency market. No convincing evidence of a lottery-related bias exhibited by professional money managers can be found; since the early 2000s, no TMAX effect can be observed in the mutual funds market. The study advocates for a mispricing explanation of the TMAX momentum in the cryptocurrency market and shows that a high risk-premium for idiosyncratic skewness, not a differing investor behaviour, explains the diverging results between the stock and cryptocurrency market's TMAX Strategy profitability. The findings in the mutual funds market indicate that the lottery anomaly in the stock market is driven by retail investors, not institutional investors.

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List of Abbreviations & Glossary

I.1 List of Abbreviations

The following table lists the abbreviations used throughout the thesis. The page on which each one appears for the first time is also given. Depending on the circumstance, the abbreviation's meaning is also described within the text; if not, please refer to the table below.

Table I.1: List of Abbreviations

Abbreviation	**Meaning**	**Page**
TMAX	Time-dependent maximum daily returns	1
AuM	Assets under management	1
U.S.	United States of America	1
MAX	Maximum daily returns	2
ICO	Initial coin offering	5
BTC	Ticker for bitcoin	5
IEO	Initial exchange offering	5
CEX	Centralised exchanges	5
DEX	Decentralised exchanges	5
AMM	Automated market makers	5
E.U.	European Union	6
UCITS	Undertakings for Collective Investment in Transferable Securities	6
AIF	Alternative Investment Fund	6
NAV	Net asset value	6
ETFs	Exchange-traded funds	6
GFC	Global Financial Crisis of 2008-2009	12
CAPM	Capital Asset Pricing Model	26
NYSE	New York Stock Exchange	26
AMEX	American Stock Exchange	26
TNA	Total net assets	33
p.p	Percentage point	52
NH	Nearness to 52-week high	55
CAGR	Compound annual growth rate	63

I.2 Glossary

The following table defines and describes the main terms that are used in the thesis. It acts as a repository for terms whose definitions are not given in the core text, for a lack of added value. Again, the page where each one first appears is also given. For completeness, some terms might be defined here even though a definition has already been given in the text; if that is the case, it is because the definition is relevant for the understanding of the relevant section within the text.

As the reader can note, there is no direct source indicated for every term that is described; the reason being that information that has been gathered from different sources has been paraphrased to fit with the needs of this thesis. As such, they should be understood as descriptions rather than definitions.

Table I.2: Glossary of Terms

Term	**Definition / Description**	**Page**
TMAX Strategy	An investment strategy based on buying (short selling) assets with the most recent maximum daily returns ranked in the bottom (top) decile of the historical return distribution	1
Lottery preference	A character trait that makes individuals seek investments that have lottery-like characteristics, i.e. a negative expected return and a small probability of a large positive payoff. Synonyms: lottery-like preference(s), investor preference for lottery-like payoffs	1
Blockchain	A decentralised and distributed digital ledger technology that securely records transactions across multiple computers. Each transaction is added to a block, and once a block is verified, it is linked to the previous one, forming an immutable chain of blocks.	1
Gartner (1995) Hype Cycle	A theory that discerns technology's life cycles into five key phases: innovation trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment, plateau of productivity	1
MAX Strategy	An investment strategy consisting of buying (short selling) stocks with the most recent maximum daily returns ranked in the bottom (top) decile of a cross-section of stock returns.	2
Lottery demand	The demand that is induced by the lottery-like preference of investors.	2
Hash algorithm	A mathematical function that takes an input and converts it into a fixed-size string of characters, known as the hash value.	4
Digital signature	A cryptographic technique used to verify the authenticity and integrity of transactions. It involves the use of a private key that is unique to the sender to create a signature for the transaction data.	4
Nonce	A random number for verifying the hash value	5
Proof-of-work	A consensus mechanism to achieve agreement on the state of the blockchain and validate new transactions. The first miner to find a valid solution to the mathematical puzzles posed by the blockchain broadcasts it to the network and receives a reward for this work.	5

Table I.3: Glossary of Terms: continued

Term	**Definition / Description**	**Page**
Smart contract	A self-executing computer program or code that runs on a blockchain platform. It automatically executes the terms and conditions of an agreement between two or more parties when certain predefined conditions are met.	6
Liquidity pool	A pool of funds that facilitates trading and provides liquidity for assets or tokens in a smart contract.	6
Mutual fund	A form of collective investment where a number of investors pool their money and invest it according to a pre-defined investment objective. Synonyms: UCITS, AIF, SICAV, investment trust, unit trust.	6
Homo economicus	A theoretical concept used in neoclassical economics and microeconomics. It represents an individual who acts in a perfectly rational and self-interested manner, making decisions based solely on maximizing their own utility or economic well-being.	7
MAX effect	A phenomenon that assets that rank in the bottom decile of maximum daily returns in period $t-1$ outperform assets that are ranked in the top decile in period $t-1$ in period t.	7
Lottery-like assets	Low-priced assets with high idiosyncratic volatility and high idiosyncratic skewness. These characteristics make assets have lottery-like payoffs.	7
reverse (T)MAX effect	The reverse phenomenon of the (time-dependent) MAX effect: assets that rank in the top decile of (time-dependent) maximum daily returns in period $t-1$ outperforms assets in the bottom decile in the following period (t). Synonyms: (T)MAX momentum (effect)	10
Self-financing portfolio	A combination of securities such that the proceeds from the short sales cover the costs of the long positions, thereby requiring no investment by the investor.	18
Welsh t-test	An extension of the standard t-test that is employed when the assumption of equal variances is violated, which means that the standard independent samples t-test might not be appropriate. The test is particularly useful when the sample sizes and variances of the two groups in a two-sample t-test are different.	23
TMAX premium (discount)	Alternative term to express that lottery-like assets are overpriced (underpriced) (i.e., trade at a premium (discount) relative to their fair value), resulting in a relative subsequent underperformance (overperformance).	28

Introduction

In a paper entitled *Time-dependent lottery preference and the cross-section of stock returns* (Lin et al., 2021), the authors highlight the profitability of an investment strategy based on buying (short selling) stocks with the most recent maximum daily returns ranked in the bottom (top) decile of the historical return distribution. In the following, we will make reference to this investment strategy by the name *TMAX Strategy*. Lin et al. (2021) postulate that these results are empirical evidence of investors' preference for lottery-like payoffs. However, the authors only consider an investment universe based on stocks.

The present Master's thesis uses a similar approach to investigate whether investors also have time-dependent lottery-like preferences in other markets, in particular, the crypto and mutual funds markets, and whether this strategy can generate statistically significant out-of-sample profits, also in times of crisis (e.g., COVID-19 crisis). Derived from this main objective, the potential profitability will also be linked to the concepts of lottery-like demand, and bubble-like behaviour.[1]

Blockchain technology, thus *in extenso* the cryptocurrency market, seems to be following the same 'hype cycle'[2] (Gartner, 1995) that has also affected other information technologies in the past (Tumasjan, 2021). As an investable asset, cryptocurrencies have therefore, after having caught the attention of retail investors, recently also entered the investment realm of asset managers. BlackRock, the largest asset management company by AuM, has only started offering cryptocurrency investments to its clients in 2022; Fidelity in 2021.[3] The moral responsibility that comes with money management, but also the related risks to financial stability (Kapsis, 2019), require a deep understanding of the products offered to investors. Due to the recency of the cryptocurrency market and its specificities compared to 'traditional' instruments, this understanding is still missing in a number of areas, most notably, regulation (Bajaj et al., 2022), investor behaviour (Ballis & Drakos, 2020), and price discovery (Borgards & Czudaj, 2020). This Master's thesis will tackle the latter two subjects.

The importance of studying the TMAX Strategy in the context of the mutual funds market resides in the fact that over 30% of U.S. corporate equity is held by U.S. investment companies and combined with investment companies outside of the U.S., the total share of U.S. equity held by these structures rises to around 50%.[4] As a consequence, limiting the discussion of the profitability of the TMAX Strategy to stock markets (as in Lin et al. (2021)) omits one of the most important sources of investment, professional investors through the funds they manage. Also, from a managerial perspective, providing empirical evidence of the TMAX Strategy's profitability in the mutual funds market, thereby laying bare behavioural biases (more on that later), should enlighten (and concern) money managers, since behavioural biases generally detract from returns (Cuthbertson et al., 2016), when funds' (past) returns are one of the main determinants of fund flows (Ippolito, 1992; Chevalier & Ellison, 1997; Sirri & Tufano, 1998).

The reason for examining two markets that seem to lack connection is to examine whether investor behaviour differs between markets (stock market vs. cryptocurrency market) and/or between individual investors and professional money managers (stock market vs. mutual funds market).

[1] The analysis of bubbles is restricted to the cryptocurrency market.
[2] https://www.gartner.com/en/research/methodologies/gartner-hype-cycle
[3] https://www.securities-services.societegenerale.com/en/insights/views/news/cryptocurrencies-asset-management-first-steps-europe/
[4] https://www.ici.org/system/files/2021-05/2021_factbook.pdf

This thesis thereby directly addresses the research gap left by the lack of application of the TMAX Strategy in other markets than stock markets, whereas the MAX Strategy, from which the TMAX Strategy is derived and which consists of buying (short selling) stocks with the most recent maximum daily returns ranked in the bottom (top) decile of a *cross-section* of stock returns, has been covered in the cryptocurrency (Grobys & Junttila, 2021; Ozdamar et al., 2021; Y. Li et al., 2021) and mutual funds market (Gao et al., 2021; Agarwal et al., 2021). As the TMAX Strategy subsumes the MAX Strategy (Lin et al., 2021), it is of academic relevance to provide findings in these markets based on the more robust of the two strategies. The academic relevance also stems from providing further evidence of deviations from the efficient market hypothesis and the predictability of (cryptocurrency) returns. This thesis' results in the mutual funds market further expand the existing research on differing investor behaviour between individual and professional investors on specific behavioural biases.

This thesis contributes to the field of behavioural finance and market anomalies by adding to the literature on time-dependent lottery-like preferences. In particular, the thesis shows that the price effects of this bias are not limited to one market, but depend on the type of investor. The research also provides evidence of a new framework for reasoning around bubbles, in particular in the cryptocurrency market. Studying lottery demand during speculative bubbles opens the door to alternative explanations of the formation of bubbles in this market via the lottery-like preferences of investors; we will show that lottery demand at least amplifies speculative bubbles and could potentially be their root cause. Also, the evidence regarding the profitability of the TMAX Strategy in the cryptocurrency market creates a bridge between 'traditional' financial markets and cryptocurrency markets, showing that, in essence, investor behaviour does not fundamentally change regarding the preference for lottery-like payoffs. Finally, this thesis addresses the research gap left by the previously observed and seemingly puzzling results regarding the outperformance of lottery-like assets in the cryptocurrency market when implementing the MAX Strategy, knowing that this asset class exhibits particularly strong lottery-like features.

The thesis is structured as follows. Chapter 2 will present a review of the literature. Chapter 3 is devoted to the methodology, explaining why and how the TMAX Strategy will be implemented in the respective markets for the purpose of this thesis. Chapter 4 will focus on the results. Chapter 5 will discuss these results, in light of the research questions and provide additional theoretical elements to expand the existing theory. Chapter 6 serves as a conclusion, by highlighting the implications of this study and its limitations, as well as future avenues for research on the topic.

Literature Review & Theoretical Framework

The aim of this literature review is to present the most important characteristics of the studied markets, that are relevant to this thesis (sections 2.1 & 2.2 and section 2.4), followed by an introduction to the concept of lottery preference (sections 2.3, 2.6 & 2.7) and existing research on the TMAX and MAX strategies (section 2.5). The literature review then concludes with the main testable hypotheses (section 2.8).

2.1 Cryptocurrency market: the basics

According to the definition given by Pernice and Scott (2021), a cryptocurrency is "a token, intended to be used as a general or limited-purpose medium-of-exchange, issued via a cryptocurrency system". From this definition, we can discern a number of important elements that will help the reader understand the broad functioning of this particular market.

An often neglected element about cryptocurrencies is that they are, at the origin, and as the name suggests, purposed as currencies, i.e. a medium of exchange.[1] Nakamoto (2008, 2009), who introduced the first cryptocurrency protocol, Bitcoin, presented it himself as a "currency in a network and cryptography mailing list". However, as opposed to fiat currencies, which are government-backed and (usually) issued by central banks, and whose worth thereby reflects the trust and credibility in the country of issuance (Tavlas, 2003; Aykens, 2005), cryptocurrencies are backed by "cryptographic proof instead of trust" (Nakamoto, 2008). This "reliance on code" to guarantee the well-functioning of cryptocurrencies (De Filippi & Wright, 2018) is tied to the "cryptocurrency system" in which the code is embedded (Pernice & Scott, 2021). The common denominator of these cryptocurrency systems is the underlying blockchain technology, "the code" which handles, regroups, and publicly displays, similar to a ledger or a register, the transactions in the system (Härdle et al., 2020).

Without going into the details of blockchain, three concepts ensure the integrity of the system: nodes, cryptography, and consensus. Blockchain transactions are validated by a peer-to-peer network of nodes, which is, in essence, a network of computers that all run the computer protocol (the code) and hold an identical copy of the ledger of transactions (Yuan & Wang, 2018). To guarantee the immutability and authenticity of all transactions, transactions are encrypted on the senders' ends via a system of mathematical algorithms, called hash algorithms. This system enables both the nodes and the recipients to verify the authenticity of a given transaction (Peters & Panayi, 2016).

Blockchain, thus cryptocurrency, transactions are referred to as being distributed, because they do not rely on any centralised intermediary, but on consensus, to validate transactions. Blocks of transactions are added to the blockchain via a consensus algorithm (whose intricacies go beyond the scope of this thesis; see Eyal and Sirer (2014) for an example of such an algorithm). A block is added to the chain if the majority (or in some cases all) of the nodes agree on the state of the ledger, i.e. that the proposed block will now be part of the ledger and that the block's transactions are valid (Swanson, 2015). Attached to each block is a timestamp, the hash value of the previous block and a nonce (which is a random number for verifying the hash value). Through these elements and the uniqueness of each hash value, fraud can be prevented since changing one of the blocks in the chain will automatically change the hash value of that block, which then no longer corresponds to the original hash value of this block attached to the next block in the chain (Nofer et al., 2017).

[1] Although it can be debated whether all cryptocurrencies are designed to be used as such.

This distinction begs the question of how the cryptocurrency tokens are created, because the supply system is not necessarily embedded in the protocol, only the secondary trading system is. A cryptocurrency's supply is managed by one of two mechanisms[2]: Proof-of-work or initial coin offering (ICO). In a proof-of-work system, tokens are generated over time as a reward for the so-called miners for their work in validating transactions and adding new blocks to the chain. This system is typically used in permissionless blockchains, which are truly distributed ledgers where the creator of the protocol has no centralised control over the nodes; therefore, anyone can become a node (i.e., a miner) (Swanson, 2015). The most famous example of a proof-of-work blockchain is Bitcoin, where the block reward is halved every 210 000 blocks (approximately every four years), and is currently at 6.25 BTC (the next halving is projected in 2024).[3] Since a new block is added about every ten minutes, around 900 BTC are generated per day. Through this system, the total supply of bitcoins is fixed at 21 million BTC, which will approximately be reached in 2140. After that moment, miners will (exclusively) be paid transaction fees, which are set by the initiator of a transaction (Halaburda & Sarvary, 2016). The second mechanism endows the creator(s) of the cryptocurrency at the time of initiation. Then, there is usually an initial coin offering (ICO) or an initial exchange offering (IEO) such that the token starts publicly trading (X. Li & Whinston, 2019).

The latter system introduces the exchange mechanism of cryptocurrencies. As a matter of fact, the cryptocurrency protocol only defines the operational setup of how a transaction is unwinded but does not connect a willing buyer to a willing seller.[4] Broadly speaking, the academic literature distinguishes between three exchange mechanisms for cryptocurrencies: centralised exchanges (CEX), decentralised exchanges (DEX), and "side channels" (Adamik & Kosta, 2019). CEXs (e.g., Binance) operate with comparable rules regarding trade execution, price discovery, and provision of liquidity to traditional securities exchanges. DEXs are platforms that facilitate peer-to-peer transactions through decentralised order matching and/or Automated Market Makers (AMM). Decentralised order matching uses order books similar to traditional exchanges, where buyers and sellers place orders specifying price and quantities; the DEX then matches and executes orders based on price. AMMs use liquidity pools and mathematical formulas to determine prices. Liquidity providers deposit funds into these pools, and trades are executed against the pooled liquidity based on the ratio of cryptocurrency and liquidity funds (which can be either another cryptocurrency or, to a lesser extent, a fiat currency) (Aspris et al., 2021). "Side channels" is an umbrella term that regroups all other exchange mechanisms, including peer-to-peer trading platforms and social media & messaging platforms (Adamik & Kosta, 2019).

As a consequence of the decentralised nature of cryptocurrency trading, the law of one price does not hold, as the market frictions introduced by the requirements of computing power and computer science skills to participate in the market (especially in DEXs) introduce a substantially higher number of arbitrage opportunities that are incompatible with the law of one price (Köchling et al., 2019; Fang et al., 2022). Therefore, the reader should be aware that cryptocurrency databases (like CoinMarketCap[5]) collect data from various exchanges and trading platforms and process it using algorithms to calculate a weighted average price, which is displayed as the cryptocurrency's price in the database, a process called price aggregation. Therefore, the prices are indicative and can vary slightly from the actual trading prices on specific exchanges at any given moment due to various factors, such as the aggregation methodology (Trimborn & Härdle, 2018).

[2] Both mechanisms can also be combined.
[3] `https://bitcoinblockhalf.com/`
[4] This statement does not imply that there are no cryptocurrency protocols that also foresee a DEX. Ethereum, the second largest cryptocurrency by market cap, has built, on top of the original protocol, a smart contract blockchain that can be assimilated to a DEX.
[5] `https://coinmarketcap.com/faq/`

2.2 Mutual funds market: the basics

As will be shown in the following, the term mutual fund can designate a number of different investment vehicles depending on the regulation, investment strategy, type of assets, etc.[6] The broadest definition of a mutual fund is that a mutual fund is a form of collective investment, where a number of investors pool their money and invest it according to a pre-defined investment objective (Khorana et al., 2007). The names and regulations differ depending on the jurisdiction; in the U.S. and North America, the term mutual fund is the most common, whereas, in the E.U., the term UCITS (Undertakings for Collective Investment in Transferable Securities) or AIF (Alternative Investment Fund) is used as a result of the names given to the respective directives; in France and Luxembourg, mutual funds are often referred to by their legal structure, SICAV (*Société d'Investissement à Capital Variable*). In the UK and most of Asia (including Australia), the term investment or unit trust is common. In this thesis, the term mutual fund will be used to refer to this form of collective investment.

A mutual fund can either be open-ended or closed-ended. Open-ended funds sell and redeem shares directly to investors based on the fund's current net asset value (NAV), i.e. the number of shares is unlimited, whereas closed-ended funds issue a fixed number of shares and subsequent trading is done on the secondary market. Exchange-traded funds (ETFs) are (generally) open-ended funds that are also exchanged on traditional exchanges.

Due to the pricing mechanism of open-ended funds, these mutual funds trade at or near (for ETFs) the fund's NAV. On the other hand, closed-ended funds can trade at a substantial premium or discount to the NAV, depending on various factors, like manager track record and supply & demand.

Mutual funds can further be classified according to the assets they hold (equity funds, bond funds, multi-asset funds, etc.), or their investment objective (passive tracker or index funds, active funds, hedge funds, etc.).

Note that hedge funds are also considered to be mutual funds. However, unlike most other long-only mutual funds, hedge funds have recourse to (physical) short selling (long-short strategy).[7]

At this stage, the reader should be aware of these differences, as this heterogeneity will influence the methodology of this thesis (see Chapter 3).

2.3 Behavioural finance, biases, and lottery-like preference

The foundational notion of neoclassical economics is the *homo economicus* introduced by Mill (1836) and formalised by Pareto (1906). One of the features of the *homo economicus* is full rationality, or the full rational behaviour of economic agents. Accordingly, individuals would have full capacity to rationally process all the available information; consequently, all taken decisions would be rational (Simon, 1986).

The rational behaviour of economic agents – which is, among others, an implicit assumption of Modern Portfolio Theory (Markowitz, 1952) - has become one of the most contentious discussion points among scholars in finance since the 1980s. This controversiality has led to two schools of thought: rational choice theory and behavioural finance. One way of differentiating between both is by looking at how their proponents justify the existence of market anomalies. According to rational choice theorists, among which Eugene Fama and Mark Rubinstein, anomalies are either "empirical illusions" (Rubinstein, 2001) or risk premia for some kind of (systematic) risk factor, therefore, rationally justified (Fama &

[6] the main source for this section is Russell (2015)

[7] Though the term UCITS can then no longer be used as a substitute for the term 'mutual fund', since UCITS cannot, by law, have recourse to physical short selling.

French, 1996). In the realm of behavioural finance, on the other hand, market anomalies are a result of cognitive biases that create persistent market situations that cannot be explained by neoclassical finance and are incompatible with the *homo economicus* (Hirshleifer, 2015). This difference in ideology can also be related to the efficient market hypothesis. Whereas for rational choice theorists, markets are efficient (therefore, there is no such thing as an anomaly), behavioural finance rejects even the weak form of efficiency (Schulmerich et al., 2014).

In some sense, lottery-like preferences are the epitome of what behavioural finance is about, since lottery-like preferences have been related to a number of cognitive biases that create a market anomaly of overvalued stocks that exhibit a small probability of a large positive return (Barberis & Huang, 2008). Investor preference for lottery-like payoffs has been related to the salience theory (Bordalo et al., 2012), cumulative prospect theory (Tversky & Kahneman, 1992; Barberis & Huang, 2008), mental accounting (Thaler, 2008) and investor sentiment/optimism (Fong & Toh, 2014).

Research suggests that not only private but also professional investors (fund managers, pension funds, etc.) are prone to behavioural biases. Interestingly, overconfidence and confirmation seem to be biases that are more present in professional than private investors (H. Baker et al., 2017). More importantly for this research, other cognitive biases seem to be less, or even not, exhibited by professional investors. The type of behavioural biases that are less prevalent in professional investors are those that are linked to assets' intrinsic characteristics, such as the anchoring effect (Kudryavtsev et al., 2013) or the herding effect (Kourtidis et al., 2011). These findings might suggest that the MAX effect cannot be found among mutual fund managers. Tentative research by Gao et al. (2021) noted that not only do professional managers not exhibit this lottery-related behavioural bias, but they can use it to their advantage. Agarwal et al. (2021) provide the most convincing evidence to date that fund managers do not exhibit lottery preferences. The authors show that, when confronted with the choice, professional investors avoid investing in lottery-like assets.

The conclusions of the research that has focused on investor preference for lottery stocks are twofold. The first conclusion is that (private) investors have a higher demand for lottery-like stocks, i.e. stocks that are low-priced with high idiosyncratic volatility and high idiosyncratic skewness (Kumar, 2009). This has been shown through the link between fund flows and fund lottery holdings (Agarwal et al., 2021) and via investor characteristics (propensity to gamble) and subsequent investment behaviour (Cheon & Lee, 2018). The second type of conclusion is linked to the future performance of lottery stocks. Research has shown that the cognitive biases that are linked to this lottery-like preference tend to make these stocks overpriced and therefore, they tend to exhibit lower returns in the future (see also Section 2.5). As a matter of fact, different papers have established that lottery stocks underperform nonlottery stocks (Fong, 2013), or, put differently, a positively skewed security can be overpriced and can earn a subsequent negative average excess return (Barberis & Huang, 2008). The papers that provide empirical evidence of the profitability of the MAX or TMAX Strategy (see section 2.5) can be added to that list of papers.

Even though Kumar (2009)'s definition of lottery stocks is generally accepted among scholars (most of the papers on lottery-like preferences use this definition), there is divergence on how to test whether a stock (or asset) conforms to lottery-like features. Section 2.5 will delve further into that matter.

2.4 Cryptocurrencies – mediums of exchange or speculative assets?

Even though the biggest cryptocurrencies by market cap, Bitcoin and Ethereum, have been introduced as mediums of exchange similar to fiat currencies by their sponsors (see for example Nakamoto (2008)), this premise is highly contested among academics.

Only a minority of users appear to use Bitcoin as a medium of exchange (Baur et al., 2018). The Bitcoin ledger shows that about a third of bitcoins are held by users that only receive bitcoins for investment purposes and never send (i.e., sell) them to others. The practical usage of the largest cryptocurrency thus seems to contradict the idea that it can serve as a medium of exchange but seems to indicate that cryptocurrencies should be assimilated to speculative assets.

Furthermore, research has demonstrated that cryptocurrencies do not fulfil the fundamental functions of mediums of exchange, such as unit of account, means of payment and store of value (Dwyer, 2015). This means that a cryptocurrency should have a stable fundamental value and command a certain level of confidence among its users to be a contender for a medium of exchange. The volatility of cryptocurrencies undermines their potential role as a unit of account and is not suggestive of a stable fundamental value (Dowd, 2014).

In summary, researchers tend to agree that cryptocurrencies are speculative assets rather than a medium of exchange. A speculative asset is an asset whose price is determined by market speculation rather than economic fundamentals (Marin & Rahi, 1997). The reason being that cryptocurrencies do not generate cash flows, and they cannot be exchanged for goods and services, like gold and silver (Cheah & Fry, 2015). As a consequence, and according to basic finance theory, cryptocurrencies cannot have a fundamental value, since the value of any financial asset is defined as the present value of expected future cash flows (Sanger & Fisher, 1907; Williams, 1938; Markowitz, 1952), cash flows which are non-existent for cryptocurrencies. Cheah and Fry (2015) have tested this theoretical postulate and provided empirical evidence that the intrinsic value of a bitcoin is zero.

Hence, the purpose of holding cryptocurrencies warrants investigation. Investors fulfilling their lottery demand may be one such purpose. The main argument that has been advanced in research for holding this asset class is its hedging and diversifying capabilities in a stock-bond-commodity portfolio (Dyhrberg, 2016; Bouri, Gupta, et al., 2017; Platanakis & Urquhart, 2020) and for currencies (Dyhrberg, 2016; Urquhart & Zhang, 2019). However, there are some limitations that weaken this premise, including that this feature only works for short-term investment horizons and in bull markets (Bouri, Molnár, et al., 2017) and that the high idiosyncratic risk of cryptocurrencies makes it difficult to hedge against (Corbet et al., 2019); Bouri, Molnár, et al. (2017) even show limited evidence for any hedging properties attributable to Bitcoin.

It is therefore not surprising that several research papers have compared cryptocurrencies' price evolution to speculative bubbles since they seem to lack any rational argument for being held by investors (Cretarola & Figà-Talamanca, 2020; Geuder et al., 2019; Chaim & Laurini, 2019). Formally speaking, a bubble occurs when the value of an economic asset deviates, persistently, from fundamental values (Diba & Grossman, 1988). Cheah and Fry (2015) consequently consider Bitcoin a speculative bubble *per se* since they attribute a fundamental value of zero to Bitcoin, which makes its prices consistently deviate from this intrinsic value (of zero).

The missing piece concerns the explanation of why the cryptocurrency market seems particularly prone to speculative bubbles. Demand for lottery-like assets could be one explanatory factor for these bubbles since cryptocurrencies are *the* lottery-like asset class *par excellence*. Coming back to Kumar (2009)'s definition of lottery-like assets, cryptocurrencies have, on average, higher positive skewness and higher idiosyncratic volatility than stocks (Chuen et al., 2017; Hu et al., 2019; Momtaz, 2021). Motivated by this phenomenon, the MAX effect has been studied in the cryptocurrency market (Grobys & Junttila, 2021; Ozdamar et al., 2021; Y. Li et al., 2021).

2.5 From MAX to TMAX Strategy

As alluded to in section 2.3, even though the definition of lottery-like preferences and lottery-like stocks is common knowledge, the question remains on how to test whether any security exhibits a "small probability of a large positive return". Bali et al. (2011) propose to use the maximum daily return (MAX) of stocks over the past month as a proxy of this lottery-like feature. Investors consider a high MAX over the past month as a signal of the possibility of a large positive return, and since investors exhibit lottery-like preferences (so the hypothesis), they are willing to pay more for these stocks with extreme positive returns; they are therefore overpriced and have a lower expected return. An implicit assumption in Bali et al. (2011) is that investors consider the cross-section of returns as a benchmark. As a consequence, the higher the MAX, the higher the lottery-like feature of the stock, and the lower the expected return. Conversely, the lower the MAX, the lower the lottery-like feature, and the higher the expected return, because these stocks tend to be overlooked, therefore underpriced. The cut-off points for “high MAX” and “low MAX” have been set by Bali et al. (2011) at the 9th and 1st decile of the cross-section of maximum daily returns during the previous month, respectively.

If Bali et al. (2011)’s hypothesis is correct, an investment strategy that consists in buying the stocks in the 1st (bottom/low) decile and short selling the stocks in the 10th (top/high) decile should earn abnormal returns in the post-formation month (the month after the one where the decile ranks have been determined). Bali et al. (2011) find an average risk-adjusted return difference of above 1 percentage point per month. Not only does the paper confirm the lower expected return of lottery stocks, but it also shows that the 'high MAX' decile portfolio complies with Kumar (2009)’s definition of lottery stocks, namely stocks with high idiosyncratic volatility and high idiosyncratic skewness.[8]

The elegance of this definition of lottery-like payoff consists in its robustness to various controls, in particular, size, book-to-market, momentum, short-term reversals, liquidity, and, most importantly, skewness. The fact that the lottery-like preference anomaly has been empirically proven even controlling for skewness really brings home the argument that lottery-like preference is a cognitive bias in the realm of behavioural finance and not a (negative) risk premium for skewness, as rational choice theorists proclaim (see Barberis and Huang (2008) that directly address this point).

The MAX Strategy (or “MAX effect” (Fong & Toh, 2014)) has been extensively covered in the literature to provide empirical evidence of investors' tendency to prefer stocks that experience extreme positive returns over the recent past (e.g., month). The most extensive study by Cheon and Lee (2018) has provided evidence of the universality of the MAX effect by examining a sample of 47 000 stocks from 42 markets. Further evidence is provided for European (Annaert et al., 2013), UK (Khasawneh et al., 2021), Australian (Zhong & Gray, 2016), South Korean (Nartea et al., 2014), Hong Kong (Chan & Chui, 2016), Chinese (Nartea et al., 2017; Wan, 2018), Taiwanese (Hung & Yang, 2018), Brazilian (Berggrun et al., 2019) and Turkish (Alkan & Guner, 2018) stock markets. There is also evidence of the MAX effect in the cryptocurrency (Grobys & Junttila, 2021) and in the mutual funds market (Agarwal et al., 2021).

However, there is some conflicting evidence regarding the prevalence of the MAX effect, in the stock market, and especially if other markets are considered. Sharma and Chakraborty (2019) found that there is no negative relationship between extreme positive returns and expected returns in the Indian stock market, suggesting that investors do not overpay for lottery-like stocks in India, i.e. investors in this market do not have a particular demand for lottery-like assets. Gao et al. (2021) found a reverse MAX effect in the Chinese mutual funds market. Ozdamar et al. (2021) and Y. Li et al. (2021) also found a reverse MAX effect in the cryptocurrency market and called it "MAX momentum".

[8]Factually, Bali et al. (2011)’s 'high MAX' decile portfolio has the highest idiosyncratic volatility and idiosyncratic skewness, as well as the lowest post-formation month return out of all decile portfolios.

The reverse or absence of a MAX effect in Sharma and Chakraborty (2019) and Gao et al. (2021) can (in part) be attributed to the peculiar regulatory setting in both markets, a limitation that the authors from both papers mention, but there seems to be one major caveat with the MAX Strategy: it may be a proxy for investor sentiment. In fact, even though the paper provides evidence *for* the MAX effect, Fong and Toh (2014) show also that, when controlling for investor sentiment, the MAX effect becomes much weaker, on the brink of statistical insignificance. On that basis, questions can be raised whether the implementation of a MAX Strategy can really test the presence of lottery-like preference or whether it can only provide evidence of how investor sentiment affects expected returns. Not to mention that the MAX Strategy does also not address the conflicting evidence regarding momentum and momentum reversal strategies.

Lin et al. (2021) therefore argue that lottery-like preferences are not exhibited through the cross-section of stock returns but through a stock's own past historical returns. The authors postulate that lottery preference is formed toward tracking stocks' performance over time, i.e., the historical trend of return pattern serves as the benchmark, not the cross-section of stock returns. This definition of lottery-like preference is robust to investor sentiment and across different periods, unlike the MAX. Even more, Lin et al. (2021) show that the TMAX Strategy subsumes the profitability of the MAX Strategy by Bali et al. (2011).

Based on Peng and Xiong (2006) and Moskowitz et al. (2012)'s findings that demonstrate that investors form their beliefs by updating and gathering information over time, Lin et al. (2021)'s "time-dependent MAX" (TMAX) strategy consists in buying stocks with the most recent maximum daily return lower than the 10th percentile of the historical distribution of the stock's MAX and short selling those with the most recent MAX values higher than the 90th percentile of the historical distribution of the stock's MAX. The authors provide empirical evidence of the profitability of such a strategy, thereby confirming the lottery-like preference of investors via their methodology.

Lin et al. (2021) not only confirm the hypothesis of Bali et al. (2011) and all related research on lottery-like preference, but they also provide a methodology (TMAX Strategy) for testing the hypothesis that is more robust, both empirically and theoretically, than the MAX Strategy. Through their research, the authors show that it is not the presence of lottery-like preference that has to be questioned, but the previously applied methodology, thereby addressing the 'counter-stream' of research that denies this investor behaviour through investor sentiment (Ozdamar et al., 2021), hedge against volatility (Barinov, 2018) or skewness (Brunnermeier et al., 2007).

The theoretical robustness of the TMAX Strategy in explaining the future performance of lottery stocks and its links to lottery-like preference can be related to the overpricing argument, prospect theory and psychological barriers. Through shorting flows, Lin et al. (2021) confirm the hypothesis that if the lottery-related anomaly is induced by overpricing, there should be some arbitrageurs entering the market to correct such mispricing, by showing that the highest TMAX decile portfolio holdings have the highest shorting flows and generate the lowest subsequent returns.[9] Moreover, in line with Kahneman and Tversky (1979)'s prospect theory, that investors are more-risk seeking in the loss region, the profitability of the TMAX Strategy is higher when investors face prior (unrealised) losses, providing evidence that investors have a stronger preference for lottery stocks when they are risk-seeking, i.e. in the loss region. Finally, Lin et al. (2021) show that the profitability of the TMAX Strategy conforms with mental accounting and recency bias theory, as well as the anchoring effect (the authors group these three biases under "psychological barriers"), when they provide empirical evidence for higher TMAX Strategy returns when stock prices are far from the 52-weeks high, which act as an anchor.

[9] Interestingly, Lin et al. (2021) show that this phenomenon is not observable in the MAX Strategy.

2.6 Cryptocurrency market - MAX momentum?

As mentioned above, the MAX effect has been tested and confirmed in the cryptocurrency market (Grobys & Junttila, 2021; Ozdamar et al., 2021; Y. Li et al., 2021). While Grobys and Junttila (2021) observe the traditional effect in the cryptocurrency market, Ozdamar et al. (2021) and Y. Li et al. (2021) provide empirical evidence for a reverse MAX effect (which they called "MAX momentum", cf. above), i.e. whereby the highest MAX decile outperforms (rather than underperforms) the lowest MAX decile portfolio.

Both Ozdamar et al. (2021) and Y. Li et al. (2021) reject Grobys and Junttila (2021) findings due to the limited sample size and time period considered. Grobys and Junttila (2021) limit their research to the 20 biggest cryptocurrencies as of January 1, 2016, and to the time period 2016 to 2020; in contrast to Y. Li et al. (2021), which analysed up to 500 cryptocurrencies.

The presence of a MAX momentum in a particular market does not automatically put into question the lottery-like preferences of investors, it merely puts into question the profitability of the related investment strategy. If there was no lottery-like investor preference, there should be no difference in returns between decile portfolios (after controlling for confounding factors), therefore, the null hypothesis of a zero average return of the (T)MAX Strategy should not be rejected (Ozdamar et al., 2021). The rejection of the null hypothesis itself can be considered empirical evidence of a lottery-related anomaly.

However, the literature so far attaches a clear directional effect to the lottery anomaly, namely that lottery assets underperform (not outperform) the rest of the market. Neither Ozdamar et al. (2021) nor Y. Li et al. (2021) question the demand for lottery-like assets of cryptocurrency investors even though the authors provide evidence of a MAX momentum effect. Unfortunately, their research is muted about possible explanations for this phenomenon and how to reconcile this effect with the findings in the stock market.

2.7 Lottery demand in times of crisis

There seems to be converging evidence that indicates a higher demand for lotteries during economic downturns. Several papers have shown that during the Great Depression of the 1930s, the popularity of gambling increased dramatically in the United States (Brenner & Brenner, 1990) and Sweden (Tec, 1965). These findings have been extended to various forms of gambling, including state lotteries (Mikesell, 1994) and to different crisis periods, including the Dot-com bubble and the Global Financial Crisis (GFC) (Meitz, 2013).

Not only demand for 'traditional' lotteries seems to be higher in times of crisis, but also demand for lottery-like stocks (Kumar, 2009). Consequently, as a result of the overpricing argument for the profitability of the (T)MAX Strategy, returns of this type of strategy should be higher in crisis periods. This hypothesis has been confirmed by Walkshäusl (2014) and Khasawneh et al. (2021).

The underlying factors that seem to explain the higher demand for lotteries and lottery stocks in crises are the socioeconomic characteristics of gamblers/investors. Kumar (2009) demonstrates that factors such as unemployment and lower disposable income explain the propensity to gamble and hold lottery stocks. As unemployment and lower disposable income correlate with economic downturns, these periods exacerbate lottery-like preferences which explain the more pronounced MAX effect.

2.8 Takeaways & Main Testable Hypotheses

The literature review aimed to introduce the reader to the research that forms the basis of this thesis. As a result of the knowledge that currently exists on the topic, we will test three (sets of) hypotheses regarding lottery-like preferences (H1a, H1b), bubble-like behaviour (H2), and lottery-like demand in times of crisis (H3a, H3b). To ensure a better reading experience, some key concepts that have been developed during the literature review will be briefly summarised hereunder.

Even though cryptocurrencies rely on decentralised ledgers and can most of the time also be exchanged via decentralised exchanges, the largest cryptos are exchanged primarily on centralised exchanges. Cryptocurrencies can be created through ICOs (or IEOs), or through mining. The supply mechanism will significantly affect the quantity and timing of the supply of new coins. The heterogeneity in exchange and supply mechanism entails that the law of one price does not hold in that market. Furthermore, certain characteristics of the exchange (centralised exchanges) & supply (ICOs/IEOs) mechanism and/or underlying blockchain protocol (permissioned blockchains) are known to be prone to price gouging and manipulation. These factors have to be considered in the sampling technique.

The term 'mutual fund' is an umbrella term that can designate different investment vehicles, investment strategies, legal structures, exchange mechanisms, redemption processes, etc.

Cognitive biases in the realm of behavioural finance seem to be at the origin of the lottery-like preference of investors. Research has shown that recency bias, risk-seeking behaviour after unrealised losses, mental accounting and investor sentiment influence the lottery demand of investors.

The main 'testing tools' for lottery-like preference are the MAX and TMAX strategies; the TMAX Strategy is theoretically and empirically more robust, but still lacks the level of research of the MAX Strategy due to its recent introduction by Lin et al. (2021).

Motivated by the novel, more robust, TMAX Strategy to test the existence of lottery-like preferences of investors, this thesis will investigate whether this lottery-like demand also exists in the cryptocurrency and mutual funds market. At this stage, only the MAX Strategy has been investigated in both of these markets and given its shortcomings, it is highly relevant to test the presence of this investor trait using the more theoretically sound TMAX Strategy. Furthermore, it is interesting to see whether the conflicting evidence regarding a ‘traditional’ MAX effect or a MAX momentum effect in the cryptocurrency market can be attributed to the limitations of the methodology or whether the TMAX Strategy will also confirm a ‘TMAX momentum’.

In particular, we hypothesise, based on the findings of Ozdamar et al. (2021) and Y. Li et al. (2021), that investors do exhibit lottery-like preferences in the cryptocurrency market, due to the clear lottery-like characteristics of cryptocurrencies; however, these preferences do not lead to a subsequent underperformance, but to a subsequent overperformance of lottery-like cryptocurrencies:

Hypothesis 1a: Profitability of the TMAX Strategy in the cryptocurrency market

The TMAX Strategy yields statistically significant (negative) risk-adjusted returns in the cryptocurrency market, thereby providing empirical evidence of a TMAX momentum effect.

The literature on behavioural biases exhibited by professional money managers and the findings by Gao et al. (2021) lead us to formulate the hypothesis of no TMAX effect in the mutual funds market. Agarwal et al. (2021) have provided evidence for a MAX effect in that market, but the authors limited their sample to high-ownership funds (i.e., funds owned by a limited number of shareholders who have a say in the fund's investment activities) because the authors' aim was to show that the more the fund managers are accountable to a specific group of investors, the more they cater to their preferences. Additionally, the authors demonstrated that professional managers exhibit an aversion to lottery-like stocks, i.e. they will avoid investing in such assets when possible. Therefore, the findings of these papers lead to the formulation of the following hypothesis:

Hypothesis 1b: Profitability of the TMAX Strategy in the mutual funds market

The TMAX Strategy does not yield statistically significant risk-adjusted returns in the mutual funds market, thereby providing no empirical evidence of lottery-like preferences of professional investors.

The second category of hypotheses is a result of the convincing evidence of speculative bubbles in the cryptocurrency market. As we have shown through existing research, cryptocurrencies are more likely to be speculative assets than mediums of exchange and do not seem to have a neoclassical economic basis to be held. Several scientific papers have made the link between cryptocurrency price evolutions and bubbles, however, with little to no theoretical explanation. Hence, our aim is to make a link between lottery-like preferences and speculative bubbles to shed light on this under-researched topic.

As a matter of fact, the TMAX Strategy assumes that the overpricing due to lottery-like preferences normalises during the post-formation period, which makes this strategy profitable. However, the whole concept of a speculative bubble is a *persistent* deviation from fundamental value, often over several months, and affecting a whole market. During such speculative bubbles, the whole market is experiencing an (irrational) increase in value, which would thereby make such a strategy unprofitable. Given that we already assume under Hypothesis 1a that the TMAX Strategy generates losses in the cryptocurrency market in general, we hypothesise that the TMAX Strategy generates even higher losses during speculative bubbles. As a consequence, we postulate the following:

Hypothesis 2: Lottery-like preference and speculative bubbles in the cryptocurrency market

The TMAX Strategy yields statistically significant losses during speculative bubbles in the cryptocurrency market that are higher than in normal times. These periods show a market-wide presence of lottery-like cryptocurrencies, thereby fuelling investor demand and in return, speculative bubbles.

Existing research has demonstrated that demand for lotteries and lottery stocks increases during economic downturns which makes the MAX Strategy more profitable. Therefore, we hypothesise that lottery-like demand is also higher for cryptocurrencies and by mutual fund managers during periods of economic crisis.

Hypothesis 3a: Lottery-like preference during economic downturns, cryptocurrency market

The TMAX Strategy is more profitable during economic downturns than in normal times due to higher lottery-like demand for cryptocurrencies which amplifies the overpricing of these assets and their subsequent lower performance.

Hypothesis 3b: Lottery-like preference during economic downturns, mutual funds market

The TMAX Strategy is more profitable during economic downturns than in normal times due to higher lottery-like demand by mutual fund managers which amplifies the overpricing of these assets and their subsequent lower performance.

Methodology

This thesis will apply the TMAX Strategy in the cryptocurrency and mutual funds market. As alluded to in the literature review, this method is justified by the ample research that has shown the (T)MAX Strategy to be a powerful tool to provide empirical evidence of lottery-like preferences.

As a consequence, this thesis uses quantitative research methods. The data is sourced from secondary databases (primarily from `www.coinmarketcap.com` (cryptocurrency market) and Eikon's Lipper Fund database (mutual funds market)) and treated to be usable for this research (cf. below). In particular, the TMAX Strategy requires the collection of panel data. The data analysis will start with descriptive statistics of the different decile portfolios, before running statistical hypothesis tests on these portfolios and finish with a regression analysis that is standard in finance, namely regressing the TMAX Strategy's returns on factor models.

The end goal being, beyond providing empirical evidence (or not) of the lottery-like preferences of investors, to test the robustness of the findings with these factor models and other robustness checks in order to accept (or not) beyond reasonable doubt the idea that the TMAX Strategy uncovers a stock market anomaly.

3.1 TMAX Strategy by Lin et al. (2021)

Lin et al. (2021) keep the same definition of a MAX as originally proposed by Bali et al. (2011). Bali et al. (2011) define the MAX of a stock as the maximum daily return within a month. Let us therefore define the MAX of stock i during month t as :

$$MAX_{i,t} = max_d(r_{i,d,t}) \qquad d = 1, 2, \ldots, D_t$$

Where $r_{i,d,t}$ is stock i's return on day d of month t, and D_t is the number of trading days in month t.

As opposed to Bali et al. (2011) who consider the cross-section of stock returns as the benchmark, Lin et al. (2021) propose a stock's own historical returns as the benchmark, thereby introducing time-dependency, the 'T', into the TMAX Strategy. The approach to constructing the TMAX portfolios is comparable to Gulen and Petkova (2018), who also construct time-dependent portfolios, in their case, to test a momentum strategy.

Lin et al. (2021) first find a stock's maximum daily return within every month from the beginning of the sample period up to month $t-1$. This series of MAX values is then ranked into deciles. If a stock's MAX in month $t-1$ ranks above the 90th percentile of its entire distribution of MAX for all months up to month $t-1$, this stock is shorted at the beginning of month t. In reference to the existing literature on the subject, this recent MAX becomes noticeable to investors, who, as a result of their lottery-like preferences, overbuy this stock, leading to overpricing which triggers a correction in month t. Therefore, shorting the stock should prove to be profitable. Conversely, the TMAX Strategy goes long if a stock's MAX in month $t-1$ is ranked below the 10th percentile of its entire distribution of MAX for all months up to month $t-1$ to construct the long leg required to create self-financing portfolios.

In order to create truly self-financing portfolios, the long and short positions are held with equal weights or value weights in month t and rebalanced every month. In other words, a new self-financing portfolio is constructed each month based on the return data and MAX deciles up until the previous month.

Lin et al. (2021) also explore alternative definitions of time-dependent lottery preference to show that significance of the results does not depend on the specific setting:

As opposed to considering a stock's entire historical distribution to construct the MAX deciles, Barberis et al. (2016), Hollstein and Sejdiu (2020) and Mohrschladt (2021) suggest using a five-year period to estimate MAX deciles. Lin et al. (2021) have added a ten-year period as a third option.

Even though the literature generally considers the maximum daily return over one month as a proxy for lottery-like preferences, there is no real scientific basis for it. Alternative lengths considered by Lin et al. (2021) are the maximum daily return over a quarter or over a year.

Lin et al. (2021) report, in addition to raw returns, also risk-adjusted returns using Fama and French (2015)'s five-factor model.

Because the TMAX Strategy computes deciles based on an asset's historical return distribution, a certain number of prior data points are required to implement the strategy. Lin et al. (2021) have used data from 1926 to 1967 to constitute the historical deciles for the first TMAX implementation date. In other words, the data from 1926 to 1967 is used as training data, whereas the actual implementation of the TMAX Strategy starts in 1967.

This thesis will closely mirror Lin et al. (2021)'s TMAX Strategy, noting that the approach has to be modified on certain points due to the specificities of the cryptocurrency and mutual funds market, as will be shown in the following.

3.2 TMAX Strategy in the context of the cryptocurrency market

Cryptocurrencies appear to be short-memory processes (Grobys et al., 2020), meaning that cryptocurrencies exhibit short-term rather than long-term reversal and/or momentum features. Furthermore, the cryptocurrency market exhibits extremely high volatility (Dwyer, 2015; Shen et al., 2020) and has a relatively short history.

Consequently, the little research that exists on the MAX effect in the cryptocurrency market has debated whether it is accurate to use the monthly timeframe proposed by Bali et al. (2011) (and *in extenso* Lin et al. (2021)) in this market. Grobys and Junttila (2021), Y. Li et al. (2021), and Ozdamar et al. (2021) all agree that it would not be accurate. However, they do not agree on an alternative time length.

Grobys and Junttila (2021) employ a weekly forecast and maximum daily returns over a week to construct their MAX portfolios. This method yields a weekly rebalancing, as opposed to a monthly rebalancing, of the portfolios. Y. Li et al. (2021) and Ozdamar et al. (2021) also use a weekly rebalancing method, however, they use the original definition of a MAX, being the maximum daily return over a month (and not a week, as in Grobys and Junttila (2021)). All three methods increase the number of observations and thereby the accuracy of the statistical inference, addressing the issue of a relatively short history of the market; also, using weekly rebalancing follows Grobys et al. (2020)'s findings and is more accurate amidst a highly volatile market. Note also that cryptocurrencies are traded 24/7, thus providing higher-frequency data, more data points, and a sound basis to use weekly rebalancing.

Decoupling the MAX computation time length from the portfolio forecasting/holding time length, similar to Y. Li et al. (2021) or Ozdamar et al. (2021), would add (unnecessary?) complexity in the context of a TMAX Strategy. The MAX Strategy is simpler in the sense that, since securities are compared in a cross-section, at each portfolio rebalancing date t, only one MAX value per individual stock is required, the one from period $t-1$, to construct the portfolio. However, in the TMAX Strategy, *all* past MAX values are required to construct the portfolio, since this distribution is considered to be the benchmark. As a consequence, using different portfolio holding and MAX computation time lengths would not only require the computation of two different distributions but also require the re-computation of the whole past MAX values series at each portfolio rebalancing date, since the cut-off points for the MAX values will move with the portfolio rebalancing date. Let us take an example: imagine that the rebalancing date is January 1st, we use weekly forecasting but Bali et al. (2011) MAX definition. On that date, all past MAX values will comprise the maximum daily return of past calendar months. Then, on January 8th, the next rebalancing date, all past MAX values will go from the 8th of month $t-n$ to the 7th of month $t-(n+1)$, requiring a re-computation of the whole historical distribution of MAX values.[1]

On these grounds, and incorporating the research just presented, we will modify Lin et al. (2021) TMAX Strategy for the analysis of the cryptocurrency market as follows:

This thesis will switch from a monthly to a weekly timeframe. In other words, the MAX is defined as the maximum daily return over the past *week* and portfolios are rebalanced (i.e. constructed) *weekly*. This method will enhance the statistical inference due to the higher number of self-financing portfolios while avoiding being overly complex, and is based on existing research (Grobys et al., 2020; Grobys & Junttila, 2021).

Regarding the alternative definitions of lottery preference, using a five- or ten-year look-back period to estimate MAX deciles is of little use in the cryptocurrency market since the data only starts at the end of 2013, leaving not enough historical data to implement these alternatives. Similarly, defining MAX as the maximum daily return within the last quarter or last year would require too many initial data points to sensibly construct MAX deciles before implementing the first portfolio, so not enough time periods would be left to actually implement the strategy and provide a meaningful analysis. Moreover, such an approach would clearly contradict the evidence regarding the short-memory process of cryptocurrency prices (see Grobys et al. (2020)).

That being said, we will also provide the monthly timeframe as per Lin et al. (2021) as a comparison and to potentially confirm Grobys et al. (2020)'s findings. Also, Fama and French (2015)'s five-factor model cannot be applied to cryptocurrencies; other explanatory variables will be used instead (see subsection 3.6.3 for more detail).

To ensure that the computed deciles are representative of the historical distribution, we require at least 30 weeks of daily returns before a cryptocurrency is eligible for investment in the TMAX Strategy. These 30 weeks are comparable to the 12 months of returns Lin et al. (2021) require before a new stock becomes part of the investment universe. Requiring more initial data points in the cryptocurrency market is a direct result of the odd behaviour of cryptocurrency prices after their launch (see also subsection 3.5.1).

3.3 TMAX Strategy in the context of the mutual funds market

For the purpose of this study, we are interested in the TMAX effect in the equity funds market, since it closely relates to the research stream on lottery-like stocks.

The interest in studying this effect in the mutual funds market is because it can serve as a proxy of the investment behaviour of professional money managers. Since their investment behaviour is of interest,

[1] Moreover, it can be seriously doubted whether investors rely on this process when forming their time-dependent lottery demand.

we want to limit as much as possible the contamination of the fund data from external factors that are not linked to the investment behaviour of professional managers.

As a consequence, closed-ended funds are excluded from the study. As explained before, these funds can trade at significant discounts or premia to their NAV due to factors out of the control of the manager. Therefore, the returns of these funds do not always accurately represent the returns of the fund's assets and thereby the investment behaviour of the managers. ETFs are also excluded for a similar reason: even though the closing prices are generally close to the fund NAV, there is (usually) a difference which is due to market factors such as supply & demand, that are not directly linked to the fund management. Logically, index funds are also excluded since they are meant to track the performance of an index, therefore leaving no space for active management by the fund manager.

To summarize, this research will focus on open-ended, actively managed equity funds that are not exchange-traded. This specification will allow us to make an effective simplification: the returns of the funds in the sample are equivalent to the weighted-average returns of the funds' underlying assets. As a consequence, we can make a portfolio-level analysis of the lottery-like preferences of professional managers.

3.4 Sub-period analysis for hypotheses H2 and H3

Since scientifically identifying periods of bubbles or crisis go beyond the purpose of this thesis, we will rely on existing academic literature to provide us with timestamps of bubbles in the cryptocurrency market and of economic downturns.

Hafner (2018) has studied bubble-like behaviour on a market level, rather than on an individual cryptocurrency level. The paper identifies the period from May 5, 2017, until December 15, 2017, as a bubble period, providing the first timestamp of bubbles in the market. In order to comply with our TMAX Strategy model, we have set May 8, 2017, and December 17, 2017, as the starting and end points, respectively, in order to fit in our weekly portfolio rebalancing timeframe.

Unfortunately, no other research has been conducted on a market level. However, numerous researchers have studied bubble-like behaviour in different cryptocurrencies on a standalone basis (Cheung et al., 2015; Corbet et al., 2018; Bianchetti et al., 2017; Z.-Z. Li et al., 2018; Phillips & Gorse, 2017; Wheatley et al., 2018; Bouri et al., 2019; Cagli, 2019; Chaim & Laurini, 2019; de Sousa & Pinto, 2019; Kyriazis et al., 2020). There seems to be an agreement among those researchers that the period from January 2013 to April 2014 has characteristics of a speculative bubble. These papers have also identified other periods; however, they are either restricted to one (or a few) cryptocurrencies and/or too short to be implemented in a TMAX Strategy.

Since the most recent paper that studied this behaviour was written in 2020, cryptocurrency price evolutions since then have not yet been scientifically analysed. That being said, practitioners tend to agree that between October 1, 2020, and November 12, 2021, cryptocurrencies experienced their biggest bubble yet.[2] Therefore, we also include the period from October 5, 2020, to November 15, 2021, in the bubble sub-sample.

The MAX effect has mainly been studied in two economic downturns/crises: the Dot-com crash and the Global Financial Crisis (Walkshäusl, 2014; Khasawneh et al., 2021). This research will do the same but add two, recent crises, the COVID-19 crisis, and the war in Ukraine and the subsequent stock market sell-off.

[2] https://www.thetimes.co.uk/article/the-bitcoin-bubbles-burst-heres-what-to-do-next-ng53zk6b2

Period	Source
07.01.2013 - 28.04.2014	Cheung et al. (2015) ; Hafner (2018) ; Su et al. (2018); Chaim & Laurini (2019); de Sousa & Pinto (2019); Wheatley et al. (2018)
08.05.2017 – 18.12.2017	Hafner (2018)
01.10.2020 – 12.11.2021	CRIX Index price chart, press reports

Table 3.1: Summary of sub-period analysis, speculative bubbles

Crisis	Period	Sources
Dot-com crash	01.03.2000 – 31.10.2002	Walkshäusl (2014); Khasawneh (2021)
Global Financial Crisis	01.09.2007 – 30.06.2009	Walkshäusl (2014); Khasawneh (2021)
COVID-19 Crisis	01.02.2020 – 30.09.2020	Press reports
War in Ukraine, stock market sell-off	24.02.2022-30.12.2022	Press reports

Table 3.2: Summary of sub-period analysis, economic downturns

Obviously, the cryptocurrency sample period only starts in 2013. Therefore, only the latter two crises will be analysed in that market.

The profitability of the TMAX Strategy in these sub-periods will be compared to its profitability in normal times, i.e. the time period where neither a bubble nor an economic downturn occurred, to provide an answer to hypotheses H2 and H3.

3.5 Data collection & treatment

3.5.1 Cryptocurrency data

CoinMarketCap[3] is a leading source of trading information on cryptocurrencies where prices are constructed using a weighted combination of closing prices from all exchanges where the asset is traded on. The idea is to weigh the closing prices by the trading volume on that particular exchange.[4] Furthermore, all cryptocurrencies that want to be listed on CoinMarketCap go through a vetting process, in order to minimise the risk of listing scam currencies (e.g., a currency whose protocol is prone to price manipulation by the sponsors). Major news outlets, Bloomberg, and even the U.S. government use CoinMarketCap's data for research and reports. Furthermore, CoinMarketCap has been used as a data source in a number of influential academic papers about the cryptocurrency market (Gandal et al. (2018), Kyriazis et al. (2020), and others), and in all three papers that have studied the MAX effect in the cryptocurrency market (Grobys & Junttila, 2021; Ozdamar et al., 2021; Y. Li et al., 2021).

Based on these elements, all cryptocurrency data has been sourced from `www.coinmarketcap.com`. In particular, data on the daily closing price, the daily exchange volume, and the market capitalisation of each cryptocurrency in the sample have been collected.

This cryptocurrency database requires a certain number of filters in order for the data to be usable for this research. As briefly mentioned in section 3.2, as opposed to the MAX Strategy, the TMAX

[3] `www.coinmarketcap.com`

[4] The reason for the industry-wide adoption of CoinMarketCap is its price construction methodology. As explained in the literature review, the law of one price does not hold in the cryptocurrency market. Therefore, prices have to be aggregated from different data sources (centralised exchanges, decentralised exchanges, distributed ledgers, etc.).

Strategy's implementation is dependent on the availability of historical data on the securities in the sample. Whereas the MAX only requires a robust cross-sectional sample size for its implementation, the TMAX Strategy also requires a robust time-series sample size. To constitute meaningful decile portfolios, the MAX Strategy is more reliant on the number of assets in the sample to create cross-sectional deciles at every portfolio rebalancing date. The TMAX Strategy, on the other hand, is reliant on the availability of historical data points to have enough training data to create the deciles for the first rebalancing date. Bearing this in mind, the historical data available in the CoinMarketCap database dates back to April 28, 2013, for the cryptocurrencies that already existed at that time. Therefore, for the oldest cryptocurrencies on the market, there is at most a little over nine years of data.

Added to this potential limitation, it is well-documented in research that cryptocurrencies with less than $5 million in market cap exhibit unusual price evolutions (see for example Y. Li et al. (2021)).

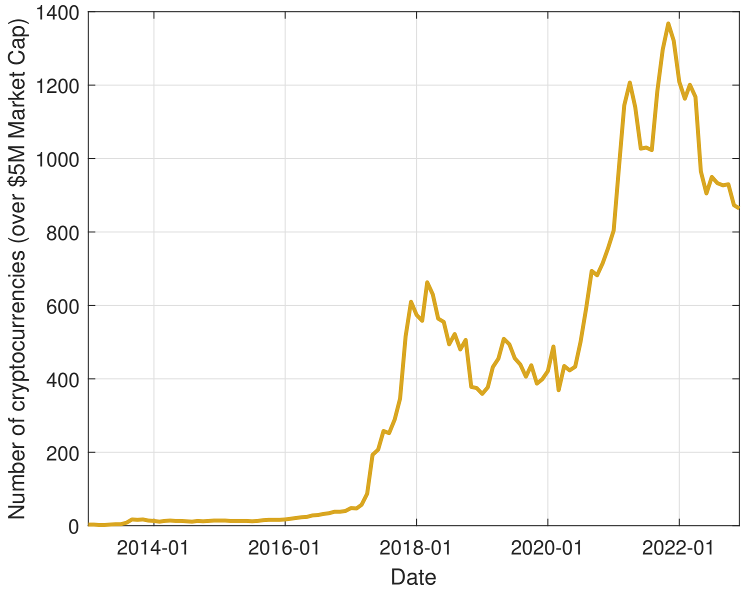

Figure 3.1: Evolution of the number of cryptocurrencies over $5M Market Cap

As can be seen in Figure 3.1, there were only 3 cryptocurrencies on April 28, 2013, that had a market capitalisation of $5 million or more, compared to over 800 at the end of 2022. This goes to show that special care had to be given to the sampling of the cryptocurrencies.

Taken together, the requirements for historical data availability, a market cap of at least $5 million, and a sample free of survivorship bias have forced us to employ a different sampling technique than Y. Li et al. (2021) and Ozdamar et al. (2021). Screening only on market cap runs the risk of including (too many) cryptocurrencies with not enough historical data, since the majority of cryptocurrencies have reached $5 million in market cap after 2019. Moreover, the TMAX Strategy is less sensitive to the cross-sectional sample size, which makes a more granular sampling possible. The sampling technique of this thesis is inspired by Grobys and Junttila (2021), who selected the 20 cryptocurrencies with the largest market cap at the beginning of their sample. This technique ensures a survivorship bias-free sample since this information would have been available to the naïve investor at that time. For this research, at the beginning of each year (starting in 2014[5]), the 10 largest cryptocurrencies by market cap are added to the sample. For the years after, the 10 largest cryptocurrencies besides the ones already included in

[5] The cryptocurrencies that fulfilled the market cap criteria on April 28, 2013, have obviously also been added to the investment universe.

the sample have been considered.[6]

Note that until mid-2016, using the just-explained sampling technique or including all cryptocurrencies with a market cap over $5 million would have yielded the same investment universe (cf. Figure 3.1).

Since the sample ends on December 30, 2022, this technique leaves us with a sample of 80 cryptocurrencies[7], with the data dating back to April 28, 2013, or the moment when a cryptocurrency crossed the $5 million market cap threshold, whichever came later. Since cryptocurrencies are traded 24/7, 365 days a year, we have 3 534 daily prices, exchange volumes, and market cap data points per cryptocurrency (for the ones that existed in 2013). In total, the sample includes 137 694 daily prices, as well as 137 694 daily exchange volumes and market caps.

Since the methodology of this thesis requires at least 30 weeks of historical data in order for a cryptocurrency to be added to the investment universe, the TMAX Strategy has been effectively implemented from the week starting on November 25, 2013, until December 30, 2022. The data from April 29 to November 25, 2013, is used to compute the deciles at the first portfolio construction date. The TMAX Strategy has therefore been implemented for 474 weeks, which is the sample size for the statistical inference.

The information bias in the CoinMarketCap database is limited since the database does not rely exclusively on self-reporting, but also on research conducted directly by the company. Moreover, coming back to the sampling technique, the sampling technique has ensured, also through cross-checks with other reputable databases (e.g., `www.coincodex.com`), that the cryptocurrencies that are added to the portfolio each year were in effect the largest by market capitalisation at that point in time.

3.5.2 Mutual funds data

The mutual funds data has been sourced from the Lipper Fund Research Database. This database is free of survivorship and information bias (Lipper states that the fund data in its database come "from multiple sources", i.e. not only self-reporting from asset managers). Furthermore, Eikon's platform allows for screenings that fit with the requirements of this thesis.

In order to comply with the methodology described in this chapter, the database has been screened for open-ended, actively managed equity funds that are not exchange-traded. In the Lipper database, an equity fund is defined as a fund whose prospectus mandates the manager to invest at least 80% of its assets in equities. This definition is in line with Agarwal et al. (2021) who examined the MAX effect in the U.S. mutual funds market. Due to the heterogeneity of the mutual funds market, a certain number of additional filters have been applied.

In order to ensure a homogeneous regulatory environment for the funds in the sample, only U.S.- and E.U.-listed (UCITS) mutual funds have been considered. Among others, the comparable regulation ensures that the sample is free of hedge funds and free of funds that engage in physical short selling, as well as that the funds only invest in securities that are traded on regulated markets. Then, the methodology requires daily price data. However, mutual funds are not obliged to compute the NAV daily. As a consequence, only funds with daily NAV computation have been included in the sample, funds with other NAV frequencies have been discarded. Finally, in order to construct meaningful deciles before integrating a fund into the TMAX Strategy, funds that have been launched after the end of 2017 have also been discarded, on the basis of not enough historical data.

[6] N.B.: As the attentive reader might have noticed in Figure 3.1, until mid-2016, there were less than 20 cryptos with a market cap of over $5 million. We have therefore made the assumption that on January 1, 2017, 26 cryptos are added to the investment universe to 'make up' for the lack of new investment possibilities in the previous years.

[7] No new cryptos were added to the sample at the beginning of 2022.

These criteria yield a sample of 2 308 mutual funds, with a 58/42 split between U.S. and E.U. funds.

The U.S. regulation that has created the mutual funds' structure as we know it today dates from the end of the 1970s, and the first UCITS directive was adopted in 1985. Therefore, our sample starts in 1980 and ends at the end of 2022 and includes 11 219 daily NAVs per mutual fund (for the funds that existed in 1980). In total, taking into consideration the training period (1980-1985), the TMAX Strategy has been implemented for 457 months, which corresponds to the sample size for the mutual funds analysis.

3.6 Estimation Methods

3.6.1 Hypothesis testing

To test the hypotheses listed in section 2.8, statistical inference will be relied upon, using two-sample t-tests. This process allows for the evaluation of whether the observed raw returns from the TMAX Strategy and whether the differences in returns between the different sub-periods are statistically significant.

Previous research exclusively implemented two-sample Welch t-tests on the difference between means of the bottom decile and top decile next-month return, rather than directly testing the vector of the actual (T)MAX Strategy, i.e. whereby, period by period, the combined return of the long and short leg is computed. There is a simple, yet powerful explanation for this method that may seem counterintuitive at first sight: using two-sample Welch t-tests reduces the bias in the t-test results when the TMAX effect is affected by a decay or emergence effect, i.e. the strategy was profitable over a restricted period of time for some time-specific reason but not 'on average' over the whole sample period. The key reason lies in the standard error estimation. In a one-sample t-test, whether the mean difference of the period-by-period changes (often referred to as 'deltas') is significantly different from zero is tested. The standard error in this case depends on the standard deviation of these deltas. When there is a decay effect, a lot of the deltas may be close to zero due to the diminishing values over time. This could result in a smaller standard deviation and consequently, a lower standard error. When the standard error is lower, it becomes easier to reject the null hypothesis (i.e., find statistical significance) because the sample means are more likely to be far from the hypothesized mean (zero in this case) relative to their variability. As a result, the one-sample t-test may incorrectly detect significant differences even if the underlying mean difference is not truly significant. This is a form of statistical noise. On the other hand, the two-sample Welch t-test takes into account the variability of both portfolios independently. By comparing the means of two independent samples (i.e., the long and short portfolios), the test takes into account the natural variation in each portfolio separately. When there is a decay or emergence effect, this approach is more robust because it does not depend solely on the deltas, which can be biased by the aforementioned statistical noise. Unintentionally, the results in the mutual funds market (cf. chapter 5) blatantly show the importance of choosing the correct methods to analyse the TMAX effect (i.e., two-sample Welch t-tests).

As will be shown in chapter 4, the empirical results have warranted a subtility compared to Lin et al. (2021) and prior research on the MAX Strategy. In our sample, the TMAX portfolios are 'empty' for some periods of time, meaning that the TMAX Strategy could not be implemented because no asset's maximum daily return over the prior period fell in the first or last decile of its historical distribution. Therefore, whereas for prior research on the MAX Strategy, the average return of the TMAX Strategy computed as the difference between the average next-month return of the bottom and top decile portfolio and the average of the long-short strategy vector was mathematically equivalent (due to the linearity of expectation), this is no longer the case since there are times in which the bottom (top) decile is empty but not the top (bottom) decile. In these cases, the bottom (top) decile return is added to the sample, but there is no corresponding return for the TMAX Strategy in that period, since it cannot be implemented due to a lack of short (long) leg.

Even though this phenomenon impacts the practical implementation of the TMAX Strategy over the sample period considered and the signal (the signal in the two-sample t-test now differs from the signal in the one-sample t-test)[8] it does not limit the theoretical findings. Indeed, the TMAX Strategy could, by nature, theoretically be implemented for one single security (while taking, for example, an opposite position in the risk-free asset to create self-financing portfolios), since only time-series data is required to implement the strategy and conclusions could be drawn on the profitability of this investment strategy for that particular security. The drawback of this type of analysis is that not in all time periods, a long or short position in that security would be taken, as explained in the previous paragraph. In essence, the aim of adding more securities to the investment universe is to, beyond making a market-wide analysis rather than an idiosyncratic one, limit the number of occurrences of an empty portfolio. Under the assumption of no perfect correlation between the maximum daily returns of the different securities in the portfolio, the probability of observing empty portfolios decreases as more assets are added to the investment universe. In the limit, i.e. in very large samples, the probability of observing empty portfolios converges to zero, and the postulate of equivalence between signals is re-established. This is confirmed by Lin et al. (2021), who did not encounter this issue due to their sample size (N = 11 562). In other words, the fact that we observe empty portfolios for some periods is a result of the (cross-sectional) sample size and does not impede the statistical inference. Note that the size of both the cryptocurrency and mutual funds investment universe is sufficient to make statistical inferences based on standard procedures, knowing that it is a limitation of the investment process to have some periods without an observation. This means that the potential out-of-sample profitability of the TMAX effect is not impeded by these empty portfolio occurrences, it just limits the practicability of the strategy (cf. also section 5.3).

As a result, the following null (H_0) and alternative (H_1) hypotheses have been tested:

For hypotheses 1a and 1b:

$$H_0\colon \mu_{D1} - \mu_{D10} = 0 \qquad\qquad H_1\colon \mu_{D1} - \mu_{D10} \neq 0$$

Where μ_{D1} is the mean next-period return of the first decile portfolio, i.e. the equally- or value-weighted portfolio of assets whose maximum daily return in the period ranks in the first decile of their historical distribution of MAX. μ_{D10} is the mean next-period return of the tenth decile portfolio.

Rejecting the null hypotheses would indicate that the TMAX Strategy's mean raw return is statistically significantly different from zero, thereby providing empirical evidence of the (out-of-sample) profitability of the TMAX Strategy and of a TMAX effect. Failure to reject the null hypothesis would lead us to conclude that there is insufficient evidence to say that investors exhibit lottery-like demand in that particular market.

Additionally, since we hypothesise that the TMAX Strategy will generate losses in the cryptocurrency market, the following left-tailed t-test will be performed:

$$H_0\colon \mu_{D1} - \mu_{D10} \geq 0 \qquad\qquad H_1\colon \mu_{D1} - \mu_{D10} < 0$$

Rejecting the null hypothesis would confirm our belief that the TMAX Strategy would generate negative

[8] The signal is the 'numerator' of the t-statistic, i.e. $\bar{x} - \mu_0$. Due to the large sample size, it can reasonably be assumed that the difference between signals is relatively small.

returns if implemented in the cryptocurrency market.

Part of Hypothesis 2 is that cryptocurrency bubbles show a market-wide presence of lottery-like cryptocurrencies, which would translate into a concentration of cryptocurrencies in the high TMAX-sorted deciles. As a result, the assumption that the TMAXs are not highly correlated is not necessarily valid in these periods. To be more conservative, we have therefore decided to test Hypothesis 2 on the actually implemented TMAX Strategy, rather than by comparing the mean difference of the low and high decile portfolio. This more conservative approach enables us to be more confident in our inference and account for potential higher correlation, i.e. a higher number of periods with empty portfolios, during cryptocurrency bubbles. This approach is also econometrically more sound since it can no longer be assumed that the difference between the signals in a two-sample and one-sample t-test is necessarily small.[9] Thus, the following left-tailed t-test has been conducted in the context of hypothesis 2:

$$H_0\colon \mu_{TMAX_{Bubbles}} - \mu_{TMAX_{Normal}} \geq 0 \qquad \mu_{TMAX_{Bubbles}} - \mu_{TMAX_{Normal}} < 0$$

Where $\mu_{TMAX_{Bubbles}}$ and $\mu_{TMAX_{Normal}}$ are the mean return of the TMAX Strategy during speculative bubbles and during normal times respectively, according to the sub-periods which have been identified as bubbles according to section 3.4. The time periods that are considered 'normal times' are the periods where neither a speculative bubble nor an economic downturn have occurred. Rejecting the null hypothesis in this test would confirm our ex-ante belief that the TMAX Strategy is less profitable during speculative bubbles than in normal times.

On the same grounds that the assumption of a small difference between signals is not valid in times of market stress, the same trade-off between two-sample and one-sample t-test has been made for hypotheses 3a and 3b, thus:

$$H_0\colon \mu_{TMAX_{Crises}} - \mu_{TMAX_{Normal}} \leq 0 \qquad \mu_{TMAX_{Crises}} - \mu_{TMAX_{Normal}} > 0$$

Where $\mu_{TMAX_{Crises}}$ is the mean return of the TMAX Strategy during economic downturns.

Rejecting the null hypothesis would lead us to conclude that the TMAX Strategy is more profitable during economic crises than in normal times, during the sample period under investigation.

In order to account for heteroscedasticity and autocorrelation when conducting the t-tests, the standard errors have been computed using Newey and West (1987) critique. Furthermore, since we have not assumed an equal variance between the two samples in any of the hypothesis tests, we have used Welsh's t-test.

The results of the hypothesis tests will give us a first, broad look at the profitability of the TMAX Strategy, in the two markets under investigation, and in different states of the economy.

3.6.2 Fama & French's (2015) five-factor model

Even though the raw returns provide preliminary evidence (or not) of the lottery-like preferences of investors, they are not sufficient to determine whether the profitability of the TMAX Strategy amounts to a stock market anomaly. To make this determination, it is necessary to determine the risk-adjusted returns of the strategy to investigate whether the investment strategy generates abnormal returns, i.e. alpha.

[9] Of course, it will be verified that the results are not significantly influenced by a time decay/emergence effect, as per what has just been described.

Furthermore, given that the hypothesis tests are not directly applied to the actually implemented TMAX Strategy whereas the factor model is, the risk-adjusted returns also act as a cross-check of the inferences made on the basis of these statistical tests. Diverging significance between both estimation methods is a cause for further investigation and can guide the analysis of the results.

The Fama and French (2015) five-factor model offers a valuable framework for examining whether an investment strategy provides evidence for an anomaly when an alpha (excess return not explained by the model) exists. The Fama and French (2015) five-factor model is an extension of the well-known Capital Asset Pricing Model (CAPM) that aims to explain the cross-section of expected stock returns by incorporating additional factors beyond the market risk.

When applying the Fama and French (2015) five-factor model, the model's factors capture different risk exposures that may explain the expected returns of a strategy. If an investment strategy consistently generates an alpha, which cannot be explained by the market risk, size, value, investment, and profitability factors, it suggests the existence of an anomaly.

The additional factors in the model help control for various systematic risks that are known to affect asset prices. By considering these factors, it becomes possible to distinguish between abnormal returns driven by the TMAX Strategy's unique characteristics, and returns attributable to common risk factors. This model has been extensively tested in empirical studies and has shown success in explaining a significant portion of the cross-sectional variation in stock returns. This empirical support lends credibility to the model's ability to capture systematic risks and allows for a reliable assessment of anomalies in investment strategies.

The model's regression equation that will be used in this thesis writes as follows:

$$\begin{gathered}R_{TMAX,t} - R_{f,t} = a_{TMAX} + b_{TMAX,Mkt}(R_{M,t} - R_{f,t}) + b_{TMAX,Size}SMB_t + b_{TMAX,Value}HML_t + \\ b_{TMAX,Profitability}RMW_t + b_{TMAX,Investment}CMA_t + e_{TMAX,t}\end{gathered}$$

Where

$R_{TMAX,t}$ is the return of the TMAX Strategy in period t,

$R_{f,t}$ is the risk-free rate in period t, thus $R_{TMAX,t} - R_{f,t}$ is the excess return of the TMAX Strategy,

a_{TMAX} is the sample estimate of α, the abnormal return generated by the TMAX Strategy,

$\vec{b}_{5x1}$ is the vector of coefficients of the different risk factors and represents the factor loadings of the TMAX Strategy,

$R_{M,t} - R_{f,t}$ captures the excess return of the market portfolio over the risk-free rate. In Fama and French (2015), the market portfolio includes all NYSE, AMEX, and NASDAQ listed firms. It reflects systematic risk associated with overall market movements and is the only risk factor considered in the CAPM,

SMB_t is the size factor and represents the historical excess returns of small-cap stocks over large-cap stocks. It suggests that small-cap stocks tend to outperform large-cap stocks in the long run,

HML_t is the value factor that measures the historical excess returns of high book-to-market (value) stocks over low book-to-market (growth) stocks. It indicates that value stocks tend to outperform growth stocks,

RMW_t is a profitability factor and captures the historical returns of high profitability firms over low profitability firms. It indicates that highly profitable companies tend to outperform less profitable ones, and CMA_t is an investment factor that represents the historical excess returns of high investment (conservative) stocks over low investment (aggressive) stocks. It suggests that conservative firms tend to outperform aggressive firms.

The data on the risks factors and the risk-free rate have been downloaded from Kenneth R. French's website.[10] Since a monthly time frame has been used to implement the TMAX Strategy in the mutual funds market, all variables in the regression are computed on a monthly basis and t refers to month t.

By utilizing the Fama and French (2015) five-factor model to examine the TMAX Strategy's alpha, we can assess whether the observed excess returns are attributable to factors incorporated in the model or if they provide evidence of an anomaly. If the alpha persists even after accounting for the known risk factors, it indicates the presence of an anomaly, suggesting the strategy is providing abnormal returns that cannot be explained by conventional asset pricing models.

The data collection process in the mutual funds market has allowed us to directly apply the Fama and French (2015) model to the sample (cf. section 3.5.2 for more detail). The selected equity funds' NAVs represent the weighted average price of the portfolio holdings and correspond therefore to portfolios that would hold the funds' stocks in the same weights as the fund. As a consequence, the data is free of other factors that could make a fund's price deviate from its NAV. This process makes sure that the returns of the funds in the investment universe are equal to the weighted average net return of the underlying stocks, making the sample eligible for the above-mentioned regression.

3.6.3 Fama-Macbeth regressions in the cryptocurrency market

The theoretical validity to use Fama and French (2015)'s five-factor model applies to investment strategies based on stocks only. Therefore, in the realm of this thesis, a different approach has to be used for the cryptocurrency analysis.

There is no universally accepted cryptocurrency pricing model (yet). The unique characteristics of the cryptocurrency market, such as its high volatility, lack of established fundamental drivers, and limited historical data, make it challenging to apply traditional asset pricing models directly. As a result, researchers have turned to alternative methodologies, with Fama-Macbeth regressions being one such approach. Therefore, we have decided to run a two-step Fama and MacBeth (1973)-type regression to test whether the TMAX effect explains the cross-section of cryptocurrency returns. Such a regression does not ex-ante assume that certain factors (e.g., market risk) can explain the returns of cryptocurrencies. Rather, this type of regression estimates the coefficient associated with the TMAX Strategy variable, which is used as the independent variable in the regression, and the cryptocurrencies' returns as the dependent variable.

If the coefficient's time-series average is statistically significant and positive (negative), it suggests that the strategy is associated with lower (higher) returns and potentially an underperformance (outperformance). Adding additional confounding variables to the regression enables to control for factors that may affect the cryptocurrency returns and for which the TMAX variable might act as a proxy for.

Through the Fama-Macbeth regression analysis, we can assess whether the TMAX explains the cross-section of cryptocurrency returns. If it does, as signaled by a significant TMAX variable coefficient and accounting for control variables, it would establish the inefficiency of the market, which could be exploited by implementing the TMAX Strategy and generate (abnormal) returns. In other words, there would be strong indications that the TMAX premium (discount) amounts to an anomaly.

[10] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

The two-step Fama-Macbeth regression procedure consists in running cross-sectional regressions in each time period before conducting hypothesis tests on the time-series averages of the coefficients.

In the first step, separate cross-sectional regressions are run, one for each week, with the TMAX (and the confounding variables) as the independent variable and the cryptocurrency returns as the dependent variable. This step produces estimates of the coefficients for each time period.

In this thesis, the following cross-sectional regressions are run, after running the simple linear regressions where the TMAX variable acts as the only independent variable: [11]

$$\begin{aligned} R_{i,t+1} - R_{f,t+1} = & a_{t+1} + b_{TMAX,t} TMAX_{i,t} + b_{Beta,t} BETA_{i,t} + b_{Size,t} SIZE_{i,t} + \\ & b_{Momentum,t} MOM_{i,t} + b_{Illiquidity,t} ILLIQ_{i,t} + e_{i,t+1} \end{aligned}$$

Where

$R_{i,t+1}$ is the return of cryptocurrency i in week $t+1$,

$R_{f,t+1}$ is the risk-free rate in week $t+1$,

a_{t+1} represents the average excess return unexplained by the specified factors or the risk-free rate across the entire sample,

$\vec{b}_{5x1}$ is the vector of coefficients. In particular, $b_{TMAX,t}$ is the coefficient associated with the TMAX variable and the one which will be analysed in step two. The remaining coefficients are linked to the control variables,

$BETA_{i,t}$ captures the beta of cryptocurrency i in period t, estimated with the CAPM using daily returns within a month. The returns of the market portfolio are considered to be the returns of the CRIX index, a cryptocurrency index that has been used in numerous studies (and by practitioners) as a proxy for the market portfolio in the cryptocurrency market. This index has been proposed by Trimborn and Härdle (2018) and its methodology allows for quick reactions to market changes, an important feature for an index in a volatile and frequently changing market. It has especially been created to "enable each interested party studying economic questions in this market" and to "invest in the market" (Trimborn & Härdle, 2018). The index data has been downloaded from the index's website[12],

$SIZE_{i,t}$ is the natural logarithm of cryptocurrency i's market capitalisation by the end of the previous week, thereby measuring the size of the cryptocurrency,

$MOM_{i,t}$ is a momentum variable and is computed as cryptocurrency i's return in week t (i.e., the lagged weekly return of the cryptocurrency),

and $ILLIQ_{i,t}$ is a measure of the illiquidity of the cryptocurrency. Its computation follows Amihud (2002), that is, the ratio of absolute daily cryptocurrency return to its mean dollar trading volume each week, as shown below.

$$ILLIQ_{i,t} = 10^6 \frac{1}{D} \sum_{d=1}^{D} \frac{|R_{i,d}|}{VOLD_{i,d}}$$

Where $VOLD_{i,d}$ is the respective (daily) trading volume in dollars and D is the total number of trading days in week t.[13]

All explanatory variables are lagged by one week. As a reminder, the TMAX Strategy uses the maximum daily returns over the *previous* period to construct the portfolios for the *next* week. Therefore, it is

[11] The simple linear regressions are meant to directly corroborate the findings of the previous hypothesis tests.

[12] `https://www.royalton-crix.com/`

[13] As a reminder, a cryptocurrency trading week generally counts 7 days.

crucial to use the lagged value of TMAX in the regression.

The second step in the Fama-Macbeth two-step procedure consists in calculating the time-series mean by taking the average of the coefficients across all time periods. The time-series average provides a single estimate that represents the average effect of the variable across the cryptocurrency market.

These estimates are then subjected to a hypothesis test to determine whether they are significantly different from zero, and, given our initial hypothesis for the TMAX effect, the related average coefficient is expected to be significantly greater than zero.

Rejecting the null hypothesis in this test would provide further empirical evidence of a lottery-related market anomaly.

To ensure a robust regression analysis, it is necessary to have a substantial cross-sectional sample of cryptocurrencies. Consequently, we have initiated the regression analysis starting from the week starting on April 11, 2016, which ensured that there were always at least fifteen cryptocurrencies in the cross-section. This leaves us with 351 cross-sectional regressions, which is still a large enough sample to perform statistical inference.

3.6.4 Additional robustness checks

In chapter 5, additional control variables will be added to the analysis of both markets, to provide an explanation for the (lack of) (reverse) TMAX effect and address the robustness of the TMAX Strategy to variables that have been put forward in the literature for which the TMAX premium (discount) might act as a proxy for (e.g., sentiment).

These additional controls will be detailed in the relevant section with the relevant context pertaining to its effect on the (T)MAX Strategy.

Results

4.1 Summary Statistics

4.1.1 Cryptocurrency market

	Low	2	3	4	5	6	7	8	9	High
Panel A: Summary statistics of TMAX-sorted portfolios (cryptocurrency market)										
MAX	9.591	9.767	9.717	8.432	9.324	9.562	9.212	8.461	10.771	9.525
# of cryptos	5	4	4	4	4	4	3	3	3	3
min # of cryptos	0	0	0	0	0	0	0	0	0	0
25% of cryptos	2	2	2	2	2	2	2	2	1	1
VOL	2.509	3.210	3.679	4.154	4.866	5.574	6.207	7.407	9.398	19.715
IVOL	3.145	3.918	4.511	5.267	5.484	5.920	7.193	7.498	10.130	17.349
SKEW	-0.477	-0.263	-0.119	-0.032	0.053	0.135	0.239	0.374	0.522	0.866
ISKEW	3.062	3.814	4.407	5.129	5.315	5.781	7.014	7.280	9.878	16.530
SIZE	6.046	8.304	8.619	10.281	11.113	11.311	11.704	13.541	13.781	13.968
Lag return	-7.016	-5.084	-3.569	-1.473	0.072	1.154	3.533	5.941	10.103	30.354
ILLIQ	128.288	4.545	25.462	57.596	8.713	47.751	257.196	140.202	584.041	28'241
Turnover (%)	77.04	83.01	87.45	88.00	89.16	89.05	88.78	88.27	85.98	77.32
Panel B: Summary statistics of TMAX-sorted portfolios (stock market)										
MAX	2.065	2.978	3.779	4.603	5.386	6.304	7.397	8.855	11.383	20.439
# of stocks	432	468	450	425	403	419	409	404	423	455
min # of stocks	11	12	23	41	65	125	112	108	78	59
10% of stocks	144	185	194	201	198	213	203	183	166	149
SIZE	2.199	1.967	1.855	1.768	1.722	1.589	1.547	1.536	1.351	1.102
Lag return	−5.063	−3.718	−2.484	−1.409	−0.423	0.656	1.922	3.516	5.906	13.563
ILLIQ	3.010	3.760	3.773	4.537	4.963	6.255	7.464	9.507	15.783	26.999
Turnover (%)	76.39	81.53	83.32	85.49	87.06	87.24	87.54	87.24	85.70	78.83
Panel C: Summary statistics of MAX-sorted portfolios (cryptocurrency market)										
SIZE	0.426	0.354	0.150	0.251	0.129	0.174	0.136	0.027	0.036	0.022
Lag return	-1.9	-1.5	-1.4	-0.6	0.0	0.9	1.2	2.1	4.2	7.7
ILLIQ	2'700	3'300	4'200	6'600	6'100	7'000	8'800	7'800	12'900	28'500

Table 4.1: Summary statistics of (T)MAX strategies in the cryptocurrency and stock market

Table 4.1 reports the summary statistics of the TMAX decile portfolios pertaining to this thesis' cryptocurrency data in Panel A. For comparison, we also report the summary statistics of the TMAX decile portfolios from Lin et al. (2021)'s stock market analysis in Panel B and some of the summary statistics of the MAX decile portfolios from Ozdamar et al. (2021) in Panel C. MAX refers to the average (time-dependent) maximum daily return of the decile portfolios' assets, while the number of cryptos/stocks indicate the average number of assets in the respective portfolio, the minimum number of cryptos/stocks indicates the lowest number of assets that has been observed in the portfolios, while 25% (10%) of cryptos (stocks) shows the first quarter (first decile) value. We also report the average values of several cryptocurrency/stock characteristics, including the volatility (*VOL*), idiosyncratic volatility (*IVOL*), skewness (*SKEW*), idiosyncratic skewness (*ISKEW*)[1], market capitalisation (in billion $) (*SIZE*), previous period return (*Lag return*), the Amihud (2002) illiquidity measure (*ILLIQ*), and the ratio of stocks that change decile from one period to the next (*Turnover (%)*). All values for *MAX*, *VOL*, *IVOL*, *ISKEW*, *Lag return*, *ILLIQ*, and *Turnover* are percentage values.

[1] The notions of idiosyncratic volatility and skewness are developed in section 5.1.5.

The empirical results in Panel A substantiate the theoretical underpinnings necessary for implementing the TMAX Strategy as a reliable method to examine investors' lottery-like preferences. The monotonic increase in skewness (as well as idiosyncratic skewness) and volatility (as well as idiosyncratic volatility) as the TMAX increases conforms with the widely-accepted definition of lottery-like preference by Kumar (2009). The high skewness and volatility of the highest TMAX decile portfolio relative to the others (and especially relative to the lowest TMAX decile portfolio) makes this portfolio exhibit more pronounced lottery-like features. As a result, the TMAX is a valid proxy for the lottery-like preferences of investors in the cryptocurrency market.

The monotonic increase in MAX from the lowest to the highest decile portfolio that has been observed by Lin et al. (2021) (Panel B) has not been confirmed in the cryptocurrency market, whose TMAX-sorted portfolios remain largely neutral to this indicator. In the cryptocurrency market, the MAX and TMAX strategies seem to be disjointed, much more than in the stock market, where the TMAX decile portfolio structure still exhibits significant MAX characteristics. Therefore, the TMAX premium is partly explained by the MAX premium in the stock market, whereas the TMAX discount in the cryptocurrency market has very different drivers than the MAX discount. This phenomenon further underlines the importance of the definition of the benchmark when investigating lottery-like preference.

As alluded to before, due to the smaller sample size of the cryptocurrency compared to the stock market sample in Lin et al. (2021), the TMAX decile portfolios have been empty for around 15-20% of the periods under examination. This does not impede the statistical inference in this research, but it shows a first limitation of the TMAX Strategy in the cryptocurrency market: in order for the strategy to be persistently implemented, a large investment universe is required, due to the correlation of the TMAX rank between different cryptocurrencies. However, given the lack of liquidity (cf. Table 4.1 & below), the practicality of an investment strategy based on a large cryptocurrency universe remains questionable.

Whereas the size of the assets decreases in the TMAX-sorted portfolios as the TMAX increases in the stock market and in the MAX-sorted portfolios in the cryptocurrency market, the trend is inversed in the TMAX-sorted cryptocurrency portfolios. These diverging observations might be a result of the sampling technique; the present thesis' sample is more homogeneous in size than other previous research.

The lagged returns in the cryptocurrency market decile follow the same upward trend between decile portfolios as in the stock market. The TMAX Strategy can thus be classified within the family of short-term reversal strategies if it is profitable as it would then negatively correlate with the decile portfolios' lagged returns, and within the family of short-term momentum strategies if it generates negative returns as it would then positively correlate with the lagged returns.

It is well-documented that the cryptocurrency market is illiquid compared to traditional markets (Dong et al., 2020), and especially if the ten biggest cryptocurrencies are excluded (Wei, 2018). It is therefore not surprising that the decile portfolios in the cryptocurrency market are much less liquid than the ones in the stock market, noting that the highest decile portfolio seems to show lower liquidity compared to the lowest one no matter the market. The advantage of constructing the investment universe according to this thesis' methodology compared to Ozdamar et al. (2021) (Panel C), which included all cryptocurrencies with a market cap of more than $5 million, resides in the (much) more liquid resulting decile portfolios. Given that an Amihud liquidity measure of 28'500 can be assimilated to a 2.85 cents increase in price for an additional 1 dollar trading volume, and given that most smaller cryptocurrencies trade at less than 1 cents on the dollar, the practicability of the (T)MAX Strategy is severely limited if small cryptocurrencies are included in the investment universe.

The turnover in the decile portfolios in the cryptocurrency and stock market are comparable. As a consequence, the transaction costs linked to the periodic rebalancing of the portfolios are similar.

However, due to the costs induced by the illiquidity of the cryptocurrency market and its associated higher spread, the total costs of the TMAX Strategy will be higher in the cryptocurrency market.

4.1.2 Mutual funds market

	Low	2	3	4	5	6	7	8	9	High
MAX	0.906	1.149	1.321	1.479	1.644	1.830	2.053	2.361	2.861	5.559
# of funds	121	118	117	115	115	115	117	119	122	132
min # of funds	0	0	1	1	1	1	1	1	0	0
10% of funds	5	7	12	14	14	16	15	13	8	3
VOL	0.656	0.733	0.783	0.833	0.890	0.938	0.996	1.073	1.191	4.042
IVOL	0.536	0.604	0.631	0.665	0.705	0.737	0.779	0.832	0.930	3.507
SKEW	-0.486	-0.377	-0.244	-0.163	-0.087	-0.009	0.105	0.182	0.350	0.642
ISKEW	0.519	0.584	0.610	0.644	0.683	0.714	0.754	0.805	0.899	3.455
SIZE	9.668	8.806	8.889	8.822	8.623	8.378	8.374	8.392	8.668	8.055
Lag return	-0.996	-0.371	0.068	0.300	0.440	0.710	0.878	1.048	1.417	10.285
Turnover (%)	78.48	84.55	86.98	87.67	88.76	87.93	87.41	87.15	83.99	74.35

Table 4.2: Summary statistics of the TMAX-sorted portfolios in the mutual funds market

Table 4.2 reports the summary statistics of the TMAX decile portfolios pertaining to this thesis' mutual funds data. The variables' definitions are consistent with Table 4.1, with two small modifications. By 'Size', we refer to the funds' total net assets (TNA) at a given date. The notion of liquidity is not applicable to the mutual funds market, since we excluded ETFs, and open-ended funds provide by construction the possibility to redeem/subscribe shares at the NAV computation frequency.

Similar to what we have observed in the cryptocurrency market, the mutual funds data conforms with the definition of lottery-like assets of Kumar (2009). (Idiosyncratic) volatility and (idiosyncratic) skewness increase monotonically with the TMAX-sorted portfolios. The TMAX Strategy thus remains a valid method to investigate lottery preferences in the mutual funds market.

Contrarily to the cryptocurrency market, the TMAX Strategy in the mutual funds market reestablishes a link with the MAX Strategy via the monotonic increase in MAX through the TMAX portfolios, similar to Lin et al. (2021) (cf. Panel B, Table 4.1). Consequently, the funds that will be held in the TMAX portfolios are similar to the ones that would be held in the MAX portfolios. This observation was expectable since the lottery characteristics of the sample's funds are the weighted average lottery characteristics of the funds' underlying stocks, thereby construing a clear link between Lin et al. (2021)'s stock market observations and the TMAX Strategy applied to mutual funds.

The sample size (N=2308) reduced to less than 10% the occurrences of empty TMAX portfolios. To be precise, in 12 out of the 457 months where the TMAX Strategy was implemented, i.e. in 2.63% of the cases, the strategy could not be implemented. Note that these occurrences were limited to the period 1985-1993, where not all sample funds had yet launched.

The TMAX Strategy in the mutual funds market establishes the same link between lagged returns and TMAX decile; the higher the TMAX decile portfolio, the higher the previous month's return. Additionally, even though the correlation seems to be weaker than in other markets (and not monotonic), the TNA of the decile portfolio's holdings decrease as the TMAX increases.

The transactions costs of the TMAX Strategy are, on average, slightly lower in the mutual funds market than in the stock market; while the lowest TMAX decile portfolio's turnover is 207 basis points higher in the mutual funds market, the highest TMAX decile portfolio's is 448 basis points lower.

An interesting observation that can be made is that the High TMAX-sorted decile portfolio exhibits significantly higher lottery characteristics than all the others, while the difference in these characteristics is not significant between the Low and 9th TMAX-sorted decile portfolios. In other markets, the pairwise lottery characteristics of the decile portfolios are less homogeneous.

4.2 Hypothesis 1a: Profitability of the TMAX Strategy in the cryptocurrency market

As elaborated in the methodology, two-sample Welsh t-tests have been conducted to test Hypothesis 1a. The two-tailed t-test either provides preliminary evidence of a lottery effect in the cryptocurrency market (rejection of H_0) or not (failure to reject H_0). The raw returns will then need to be subjected to the Fama-Macbeth regression detailed in the methodology to make sure that the TMAX Strategy's returns do not act as a proxy of some other risk factor.

	Equal Weights	Value Weights
Panel A: Raw returns of the TMAX-sorted portfolios		
Low	-0.810	-1.310**
	(-1.31)	(-2.30)
2	0.345	0.487
	(0.49)	(0.70)
3	0.801	-0.035
	(1.09)	(-0.05)
4	0.261	0.258
	(0.35)	(0.32)
5	0.719	0.375
	(1.04)	(0.53)
6	1.538*	0.345
	(1.68)	(0.45)
7	3.001***	2.008**
	(2.80)	(2.13)
8	5.695***	4.435***
	(3.62)	(3.18)
9	5.712***	2.162**
	(3.56)	(2.11)
High	3.565**	4.700**
	(2.46)	(2.48)
Panel B: Profitability of the TMAX Strategy		
Low-High	-4.375***	-6.010***
	(-3.05)	(-3.04)
Panel C: Profitability of the MAX Strategy (Li et al., 2021)		
Low-High	-7.415***	-5.216***
	(-6.15)	(-2.92)
Panel D: Profitability of the MAX Strategy (Ozdamar et al., 2021)		
Low-High	-2.520***	-3.015***
	(-3.22)	(-4.10)

Table 4.3: Returns of the TMAX Strategy in the cryptocurrency market

Table 4.3 reports the average returns of portfolios on TMAX for the cryptocurrency market from November 2013 to December 2022. The portfolios are constructed following Lin et al. (2021), as explained in the methodology. The cryptocurrencies are allocated into deciles based on their values of MAX in week $t-1$ compared with their historical distribution of MAX. Panel A reports the time-series averages of raw returns calculated with equal and value weights for each decile portfolio, whereas Panel B shows the difference in returns between the lowest and the highest deciles, i.e. the time-series average raw return of the TMAX Strategy. Panels C and D report the average raw return of the MAX Strategy from Y. Li et al. (2021) and Ozdamar et al. (2021) respectively. Numbers in the parentheses are the t -statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Over the sample period, the TMAX Strategy generates average weekly returns of -4.375% with a t -statistic of -3.05 under equal weights and -6.010% with a t -statistic of -3.04 under value weights. The null hypothesis of zero return difference between the lowest and highest decile portfolio can therefore be rejected at the 1% confidence level under both equal and value weights. Given that these values represent weekly returns (!), we observe a strong reverse TMAX effect in the raw returns of the cryptocurrency market, which potentially uncovers a "TMAX momentum" similar to the the "MAX momentum" findings by Y. Li et al. (2021) and Ozdamar et al. (2021).

The TMAX Strategy yields significant losses over the time period considered, which is confirmed by the left-tailed t-test under equal weights (p-value: 0.12%) and value weights (p-value: 0.03%). Conversely, a 'reverse' TMAX Strategy, i.e. going long in the highest decile portfolio and going short in the lowest decile portfolio would have generated significant positive returns on average.

The reverse TMAX effect is more pronounced under value than equal weights, which indicates that the relatively larger cryptocurrencies play a critical role in driving the losses of the TMAX Strategy. This phenomenon has been confirmed by the MAX Strategy in Ozdamar et al. (2021) while Y. Li et al. (2021) observed the opposite. Either way, it seems to be that the TMAX Strategy is less affected by the illiquidity of the smaller cryptocurrencies than the MAX Strategy, whose profitability is more reliant on the inclusion of smaller, i.e. more illiquid, coins.

In terms of magnitude, the reverse (T)MAX effect is less pronounced in the TMAX Strategy under equal weights than in the MAX Strategy of Y. Li et al. (2021), but higher than the one in Ozdamar et al. (2021). Under value weights, the TMAX Strategy generates higher losses than the MAX Strategy in both papers. This goes to show that the reverse time-dependent MAX effect is more prevalent in larger cryptocurrencies than the cross-sectional MAX effect is.

After having observed a strong reverse TMAX effect in the raw returns, we have double-checked if this effect does not act as a proxy of another risk factor with the Fama-Macbeth regressions. This necessary step allows us to conclude whether the profitability of the TMAX Strategy amounts to a market anomaly and whether the analysis provides evidence of the lottery-like preference of investors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TMAX	11.207**					10.706**	10.956**	14.380***	12.786**	13.005**
	(2.03)					(2.10)	(1.98)	(2.66)	(2.12)	(2.00)
Beta		1.327				1.450				1.262
		(1.08)				(1.21)				(1.02)
Size			-0.140				0.079			0.331
			(-0.40)				(0.24)			(0.86)
Momentum				1.687				-1.831		-1.892
				(0.75)				(-0.78)		(-0.76)
Illiquidity					-0.259				-0.264	-0.200
					(-0.75)				(-0.28)	(-0.50)
Intercept	2.130***	1.846**	2.933***	2.744***	2.793***	1.145	2.226***	1.822**	2.134***	1.268
	(2.78)	(2.16)	(4.10)	(4.03)	(3.82)	(1.36)	(2.86)	(2.40)	(2.69)	(1.53)
Adj. R^2	7.06%	6.95%	1.66%	7.29%	6.25%	13.73%	8.69%	13.01%	12.61%	25.78%

Table 4.4: Time-series averages of Fama-Macbeth weekly cross-sectional regressions

Table 4.4 presents the time-series averages of the slope coefficients and intercepts from the cross-sectional regressions of one-week-ahead cryptocurrency excess returns on TMAX individually (column (1)) or jointly with other cryptocurrency characteristics (in columns (6)–(10)). Columns (2)-(5)

present the simple linear regression coefficients of next-week cryptocurrency excess returns on different cryptocurrency characteristics. Additionally, the average adjusted R^2 is provided for each batch of regressions. Numbers in the parentheses are the t -statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

In all columns where the TMAX variable appears in the regressions, its coefficients are significantly positive at the 1%, or 5% level, implying that the reverse TMAX effect is not subsumed by other factors that may influence cryptocurrency returns. Furthermore, the intercept is not statistically significant in the regressions including all control variables (column (10)), which gives us a certain comfort that the most important characteristics that drive cryptocurrency returns have been controlled for (see also the relatively high adjusted R^2 in column (10) compared to other Fama-Macbeth regressions that can be found in the literature)

Regarding the control variables, none of the coefficients are statistically significant on average. The lack of significance of the 'market' factor confirms previous findings that the cryptocurrency market is relatively heterogeneous in that aspect and that the returns, especially of smaller cryptocurrencies, do not move with the overall market (knowing that evidently, the CRIX Index is tilted towards the biggest cryptocurrencies). In our sample, the size has already to a certain extent been controlled for, due to the sample's bias towards larger cryptocurrencies as a result of the sampling technique. It is therefore not surprising that the $SIZE$ coefficient is not statistically significant. No significant effect of the MOM and $ILLIQ$ variable has also been observed in Y. Li et al. (2021) and Ozdamar et al. (2021).

The results from column (8), which reports the time-series averages of the Fama-Macbeth cross-sectional regressions on the TMAX and Momentum variables, are especially interesting to point out. Column (8) not only shows that the TMAX is not subsumed by (short-term) momentum, but that the TMAX discount becomes even more pronounced (significance at the 1% level) when we control for this characteristic. In other terms, the reverse TMAX effect is stronger when we keep momentum constant. This important finding underlines that the profitability of the reverse TMAX Strategy is clearly distinct from any potential profitability of momentum strategies (or to that effect, reversal strategies) in the cryptocurrency market. The fact that the (T)MAX Strategy is often assimilated to reversal/momentum strategies is thus an amalgam and should not be taken literally, but rather as a way of caricaturing that the (T)MAX Strategy relies on the underlying principle that well-performing (defined in this case as having an extreme past return) securities continue to perform well (momentum) or underperform subsequently (reversal).

All in all, our Fama and MacBeth (1973) regression results support our previous findings of the significant and positive relationship between the extreme returns in the previous week and the returns in the subsequent week, confirming the presence of a reverse TMAX effect in the cryptocurrency market.

Since both the raw returns and the risk-adjusted returns provide empirical evidence of the profitability of the reverse TMAX Strategy, we reject the null hypothesis under 1a. As hypothesised, the TMAX Strategy yields significantly negative returns in the cryptocurrency market over the sample period considered, on average.

The findings suggest that gambling in the cryptocurrency market pays off. By 'betting' on cryptocurrencies with a small probability of an extreme return, i.e. lottery-cryptos, i.e. cryptos with high skewness and high volatility, i.e. high TMAX cryptos, an investor can earn higher risk-adjusted returns. This inefficiency in the cryptocurrency market can be exploited by going long in the highest TMAX-sorted decile portfolio and short in the lowest TMAX-sorted decile portfolio.

4.3 Hypothesis 1b: Profitability of the TMAX Strategy in the mutual funds market

Using the same methodology as in the previous section, we test the profitability of the TMAX Strategy in the mutual funds market. Under Hypothesis 1b as detailed in section 2.8, we do not expect to find evidence supporting a significantly profitable (or loss-making) TMAX Strategy.

	Equal Weights	Value Weights
Panel A: Raw returns of the TMAX-sorted portfolios		
Low	0.357*	0.338*
	(1.74)	(1.83)
2	0.383**	0.429**
	(2.16)	(2.08)
3	0.556***	0.727***
	(2.66)	(3.03)
4	0.429**	0.583***
	(2.34)	(2.63)
5	0.462**	0.506**
	(2.54)	(2.55)
6	0.594***	0.743***
	(3.27)	(4.02)
7	0.521***	0.616***
	(2.85)	(3.11)
8	0.640***	0.597***
	(3.42)	(2.77)
9	0.605***	0.597***
	(3.08)	(2.85)
High	0.603***	0.853***
	(2.72)	(3.66)
Panel B: Profitability of the TMAX Strategy		
Low-High	-0.246	-0.515*
	(-0.82)	(-1.73)

Table 4.5: Returns of the TMAX Strategy in the mutual funds market

Table 4.5 reports the average returns of portfolios on TMAX for the mutual funds market from January 1985 to December 2022. The portfolios are constructed following Lin et al. (2021), as explained in the methodology. Mutual funds are allocated into deciles based on their values of MAX in month $t-1$ compared with their historical distribution of MAX. Panel A reports the time-series averages of raw returns calculated with equal and value weights (where the weights are determined by the funds' TNAs) for each decile portfolio, whereas Panel B shows the difference in returns between the lowest and the highest deciles, i.e. the time-series average raw return of the TMAX Strategy. Numbers in the parentheses are the t -statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Over the sample period, the TMAX Strategy has generated an average raw loss of 0.246% per month with a t-statistic of -0.82 under equal weights and 0.515% per month with a t-statistic of -1.73 under value weights. While we cannot reject the null hypothesis of zero mean return under equal weights, we can reject the null hypothesis at the 10% confidence level under value weights. We can also reject the null hypothesis of the left-tailed t-test at the 5% confidence level under value weights.

Overall, the results indicate that the TMAX Strategy is not profitable in the mutual funds market. The reverse TMAX Strategy, however, generates significant profits when giving relatively more weight to larger funds, i.e. under value weights. In other words, a reverse TMAX effect can be observed in larger funds but it does not dominate the market when each fund is given the same representation, i.e. under equal weights.

After examining the raw returns of the TMAX Strategy, we have analysed this investment strategy on the basis of the Fama-French five-factor model. Since we have not found evidence of a profitable TMAX Strategy under equal weights, an insignificant alpha should be observed when controlling for the Fama-French risk factors. Under value weights, we should observe a significantly negative alpha for the anomaly to persist on a risk-adjusted basis.

	Equal Weights	Value Weights
FF5 alpha	-0.494**	-0.727***
	(-2.28)	(-3.46)
RMRF	-0.16***	-0.21***
	(-3.05)	(-4.32)
SMB	-0.031	0.032
	(-0.40)	(0.42)
HML	-0.060	-0.028
	(-0.66)	(-0.32)
RMW	0.12	0.12
	(1.20)	(1.30)
CMA	0.20	0.18
	(1.45)	(1.38)

Table 4.6: TMAX Strategy Fama-French 5-factor model exposures

Table 4.6 reports the factor loadings of the TMAX Strategy's excess returns in the context of the Fama-French five-factor model, as well as the alpha generated by the strategy (*FF5 alpha*). As a reminder, the factors considered by Fama and French (2015) are the excess return of the market portfolio ($RMRF$), the size factor (SMB), the value factor (HML), the profitability factor (RMW) and the investment factor (CMA). Numbers in the parentheses are the t -statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Contrarily to what could have been expected based on the previous results, the TMAX Strategy generates significant negative alpha under both equal and value weights in the mutual funds market. The negative alpha seems to indicate that the TMAX Strategy significantly underperforms compared to what an investor should expect based on the risk exposures of the strategy. This result goes hand in hand with significant abnormal returns of the reverse TMAX Strategy, i.e. going long in the High decile portfolio and short in the Low decile portfolio. Moreover, the loading on the market factor is the only one to be significant. The negative loading on that particular factor seems to indicate that the TMAX Strategy in the mutual funds market is a contrarian strategy, generating profits when the market is down and generating losses when the market is up. The TMAX Strategy is largely neutral to the other four factors, which gives us confidence that the strategy's returns are not even in part explained by these risk factors.

Given what has been explained before, this result is puzzling, especially the significant (negative) alpha under equal weights. This calls for a deeper analysis of the TMAX Strategy in the context of the mutual funds market, also in light of the literature, which can be found in the Discussion (section 5.2). This deeper analysis is also relevant given the low adjusted R^2 of the Fama-French five-factor model regression analysis compared to what research has shown for other well-known investment strategies. While traditional active strategies usually yield an adjusted R^2 in the range of 20%-70% when controlling for the Fama-French factors, the TMAX Strategy's is only 4.28% under equal weights and 6.95% under value weights.

4.4 Hypothesis 2: Lottery-like preference and speculative bubbles in the cryptocurrency market

In this section, we compare the profitability of the TMAX Strategy during bubbles and in normal times. We hypothesise that during bubbles, the high presence of cryptocurrencies exhibiting lottery-like features creates a herding effect among investors seeking lottery payoffs, and this sustained demand further generates deviations from intrinsic value and therefore, the lottery-like cryptos outperform the cryptocurrencies in the lowest TMAX-sorted portfolios even more than during normal times.

	Bubbles		Normal Times	
	EW	VW	EW	VW
Panel A: Raw returns of the TMAX-sorted portfolios				
Low	0.931	-0.322	-1.541**	-1.852**
	(0.88)	(-0.31)	(-2.00)	(-2.19)
2	4.426***	4.260**	-1.191	-0.759
	(2.70)	(2.61)	(-1.31)	(-0.83)
3	3.002	2.781	0.302	-0.956
	(1.57)	(1.51)	(0.30)	(-0.89)
4	4.012**	3.874*	-1.025	-1.262
	(2.25)	(1.90)	(-0.94)	(-1.14)
5	3.131*	1.939	-0.602	-0.040
	(1.99)	(1.19)	(-0.67)	(-0.05)
6	3.762*	1.755	0.222	0.307
	(1.95)	(1.17)	(0.21)	(0.26)
7	5.551***	5.866***	0.528	-0.307
	(2.92)	(2.71)	(0.45)	(-0.25)
8	9.745***	7.337***	4.375**	3.471
	(2.93)	(2.78)	(2.14)	(1.52)
9	9.771***	6.085***	6.479*	1.33
	(4.33)	(3.27)	(1.81)	0.92
High	5.823***	6.135***	3.933	9.731
	(3.20)	(2.88)	(0.98)	(1.59)
Panel B: Profitability of the TMAX Strategy				
Low - High	-4.892**	-6.457***	-5.474	-11.583*
	(-2.32)	(-2.72)	(-1.33)	(-1.87)

Table 4.7: Returns of the TMAX Strategy during bubbles and in normal times

Table 4.7 reports the returns of the TMAX Strategy during bubbles and in normal times. The periods that this thesis considers cryptocurrency bubbles can be found in Table 3.1. Panel A reports the time-series averages of raw returns calculated with equal and value weights for each decile portfolio, during bubbles and in normal times, whereas Panel B shows the difference in returns between the lowest and the highest deciles, i.e. the time-series average raw return of the TMAX Strategy. Numbers in the parentheses are the t -statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The strong reverse TMAX effect can be observed during bubbles and in normal times, under both equal and value weights. These results conform with our expectations. When comparing these results with the results from Table 4.3, we find that the raw returns during bubbles are on average higher (in absolute terms) than over whole business cycles, under equal weights (4.89% vs 4.38%) and value weights (6.46% vs 6.01%). Additionally, comparing the returns during normal times and over the whole time period, we also observe a stronger average reverse TMAX effect in normal times. Taken together, these findings already seem to preclude the findings of Hypothesis 3a, namely that no TMAX effect can be observed during economic downturns, which waters down the effect when the whole time period is considered.

The results in Table 4.7 have to be treated with caution for several reasons. First, during normal times, we fail to reject the null hypothesis of zero mean return of the highest TMAX-sorted decile portfolio, under both equal and value weights. The average difference between the Low and High portfolio as reported in Panel B might thus be artificially high, since we cannot exclude the possibility that the true population parameter of the highest decile portfolio's mean might be smaller than the average we have observed in our sample (or even zero). As a result, the 11.58% (respectively, 5.47%) average weekly underperformance of the lowest decile portfolio should be considered at the high end of estimated population parameters. While we can be confident that the difference between the returns of the lowest and highest TMAX-sorted decile portfolios is smaller than zero (the corresponding one-tailed t-test's null hypothesis can be rejected at the 10% (equal weights) and 5% (value weights)), the magnitude of the difference is subject to variation. Second, caution is also required for the interpretation of the results for the bubble periods. As explained in the methodology, the cross-sectional correlation between TMAX ranks is expected to be higher during speculative bubbles. The assumption that the empty portfolio occurrences converge to zero as the sample increases is therefore less valid than in normal times. The magnitude of the profitability of the TMAX Strategy during bubbles (Panel B) should therefore also be treated with similar caution to the one in normal times. Third, while we can reject the null hypothesis for the left-tailed t-tests, we cannot for the two-tailed t-test under equal weights. As a consequence, one needs to be aware that even though there is some evidence of a significant reverse TMAX effect during normal times under equal weights, the more conservative and strict criteria of the two-tailed t-test caution that the true mean return might still be zero.

	Bubbles	Normal Times
Percentage of empty portfolios	66.67%	38.26%

Table 4.8: Proportion of empty portfolios during bubbles and in normal times

Table 4.8 shows the proportion of time periods during which the TMAX Strategy could not be implemented due to a lack of observations in the first and/or last decile, during bubbles and in normal times. As expected, empty portfolios occur nearly twice as much during speculative bubbles as in normal times, confirming our hypothesis that the cross-section of cryptocurrency TMAX ranks are highly correlated during speculative bubbles. Whereas the TMAX Strategy could not be implemented in two-thirds of the cases during bubbles, it could only not be implemented during a little more than one-third of the time periods during normal times (this proportion in normal times drops to just under a quarter when we exclude the beginning of the sample where less than fifteen cryptocurrencies with a market cap over $5 million existed). It is thus more conservative to run the hypothesis tests for Hypothesis 2 (and 3) on the actually implemented TMAX Strategy, rather than on the mean difference between the low and high decile portfolios to account for this higher correlation; this method is also econometrically more sound, which is not true for Hypothesis 1.

	Equal Weights	Value Weights
Mean Difference (Bubbles-Normal Times)	-8.472**	-8.226*
T-statistic	(-2.06)	(-1.61)

Table 4.9: Results of the left-tailed hypothesis tests (H2)

Table 4.9 shows the results of the left-tailed hypothesis tests under equal and value weights. This left-tailed t-test measures whether there is evidence to suggest that the mean of the TMAX Strategy during speculative bubbles is significantly lower than the mean during normal times. Numbers in the parentheses are the t-statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

We can reject the null hypothesis formulated in Hypothesis 2 both under equal (at the 5% confidence level) and value weights (at the 10% confidence level). The results confirm our belief that the TMAX Strategy is less profitable during speculative bubbles than in normal times, or conversely, that the reverse TMAX Strategy is more profitable when bubbles occur.

To confirm the second part of Hypothesis 2, namely that cryptocurrency bubbles show a market-wide presence of lottery-like cryptos, we compare the time-series average percentage of the weekly cross-section of cryptocurrencies' TMAX ranking in each decile. In other words, at each time period, we compute the percentage of TMAXs that rank in each decile and then take the time-series average.

	Bubbles	Normal Times
Low	8.66%	13.94%
2	7.60%	13.97%
3	6.56%	12.52%
4	7.71%	10.81%
5	9.61%	10.98%
6	10.68%	9.36%
7	10.47%	9.08%
8	13.42%	8.22%
9	11.37%	6.29%
High	13.91%	4.83%

Table 4.10: Distribution of TMAX during bubbles and in normal times

Table 4.10 reports the distribution of TMAX ranks during bubbles and in normal times. The proportion of cryptocurrencies that rank in the highest decile is nearly three times as high during speculative bubbles as in normal times. Unsurprisingly, we can reject the null hypothesis of the right-tailed t-test testing the difference in mean percentage between the High decile during bubbles and in normal times at the 1% confidence level (t-statistic: 5.40). We can therefore conclude that significantly more cryptocurrencies rank in the tenth decile during speculative bubbles than in normal times.

These results confirm the second part of Hypothesis 2, namely that speculative bubbles show a market-wide presence of lottery-like cryptocurrencies (exemplified by the three times higher frequency of lottery-like cryptos), relative to their presence in normal times.

Moreover, analysing tables 4.8 and 4.10 further supports our ex-ante belief that the TMAX ranks are highly correlated during speculative bubbles. While on average only 18.77% of TMAXs rank in either the first or the last decile in normal times, versus 22.57% during cryptocurrency bubbles, the frequency of empty portfolios is significantly lower in normal times. This suggests that the dispersion of TMAX ranks is higher in normal times, causing a lower average proportion of TMAXs ranking in the low or high decile, but also a lower frequency of observing no TMAX in either the first or tenth decile (or both). On the other hand, speculative bubbles are characterised by alternating periods of high and low proportions of lottery-like cryptos, causing a higher average proportion of TMAXs ranking in the low or high decile, but also a higher frequency of empty portfolios, as a result of the higher correlation of TMAXs.

To summarise, we are able to confirm Hypothesis 2 by rejecting the null hypothesis pertaining to the profitability of the TMAX Strategy during speculative bubbles. The TMAX Strategy is less profitable during bubbles than in normal times. Moreover, speculative cryptocurrency bubbles are characterised by a market-wide presence of lottery-like cryptos, i.e. a high(er) number of cryptocurrencies exhibiting lottery-like features.

4.5 Hypothesis 3a: Lottery-like preference during economic downturns, cryptocurrency market

Using the same concepts as under Hypothesis 2, we compare, in this section, the profitability of the TMAX Strategy during economic downturns and in normal times. Based on the literature that suggests that economic crises increase the propensity of investors to gamble, as well as the research stream that finds a more pronounced traditional MAX effect during economic crises, we postulate that during economic downturns, the TMAX Strategy is more profitable than in normal times.

	Economic downturns	
	EW	VW
Panel A: Raw returns of the TMAX-sorted portfolios		
Low	-0.749	-1.020
	(-0.48)	(-0.97)
2	0.087	-0.126
	(0.07)	(-0.10)
3	-0.050	-0.632
	(-0.04)	(-0.58)
4	-0.607	-0.128
	(-0.58)	(-0.10)
5	0.617	-0.463
	(0.48)	(-0.37)
6	1.260	-1.154
	(0.62)	(-0.82)
7	3.994	0.921
	(1.37)	(0.83)
8	0.780	1.269
	(0.52)	(0.88)
9	-1.343	-2.759
	(-0.66)	(-1.66)
High	-0.152	-1.678
	(-0.07)	(-0.99)
Panel B: Profitability of the TMAX Strategy		
Low - High	-0.597	0.658
	(-0.23)	(0.33)

Table 4.11: Returns of the TMAX Strategy during economic downturns

Table 4.11 reports the returns of the TMAX Strategy during economic downturns. The periods that this thesis considers economic downturns can be found in Table 3.2. Panel A reports the time-series averages of raw returns calculated with equal and value weights for each decile portfolio, during economic downturns, whereas Panel B shows the time-series average raw return of the TMAX Strategy. Numbers in parentheses are the t-statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The TMAX Strategy is not statistically significantly profitable during economic downturns, neither under equal nor under value weights. We can reject the null hypothesis that the TMAX Strategy generates losses during economic downturns, providing a novel result compared to the previous findings that unanimously suggested a negative average return for this strategy, and qualitatively indicates higher returns during economic downturns than in normal times.

The results are nevertheless surprising as they show a lack of any lottery-like behaviour by investors during these times on average (since we cannot reject the null hypothesis of zero mean return). The cryptocurrency returns are (relatively) uniformly distributed when sorted by previous-week TMAX. It is thus not possible to implement a profitable TMAX Strategy or reverse TMAX Strategy. The observations suggest that the underlying behavioural bias that makes these strategies profitable is not exhibited by investors during economic downturns. This empirical evidence conflicts with previous research on the (T)MAX effect during crises.

	Equal Weights	Value Weights
Mean Difference (Downturns-Normal Times)	-3.171	-0.227
T-statistic	(-0.60)	(-0.05)

Table 4.12: Results of the right-tailed hypothesis tests (H3a)

Table 4.12 shows the results of the right-tailed hypothesis tests under equal and value weights. This right-tailed t-test measures whether there is evidence to suggest that the mean of the TMAX Strategy during economic crises is significantly higher than the mean during normal times. Numbers in the parentheses are the t -statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Added to the lack of investor preference for lottery-like cryptos during economic crises, we find no significant evidence to support higher returns of the actually implemented TMAX Strategy relative to the returns in normal times. Therefore, we cannot confirm Hypothesis 3a due to the failure to reject the null hypothesis formulated under 3a.

4.6 Hypothesis 3b: Lottery-like preference during economic downturns, mutual funds market

Applying the same methods as under hypothesis 3a, we investigate whether professional money managers exhibit a (stronger) lottery-like preference during economic downturns, given what previous research suggests.

Table 4.13 reports the returns of the TMAX Strategy during economic downturns and in normal times. Panel A reports the time-series averages of raw returns calculated with equal and value weights for each decile portfolio, during economic downturns and in normal times, whereas Panel B shows the time-series average raw return of the TMAX Strategy. Numbers in parentheses are the t -statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Under equal weights, the TMAX Strategy does neither generate significant losses nor profits, no matter the state of the economy. Moreover, the difference in profitability between downturns and normal times is close to zero, given the extremely low t-statistics of 0.04 (cf. Table 4.14). Logically, the null hypothesis of the right-tailed t-test cannot be rejected. Therefore, we cannot confirm Hypothesis 3b, i.e. we cannot conclude that the TMAX Strategy is more profitable during economic downturns than in normal times. These results suggest that overall, professional money managers are not inclined to gamble when managing their funds, neither during economic downturns nor in normal times.

A positive average return of the TMAX Strategy can be observed under value weights during economic downturns, albeit not significant. The returns during normal times confirm the findings from Hypothesis 1b, namely that the reverse TMAX Strategy generates significant profits under value weights. However, the TMAX Strategy is not significantly more profitable during economic downturns

	Economic Downturns		Normal Times	
	EW	VW	EW	VW
Panel A: Raw returns of the TMAX-sorted portfolios				
Low	-1.393**	-1.026*	0.680***	0.590***
	(-2.48)	(-1.91)	(3.14)	(3.06)
2	-1.264**	-0.785	0.690***	0.658***
	(-2.03)	(-1.16)	(4.02)	(3.16)
3	-1.647***	-1.256**	0.976***	1.105***
	(-2.92)	(-2.24)	(4.46)	(4.24)
4	-1.666***	-1.695***	0.828***	1.017***
	(-2.76)	(-2.80)	(4.64)	(4.41)
5	-1.406**	-1.616**	0.818***	0.911***
	(-2.30)	(-2.58)	(4.63)	(4.61)
6	-1.353**	-1.309**	0.966***	1.134***
	(-2.22)	(-2.26)	(5.47)	(6.16)
7	-1.272**	-1.030	0.863***	0.930***
	(-2.07)	(-1.53)	(4.82)	(4.78)
8	-1.181*	-1.189*	0.987***	0.937***
	(-1.85)	(-1.97)	(5.43)	(4.15)
9	-1.152*	-1.078*	0.942***	0.919***
	(-1.68)	(-1.70)	(4.97)	(4.29)
High	-1.271	-1.321*	0.965***	1.273***
	(-1.59)	(0.32)	(4.59)	(5.47)
Panel B: Profitability of the TMAX Strategy				
Low - High	-0.122	0.295	-0.285	-0.683**
	(-0.12)	(0.32)	(-0.94)	(-2.26)

Table 4.13: Returns of the TMAX Strategy during economic downturns and in normal times

	Equal Weights	Value Weights
Mean Difference (Downturns-Normal Times)	0.026	0.932
T-statistic	(0.04)	(1.33)

Table 4.14: Results of the right-tailed hypothesis tests (H3b)

than in normal times (cf. Table 4.14). Even though the difference in average returns is not significant, these results still add to the TMAX puzzle in the mutual funds market, since they seem to indicate that the managers of larger funds are both able to exploit the lottery anomaly to their advantage under normal times (leading to the losses of the TMAX Strategy) and succumb to the lottery anomaly during economic downturns (leading to the statistically insignificant, yet profitable TMAX Strategy); the TMAX Strategy in the mutual funds market thus warrants further investigation.

4.7 Alternative specifications of the TMAX Strategy

4.7.1 Monthly framework as per Lin et al. (2021)

As discovered through the literature review, cryptocurrency price evolutions appear to be short-memory processes. As a result, we have adapted the monthly framework from Lin et al. (2021) to a weekly framework. To investigate to what extend this cryptocurrency price characteristic affects the profitability of the (reverse) TMAX Strategy, we have applied the monthly framework directly from Lin et al. (2021) to our cryptocurrency sample in order to compare the monthly framework results to the weekly returns from section 4.2.

	Equal Weights	Value Weights
Panel A: Raw returns of the TMAX-sorted portfolios		
Low	3.783	2.850
	(0.90)	(0.71)
2	2.954	10.906
	(0.70)	(1.61)
3	0.781	1.036
	(0.25)	(0.32)
4	4.879	4.344
	(1.26)	(1.08)
5	2.198	1.905
	(0.56)	(0.48)
6	14.294**	16.107*
	(2.24)	(1.98)
7	22.193**	11.024**
	(2.62)	(2.14)
8	3.006	3.365
	(0.56)	(0.72)
9	26.856*	45.518**
	(1.87)	(2.25)
High	20.579	7.672
	(1.55)	(0.63)
Panel B: Profitability of the TMAX Strategy		
Low-High	-16.796	-4.822
	(-1.20)	(-0.38)

Table 4.15: Returns of the TMAX Strategy in the cryptocurrency market, monthly framework

Table 4.15 reports the average returns of portfolios on TMAX for the cryptocurrency market from January 2014[2] to December 2022. The cryptocurrencies are allocated into deciles based on their values of MAX in *month* $t-1$ compared with their historical distribution of MAX. Panel A reports the time-series averages of raw returns calculated with equal and value weights for each decile portfolio, whereas Panel B shows the difference in returns between the lowest and the highest deciles, i.e. the time-series average raw return of the TMAX Strategy. Numbers in the parentheses are the t-statistics

[2]The period from April 2013 to January 2014 has been used to create meaningful deciles for the first implementation period.

calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The significance of the reverse TMAX effect disappears when using the monthly framework as defined in Lin et al. (2021). Lottery-like preferences in the cryptocurrency market are not exhibited when the TMAX is defined as the maximum daily return during a month and by rebalancing only monthly, and not weekly. The null hypothesis of zero mean return of the TMAX Strategy cannot be rejected. It is therefore not possible to conclude that investors have lottery-like preference when the benchmark is defined in a monthly framework.

Table 4.15 therefore underlines the claims made in the literature. The high volatility of the decile returns does not allow us to reject the null hypotheses under equal or value weights, even though, for example, the average return of the TMAX Strategy under equal weights (-16.796%) is close to four times higher in the monthly framework than in the weekly framework (-4.375%). The standard error is too high to lead to the rejection of the null hypothesis even though the absolute distance to zero is higher when using a monthly basis.

Furthermore, the results from the monthly framework suggest as predicted that cryptocurrency price evolutions are short-memory processes. No persistence (nor reversal) of returns could be observed when holding portfolios for longer and when defining extreme returns using a longer time period. The first (tenth) TMAX-sorted decile portfolio does not significantly outperform (underperform) the tenth (first) decile portfolio over the month after rebalancing. However, when the holding period and decile ranking benchmark is reduced to a shorter time period (in this thesis, a week), the underperformance of the first decile becomes significant at the 1% confidence level.

4.7.2 Multi-day maximum returns

To check whether the (lack of) profitability of the TMAX Strategy in the mutual funds market is robust to alternative specifications of TMAX, we investigate other definitions that have commonly been used in the literature. Previous research has shown that the TMAX Strategy (in the stock market) remains profitable, no matter the particular specification of TMAX.[3] It is true that both the look-back period that investors rely on as well as the specific definition of extreme returns that investors consider when forming their lottery preference has not been scientifically investigated. Therefore, any related anomaly should be robust to common-sense alternative definitions of (T)MAX.

The first alternative definition of TMAX commonly considered is the use of multi-day maximum returns as the measure for extreme returns, rather than the single-day maximum return. We therefore define $MAX(N)$ as the average of the N (N = 2, 3, 4, 5) highest daily returns over a month. Except for this point, the procedure remains unchanged with respect to Hypothesis 1b.

Table 4.16 shows the average raw return of the first and tenth decile portfolio based on multi-day maximum returns ($MAX(N)$) in Panel A. Panel B reports the profitability of the TMAX Strategy along with the abnormal return (*FF5 alpha*). Numbers in the parentheses are the t-statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

As soon as the definition of extreme returns is altered, there is no longer an observable, significant (reverse) TMAX effect, neither under equal nor, importantly, value weights. The average raw returns of the Low and High decile portfolios converge as N increases. The results indicate that the significant reverse TMAX effect under value weights observed when considering single-day maximum returns (cf.

[3] As explained in the methodology, investigating the alternative specifications that follow in the realm of the cryptocurrency market is of little interest due to a) the recency of the market and b) in the context of multi-day maximum returns, identifying multiple 'highest' daily returns within a week has a limited rationale.

	MAX(2)		MAX(3)		MAX(4)		MAX(5)	
	EW	VW	EW	VW	EW	VW	EW	VW
Panel A: Raw returns of the TMAX-sorted portfolios								
Low	0.404*	0.325	0.448**	0.372*	0.463**	0.390**	0.487**	0.432**
	(1.91)	(1.63)	(2.10)	(1.85)	(2.14)	(1.98)	(2.22)	(2.20)
High	0.578**	0.774***	0.536**	0.704***	0.467**	0.586**	0.434*	0.536**
	(2.51)	(3.06)	(2.30)	(2.89)	(2.00)	(2.36)	(1.84)	(2.15)
Panel B: Profitability of the TMAX Strategy								
Low - High	-0.174	-0.449	-0.088	-0.332	-0.004	-0.196	0.053	-0.104
	(-0.56)	(-1.40)	(-0.28)	(-1.05)	(-0.01)	(-0.62)	(0.16)	(-0.33)
FF5 alpha	-0.474**	- 0.686***	-0.343	-0.531**	-0.243	-0.364	-0.169	-0.262
	(-2.03)	(-2.91)	(-1.38)	(-2.23)	(-0.98)	(-1.52)	(-0.66)	(-1.08)

Table 4.16: Returns of the TMAX Strategy based on multi-day maximum returns

Table 4.5) is not robust to alternative specifications of extreme returns. Also, the (negative) alpha is no longer significant under equal weights starting from N = 3 under equal, and from N = 4 under value weights. All in all, the present analysis provides preliminary evidence that the reverse TMAX effect that has been observed using single-day maximum returns is peculiar to that specific setting, rather than empirical evidence of a lottery-related anomaly in the mutual funds market, that should be robust to these alternative specifications to be classified as such.

The monotonic increase in profitability of the TMAX Strategy as N increases conforms with, among others, Bali et al. (2011) and Lin et al. (2021) who show similar slight increases in profitability. The TMAX Strategy becomes even net profitable for $MAX(5)$ under equal weights, although the average return is not significant.

4.7.3 Extended evaluation periods

The definition of MAX as the maximum daily return within the last *month* as the benchmark for constructing either the MAX or TMAX Strategy is relatively arbitrary. It is thus relevant to relax this assumption and accommodate other potential benchmarks. In the literature, the maximum daily return within the last 3 months, thereby construing a sort of quarterly benchmarking, and within the last 12 months, i.e. a yearly benchmark, have often been considered.

	MAX within past 3 month				MAX within past 12 months			
	Low	High	Low-High	FF5 α	Low	High	Low-High	FF5 α
EW	0.155	0.674***	-0.519	-0.896***	0.215	0.622***	-0.407	-0.769***
	(0.65)	(3.15)	(-1.62)	(-3.72)	(1.31)	(3.07)	(-1.46)	(-5.35)
VW	0.349	0.809***	-0.460	-0.764***	0.316	0.754***	-0.438	-0.739***
	(1.23)	(3.64)	(-1.28)	(-2.75)	(-1.46)	(3-58)	(-1.46)	(-3.91)

Table 4.17: Returns of the TMAX Strategy based on alternative evaluation periods

Table 4.17 reports the average return of the Low and High decile portfolios, as well as the average return of the TMAX Strategy and the abnormal return under the Fama-French five-factor model, under equal (*EW*) and value (*VW*) weights, considering different evaluation periods. Numbers in the parentheses are the t-statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The first element to note is that the reverse TMAX effect is no longer significant under value weights when the evaluation period is modified from 1 to 3, respectively 12 months. Evidently, the reverse TMAX effect is lower than under the initial specification (-0.460%/-0.438% vs -0.515% per month). Conversely, under equal weights, the reverse TMAX effect is nearly two times higher in absolute terms, albeit still not statistically significant (-0.519%/-0.407% vs -0.246% per month).

Under both equal and value weights, the reverse TMAX effect is lower under the 12 months compared to the 3 months evaluation period, making the case for shorter evaluation periods, especially under value weights.

4.7.4 Shortened look-back periods

When construing the TMAX Strategy, it is not entirely clear whether investors consider the entirety of the historical MAX distribution or part of it when forming their lottery preference. In line with Lin et al. (2021), we therefore investigate whether a five- or ten-year reference period, as opposed to considering the whole historical distribution, significantly changes the outcomes of the strategy.

	5-year reference period				10-year reference period			
	Low	High	Low-High	FF5 α	Low	High	Low-High	FF5 α
EW	0.310	0.697***	-0.387	-0.650***	0.330*	0.701***	-0.371	-0.601***
	(1.59)	(3.30)	(-1.34)	(-3.17)	(1.67)	(3.25)	(-1.27)	(-2.89)
VW	0.354*	0.844***	-0.490*	-0.754***	0.318*	1.031***	-0.713**	-0.902***
	(1.94)	(3.82)	(-1.70)	(-3.54)	(1.70)	(4.54)	(-2.43)	(-4.31)

Table 4.18: Returns of the TMAX Strategy based on alternative reference periods

Table 4.18 reports the profitability of the TMAX Strategy under equal and value weights over a five-year and ten-year look-back period, as well as the abnormal returns. Numbers in the parentheses are the t-statistics calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The TMAX Strategy's profitability is largely unchanged and insignificant under equal weights, no matter the reference period; the FF5 alphas are also in line with the initial specification of the TMAX Strategy. The reverse TMAX effect remains significant under value weights under both reference periods, and becomes stronger as the reference period increases from five to ten years. Under both reference periods, the losses of the TMAX Strategy are higher than when the entire historical distribution is considered. These findings are in line with Lin et al. (2021), who also observed lower profitability of the TMAX Strategy when the reference period is shortened.

Discussion

In the following, the findings from the previous chapter will be analysed, both in light of existing literature and by further, more granular investigation of certain results.

5.1 Potential explanations for the TMAX discount in the cryptocurrency market

The TMAX discount observed in this research confirms the existing literature on the MAX effect in the cryptocurrency market. However, it is at odds with the profitability of the (T)MAX Strategy in other markets. It is therefore of scientific importance to identify the factors underlying the different behaviour of cryptocurrency prices compared to other asset prices. Note that there is a lack of literature regarding potential explanations of the TMAX discount in the cryptocurrency market. The investigations hereunder should therefore be seen as exploratory to stimulate further, more detailed research on the observed reverse TMAX effect. Section 5.1 groups potential explanations of the TMAX discount. First, a step-by-step, critical investigation of the underlying factors explaining the TMAX premium according to Lin et al. (2021) will be provided (subsections 5.1.1-5.1.4). After that, separate hypotheses are made that might explain the observed TMAX discount (subsection 5.1.5).

Lin et al. (2021) put forward four potential sources of the TMAX premium: investor sentiment, shorting flow, unrealized capital gains, and psychological barriers. The hypothesis behind each of these behavioural explanations will be explained and tested (when possible) accordingly. The reason for choosing Lin et al. (2021) is a result of the extensive investigation of potential sources for the profitability of the TMAX Strategy. Other papers have limited the interpretation of the lottery-related anomaly to the mispricing argument (grouped by Lin et al. (2021) under shorting flow).

5.1.1 Investor sentiment

The idea of the MAX effect acting as a proxy of investor sentiment has already been touched upon in the literature review. Fong and Toh (2014) show that the MAX effect in the stock market becomes significantly less significant when controlling for investor sentiment. In particular, the authors show that the MAX Strategy's profitability is concentrated in periods following high investor sentiment. Fong and Toh (2014) argue that periods of high investor sentiment are characterised by general investor optimism which causes investors to be more optimistic about the future payoffs of assets; hence, these assets are more overpriced during high sentiment periods. Furthermore, they empirically prove that, even in the high sentiment periods, the profitability of the MAX Strategy is induced solely by the low performance of the high MAX-sorted decile portfolio, and not by the good performance of the low decile portfolio. Fong and Toh (2014) thus postulate that the MAX effect is due to overpricing that affects the market as a whole, which causes the MAX Strategy to be profitable, and not a direct consequence of the lottery preference of investors.

Reasonably extending these findings to the TMAX discount that has been observed in this study, the reverse TMAX effect should be stronger during periods of low investor sentiment.

To empirically test the effect of investor sentiment on the returns of the TMAX Strategy, we use the sentiment index constructed by M. Baker and Wurgler (2006)[1] and create two sub-samples: periods

[1] The sentiment index has been downloaded from Jeffrey Wurgler's website (`http://pages.stern.nyu.edu/~jwurgler/`). We used

of high investor sentiment and periods of low investor sentiment. Week t is a period of high (low) investor sentiment if the sentiment index in week $t-1$ is higher (lower) than the median since July 1965 (see M. Baker and Wurgler (2007), Stambaugh et al. (2012) and Fong and Toh (2014) for a similar construction).

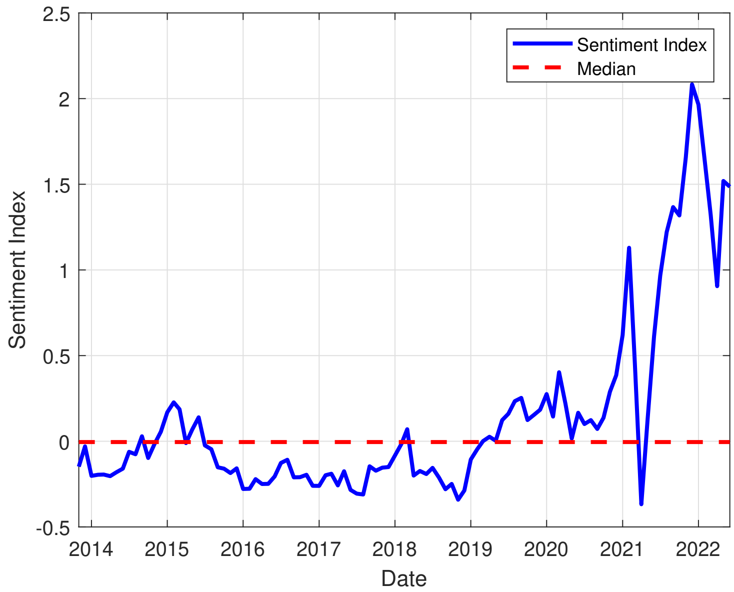

Figure 5.1: Sentiment Analysis

Figure 5.1 plots the sentiment index, as well as the median sentiment value, over the cryptocurrency sample period. We can deduct from the graph that investor sentiment is not perfectly correlated with the state of the economy or the stock market. For example, investors were more or similarly optimistic during the 2022 bear market than they were during the 2021 bull market. Therefore, the investigation of investor sentiment has not to be confounded with the analysis in the context of hypotheses 2 and 3.

	EW returns			VW returns		
	Low sentiment	High sentiment	High - Low	Low sentiment	High Sentiment	High - Low
Panel A: Raw returns of the TMAX-sorted portfolios						
Low	-1.986**	-0.121	1.865	-2.350***	-0.392	1.958*
	(-2.02)	(-0.14)	(1.42)	(-2.65)	(-0.54)	(1.71)
High	5.781	3.262**	-2.519	9.828**	1.893	-7.935**
	(1.51)	(2.20)	(-0.61)	(2.15)	(1.27)	(-2.02)
Panel B: Profitability of the TMAX Strategy						
Low - High	-7.767**	-3.383**	4.384***	-12.178***	-2.285	9.893***
	(-1.97)	(-1.97)	(2.78)	(-2.62)	(-1.43)	(7.16)

Table 5.1: Effects of investor sentiment on TMAX Strategy returns

Table 5.1 reports the average raw returns of the first ('Low') and tenth ('High') TMAX-sorted portfolio in Panel A, during low sentiment and high sentiment periods, as well as the difference in average raw returns between periods of high and low sentiment ('High – Low'), under both equal and value weights. Panel B reports the profitability of the TMAX Strategy. Numbers in parentheses are the t-statistics

the orthogonalized version from July 1965 to June 2022. June 2022 is the last available data point; the sample has therefore been truncated at that date.

calculated using Newey and West (1987)'s robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The profitability of the TMAX Strategy varies significantly with investor sentiment. Whereas the TMAX Strategy generates negative returns of about 8% (under EW; 12% under VW) per week in low sentiment periods, it only loses a little more than 3% (under EW; 2% under VW) during high sentiment periods. The results confirm our hypothesis of a stronger reverse TMAX effect during low sentiment periods. The difference in average return is significant at the 1% confidence level under both equal and value weights. Interestingly, the reverse TMAX effect is no longer significant during high sentiment periods under value weights, indicating that for larger cryptocurrencies, the link between the (reverse) TMAX effect and investor sentiment is stronger.

The results confirm that the reverse TMAX effect is, in part, due to investor sentiment. Furthermore, for large cryptocurrencies, it is concentrated in periods of low sentiment; during these periods, the reverse TMAX effect is particularly strong (12.18% average return of the reverse TMAX Strategy per week). The effect in the cryptocurrency market seems to be partially linked to periods of market underpricing (see also subsection 5.1.2 just below) that correlate with low investor sentiment (Fong & Toh, 2014).

5.1.2 Mispricing degree

In the literature on the (T)MAX effect, there are two main lines of thought regarding the profitability of the (T)MAX Strategy: a (negative) risk premium for lottery-like characteristics, and mispricing. Unfortunately, past research on the topic has often postulated one of both theories without testing its merits.

As this thesis has shown, the negative risk premium theory does not hold. According to this postulate, there is some negative risk premium attached to lottery-like assets which leads to their lower expected return. In other words, when it comes to lottery-like assets, investors suddenly become risk-seeking, which contradicts fundamental principles of risk and return in finance. Moreover, the postulate that people gamble because/if they are risk-seeking has been refuted by numerous academics (see for example, Garrett and Sobel (1999)) If anything, our results report a positive risk premium attached to lottery-like cryptocurrencies, i.e. a higher expected return for cryptocurrencies conforming to lottery-like features. However, a positive risk premium conflicts with the proven demand for lottery assets by investors.

In a groundbreaking paper, Zhong and Gray (2016) find no evidence of a risk factor associated with lottery-like payoffs (confirming our findings and what has just been exposed), but strong evidence of a mispricing explanation. The authors show that the MAX effect is concentrated among overpriced stocks and, astonishingly, a reverse MAX effect is observed for the most underpriced stocks.

If this is true, we should observe, in a similar fashion, that the reverse TMAX effect is limited to underpriced cryptocurrencies. This idea links also to the previous section on investor sentiment, as low investor sentiment periods generally correlate with periods of underpricing. Alas, testing this hypothesis is challenging in the cryptocurrency market. The most common technique to proxy mispricing is by constructing a “mispricing index” à la Stambaugh et al. (2015) based on known anomalies in the stock market and then partitioning the sample along the computed mispricing index. Due to the recency of the cryptocurrency market, not as many anomalies have yet been identified in this market. That being said, we will follow the approach by Y. Li et al. (2021) who also investigated mispricing in the cryptocurrency market. The retained anomalies are the momentum and size effect (Liu et al., 2022). The idea is to assign, on a weekly basis, a percentile rank to each cryptocurrency for each anomaly variable. Thus, the most underpriced cryptos, i.e. those with the highest expected return, are awarded the lowest rank while the most overpriced cryptos, i.e. with the lowest expected return, are awarded the highest rank. Then, the average between the ranks for both anomalies is taken to compute a composite rank. Finally, each week, the cryptocurrencies are sorted into quintiles based on their composite rank.

Note that over- or underpricing as defined here might not adhere to the reader's definition of over/underpricing. Mispricing as defined by Stambaugh et al. (2015) considers the degree to which an asset's characteristics make it follow a reported stock market anomaly, not so much its price relative to its fundamental value (however 'fundamental value' may be defined). Therefore, cryptocurrencies might vary on their level of mispricing as construed in this section while the reader can still, at his discretion, consider the whole market to lack fundamental value, i.e. be overpriced; there is no direct conflict between both.

	EW returns			VW returns		
	Low	High	TMAX Strategy	Low	High	TMAX Strategy
Most underpriced	0.064	10.560**	-10.496**	0.057	10.392**	-10.335**
	(0.07)	(2.08)	(-2.04)	(0.06)	(2.05)	(-2.02)
2	-0.824	2.633	-3.457*	-0.629	3.209*	-3.838*
	(-1.12)	(1.50)	(-1.81)	(-0.83)	(1.70)	(-1.88)
3	-0.291	3.425*	-3.716*	-0.753	3.947*	-4.700**
	(-0.47)	(1.90)	(-1.95)	(-1.20)	(1.96)	(-2.23)
4	0.677	4.061	-3.384	0.652	3.731	-3.079
	(0.34)	(1.53)	(-1.02)	(0.33)	(1.42)	(-0.94)
Most overpriced	1.045	2.639	-1.594	1.018	2.926	-1.908
	(0.42)	(0.69)	(-0.35)	(0.41)	(0.76)	(-0.42)
Underpriced - Overpriced	-0.981	7.921		-0.961	7.466	
	(-0.37)	(1.24)		(-0.37)	(1.18)	

Table 5.2: Effects of mispricing on TMAX Strategy returns

Table 5.2 shows the average next-week return of portfolios sorted on mispricing (rows) and TMAX (columns), under equal and value weights. The average return of the TMAX strategy is reported in the "TMAX strategy" columns. Newey and West (1987) adjusted t-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

The empirical results confirm our hypothesis: the reverse TMAX effect is concentrated among underpriced cryptocurrencies, under both equal and value weights. While the TMAX strategy generates statistically significant (at the 5% confidence level) losses of 10.5% (10.3%) per week for the most underpriced cryptocurrencies, the losses are insignificant for the most overpriced. Moreover, the reverse TMAX effect is significantly larger for the most underpriced cryptocurrencies, compared to the next quintile (row '2') (at the 5% confidence level). The reverse TMAX effect is largely driven by the performance of the lottery cryptos ('High' decile), and less by the underperformance of the 'non-lottery' cryptos ('Low' decile), indicating that, indeed, it is the underpricing (overpricing) of the lottery-like assets in the sample that makes the effect significant (insignificant). This observation is also underpinned by comparing the returns of the most underpriced and most overpriced decile portfolios: while the average return of the Low decile portfolio differs by 0.98 p.p. (0.96 p.p.) between the most under- and most overpriced cryptos, this difference is significantly higher (7.92 p.p.; 7.47 p.p.) for the High decile portfolios. All in all, Table 5.2 provides strong empirical evidence that the reverse TMAX effect is attributable to mispricing.

These findings are crucial in two ways. First, the results provide an explanation for the observed TMAX discount in the cryptocurrency market. Arbitrage risk, i.e. the risk of losses that arbitrageurs take when trading on inefficiencies, prevents markets from fully correcting mispricing (Mendenhall, 2002). The higher the idiosyncratic volatility of the underlying asset, the higher the arbitrage risk

(Stambaugh et al., 2015). Controlling for the level of mispricing (i.e. reading Table 5.2 across a given row), High TMAX cryptocurrencies are therefore expected to be the most prone to mispricing that is not arbitraged away due to high arbitrage risk, since idiosyncratic volatility monotonically increases with TMAX (see Table 4.1). In the case of underpriced cryptocurrencies, arbitrage risk thus deters investors from entering the long positions in High TMAX cryptocurrencies that would correct the related underpricing. High TMAX cryptocurrencies consequently outperform Low TMAX cryptocurrencies in the subset of underpriced cryptos. The Low-High spread, i.e. the return of the TMAX strategy, averages -10.5% (*EW*) per week. Conversely, in the case of overpriced cryptocurrencies, high arbitrage risk prevents investors from entering the short positions in High TMAX cryptos to reduce their returns. However, there is a specificity in the cryptocurrency market compared to stock markets: high constraints on short selling due to the associated costs or unavailability of counterparties. Only select cryptocurrency exchanges offer the possibility to short-sell cryptos[2], and if they do, only for the most liquid and largest ones. Lamont (2004) showed that assets with high constraints on short sales could potentially be overpriced indefinitely. Added to Lin et al. (2021)'s shorting flow argument for the TMAX premium, i.e. that the TMAX premium only exists among stocks where shorting activity is high, it is not surprising that we find no TMAX effect in either direction for the most overpriced cryptocurrencies. This thesis seems to indicate that a TMAX premium cannot exist in a market with such limited short selling activity.

Second, the results from Table 5.2 reconcile the TMAX effect observed in stock markets with the reverse TMAX effect (or 'TMAX momentum') observed in the cryptocurrency market. If we break it down, whether a traditional or reverse TMAX effect is noted across the market depends on the magnitude of the anomaly along the degree of mispricing, which is influenced by arbitrage risk and short sale constraints. As (or if) the cryptocurrency develops and becomes more deeply integrated, i.e. more liquid, short selling should become less costly. In that case, theoretically, the same, 'traditional' TMAX effect that has been observed by Lin et al. (2021) in the stock market should also be present in the cryptocurrency market, according to the arbitrage risk theory[3]. As such, both markets do not differ on investor preference for lottery-like assets (as has been established, both markets host investors with lottery-like preference) but on the differing availability of short selling, which renders void the overpricing argument, a major pillar of the lottery anomaly.

5.1.3 Unrealised gains/losses

A key feature of Kahneman and Tversky (1979)'s prospect theory is the tendency of investors to overweight the small probability of extreme returns. No product's existence showcases this behavioural bias more than lotteries, thus also lottery-like assets.

Prospect theory advocates that investors are more risk-seeking when they face prior losses. An et al. (2020) hypothesise therefore that the profitability of the MAX Strategy depends on whether investors are in a gain or loss region relative to a reference point. The authors show that the MAX effect is more pronounced among stocks with prior losses, but weaker or even reversed among stocks with prior gains. Following this logic, we should observe a stronger reverse TMAX effect in the cryptocurrency market when investors face prior gains.

The lack of cryptocurrency data makes empirical testing of this hypothesis difficult.[4] The solution proposed by Y. Li et al. (2021) is to make a rough examination of the TMAX Strategy during market

[2] To the author's knowledge, there is no cryptocurrency to date that offers the possibility to short-sell cryptos directly on the blockchain

[3] This hypothesis is also consistent with the notion of "arbitrage asymmetry" (Stambaugh et al., 2015)

[4] Y. Li et al. (2021) make the same argument. Moreover, the empirical test that Lin et al. (2021) use is not replicable in the cryptocurrency market, since it necessitates both extended-term (e.g. monthly) and near-term (e.g. weekly) data. Since the TMAX Strategy in the crypto market requires a weekly framework, using for example daily data as the near-term sample is suboptimal due to its reliance on single-point estimates that might pollute the results.

upturns and market downturns. Usually, investors make profits when the market performs well and losses when the market does not perform well. This is one of the reasons why we investigated the profitability of the TMAX Strategy during speculative bubbles (Hypothesis 2) and during economic downturns (Hypothesis 3a).

Results from Table 4.7 and Table 4.11 confirm the effect of unrealised capital gains/losses on the TMAX discount. During economic downturns, used here as a proxy for prior losses, the average TMAX Strategy return is not significant. It is not unusual to observe this lack of statistical significance instead of a significant positive average TMAX return given what has been described in the previous section regarding the effect of high short-sale constraints in the cryptocurrency market. On the other hand, during speculative bubbles, used here as a proxy for prior gains, the TMAX Strategy generates statistically significant losses.

We formulated Hypothesis 3 based on the existing literature on lottery demand in times of crisis. We can now comprehend why we did not discover evidence that substantiates the existing literature, by utilizing prospect theory, and place the empirical outcomes in their scientific context. Also, prospect theory enables us to understand why the TMAX Strategy generates losses during speculative bubbles. Periods of prior losses make the TMAX Strategy more profitable due to an (even) higher demand for lottery-like assets, while the reverse is true for periods of prior gains.

5.1.4 Psychological barriers

Another explanation for the lottery anomaly is proposed by Byun et al. (2020) who provide evidence of a link between lottery preference and psychological barriers. The authors argue that the 52-week high acts as a "psychological barrier". Investors consider the 52-week high as an upper limit and this psychological barrier affects their preferences for lottery-like stocks. In particular, investors are more prone to overestimate the probability of extreme positive returns in cases where current prices are far from their 52-week high, making the MAX Strategy most profitable in the subset of these stocks. The role between lottery preference and psychological barriers has been confirmed for the TMAX Strategy also (Lin et al., 2021).

To test this hypothesis, we compute the nearness to 52-week high price (*NH*) as the ratio of the closing price in week $t-1$ to the highest daily closing price over the past 52 weeks ending in week $t-1$ (adapted from George and Hwang (2004) and Lin et al. (2021)). After that, cryptocurrencies are partitioned each week into three groups based on their nearness to the 52-week high.

	EW returns			VW returns		
	Low NH	Median NH	High NH	Low NH	Median NH	High NH
Panel A: Raw returns of the TMAX-sorted portfolios						
Low	-1.328	-0.752	0.446	-1.418	-0.283	1.469
	(-1.52)	(-0.96)	(0.27)	(-1.42)	(-0.33)	(0.67)
High	3.560	4.219	3.610*	2.152	5.701*	4.344*
	(1.62)	(1.53)	(1.90)	(1.00)	(1.85)	(1.85)
Panel B: Profitability of the TMAX Strategy						
Low - High	-4.888**	-4.971*	-3.164	-3.570*	-5.984*	-2.875
	(-2.06)	(-1.73)	(-1.26)	(-1.70)	(-1.87)	(-0.89)

Table 5.3: Effects of psychological barriers on TMAX Strategy returns

Table 5.3 reports the average raw returns of the TMAX Strategy conditional on the 52-week high. Panel A reports the average raw returns of the first ('Low') and tenth ('High') TMAX-sorted decile portfolios, Panel B the average raw returns of the TMAX Strategy ('Low – High'). As we move from the Low NH to the High NH portfolios, the nearness to the 52-week high increases (e.g. the 'High NH' column reports the portfolio returns of the cryptocurrencies that are closest to their 52-week high). Newey and West (1987) adjusted t-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

The link between the (reverse) TMAX effect and psychological barriers is not as clear in the cryptocurrency market. While it can be confirmed that the *reverse* TMAX Strategy's profits are higher in the Low NH group than in the High NH group (4.89% vs 3.16%; 3.57% vs 2.88%), they are at least as high in the Median NH group than in the Low NH group (4.97% vs 4.89%; 5.98% vs 3.57%). Under value weights, the reverse TMAX strategy's returns are even higher in the Median NH group than in the Low NH group.

Interestingly, the reverse TMAX effect is significant under both weights in the *Low* NH group, while it is not in the *High* NH group, contrary to what one would expect given the findings for the TMAX Strategy in the stock market. The behaviour of the Low decile portfolios is in conflict with what the hypothesis would predict: the low lottery-like cryptocurrencies perform worse when they are far from their 52-week high than when they are close. However, the psychological barrier created by the 52-week high should leave less space for price increases in the High NH group than in the Low NH group.

In the cryptocurrency market, prices are significantly affected by attention (Piccoli & Chaudhury, 2019). For example, Sridhar and Sanagavarapu (2021) show that the price of Dogecoin is closely linked to the attention generated by Elon Musk's tweets: prices are positively correlated with a tweet from Elon Musk, while they are negatively correlated with announcements that the support might be a joke rather than a formal endorsement. Our conjecture is that the 52-week high acts as a similar attention drawer: when cryptocurrency prices approach recent highs, it draws attention from investors, and due to slow transmission of information in the market (Joo et al., 2020), the nearness to 52-week highs generates positive subsequent returns as attention grows. Conversely, when cryptocurrency prices are far from 52-week highs, they become 'forgotten'[5] (especially smaller cryptocurrencies, which could explain the more pronounced link between psychological barriers and reverse TMAX effect under equal weights), therefore relatively lower subsequent performance is expected due to a lack of demand. Add to this phenomenon that low lottery cryptos have in general a lower demand than high lottery cryptos due to the lower lottery characteristics, low lottery cryptos underperform high lottery cryptos most when they are far from 52-week highs. Put bluntly, at least high lottery-like cryptos still have a reason to be held even when they are far from recent highs (due to investor demand for lottery-like assets) while low lottery-like cryptos lack also this demand factor.

5.1.5 Idiosyncratic volatility and skewness

Since lottery-like assets are characterised by high idiosyncratic volatility and high idiosyncratic skewness (Kumar, 2009), there are obvious links between TMAX and these measures. Table 4.1 confirms that the highest TMAX decile portfolio exhibits significantly higher idiosyncratic volatility and skewness than, in particular, the lowest TMAX decile portfolio. Consequently, idiosyncratic volatility and skewness might subsume the reverse TMAX effect.

To test the statistical significance of this link, we run another series of Fama-Macbeth regressions. Idiosyncratic volatility is defined as the standard deviation of residuals obtained from monthly regressions of the daily excess cryptocurrency returns on the daily excess market returns, where the market portfolio is represented by the CRIX Index (cf. Methodology). Idiosyncratic skewness is the

[5] See the numerous examples of 'pump and dump' cryptocurrency schemes (E-coins, Quark, U.cash, Dogecoin (?) (see above), ...) or cryptocurrencies that failed to gain traction after initial attention (Titcoin, Mycelium Token, Coinye, ...)

standard deviation of residuals from monthly regressions of daily excess cryptocurrency returns on the daily excess market returns and squared daily excess market returns.

	(1)	(2)	(3)	(4)
TMAX	11.207**			-11.869**
	(2.03)			(-1.96)
IVOL		55.729***		-168.360
		(5.09)		(-1.36)
ISKEW			63.624***	244.100*
			(4.31)	(1.91)
Intercept	2.130***	-1.413*	-1.717*	-1.109
	(2.78)	(-1.69)	(-1.83)	(-1.38)
Adj. R^2	7.06%	10.73%	10.74%	22.54%

Table 5.4: Fama-Macbeth regressions on volatility and skewness

Table 5.4 presents the time-series averages of the slope coefficients and intercepts from the cross-sectional regressions of one-week-ahead cryptocurrency excess returns on TMAX individually (column (1)) or jointly with idiosyncratic volatility and idiosyncratic skewness (in column (4)). Columns (2) and (3) present the simple linear regression coefficients of next-week cryptocurrency excess returns on idiosyncratic volatility, respectively idiosyncratic skewness. Additionally, the adjusted R^2 is provided for each batch of regressions. The slope coefficients represent percentage values (for example, the TMAX coefficient in column (4) is -11.869%). Numbers in the parentheses are the t-statistics calculated using Newey and West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

There is a strong correlation between idiosyncratic volatility and skewness and the cross-section of cryptocurrency excess returns. Columns (2) and (3) provide convincing empirical evidence for a risk premium attached to these measures.

Column (4)'s results are quite frankly, astounding. When controlling for idiosyncratic volatility and skewness, the relationship between future returns and TMAX becomes significantly negative. This indicates that, keeping *IVOL* and *ISKEW* constant, a 'traditional' TMAX effect can be observed in the data.

These findings provide a novel, highly relevant explanation of the TMAX discount in the cryptocurrency market. Due to a significant positive relation between idiosyncratic skewness and the cross-section of cryptocurrency returns, the observed TMAX discount is actually a reward for a risk-premium, namely idiosyncratic skewness. The high level of risk with respect to (idiosyncratic) skewness that is taken when investing in cryptocurrencies dominates the TMAX effect: as a matter of fact, the slope coefficient of *ISKEW* is more than 20 times the coefficient of TMAX. To illustrate, Bali et al. (2011) found an average idiosyncratic skewness $\hat{\beta}$ of 0.04, while we observed an average of 2.44, i.e. about 60 times higher. As the implemented TMAX Strategy does not control for the level of idiosyncratic skewness, its returns are the ex-post compensation for the high level of risk that has been taken.

Had it been possible to control for the level of idiosyncratic skewness, the TMAX Strategy would have been profitable, as column (4) shows. Besides the previously mentioned explanations for the TMAX discount, these results (again) reconcile previous research on the (T)MAX effect in the stock market with the seemingly different effect in the cryptocurrency market. The lottery-preference anomaly can also be found in the cryptocurrency market (cf. the TMAX slope coefficient in column (4)). The difference between both markets resides only in the level of 'idiosyncratic skewness risk' that is taken when the TMAX Strategy is implemented. In the stock market, this risk is relatively low. Therefore, when taking the short position in the High TMAX-sorted decile portfolio, i.e. also the portfolio with the highest (idiosyncratic) skewness, the returns associated with the TMAX effect dominate the returns associated with the higher level of skewness, resulting in an underperformance of the High decile portfolio relative to the Low decile portfolio, making the TMAX strategy profitable. In the cryptocurrency market, however, the short position in the High decile portfolio is characterised by much higher levels of (idiosyncratic) skewness, both relative to the stock market and the Low decile portfolio. This risk spread yields a situation where the risk-return trade-off for idiosyncratic skewness dominates the TMAX effect, causing a subsequent outperformance of the High decile portfolio.

To summarise, the high risk-premium attached to idiosyncratic skewness that has been documented in the cryptocurrency market has significant repercussions on the profitability of the TMAX Strategy, so much so that it reverses the traditional TMAX effect that has been observed in the stock market. Consequently, the characteristics of the underlying assets in both markets yield a difference in profitability of the related investment strategy, not the underlying behavioural bias(es) of investors. When controlling for idiosyncratic skewness and volatility, we are able to provide empirical evidence of a similar effect that results from the lottery-like preference of investors. These observations go hand-in-hand with a decoupling of the lottery anomaly from (idiosyncratic) skewness and volatility in the cryptocurrency market. Given the extensive research that advocates for the (T)MAX Strategy as a tool to investigate (and exploit) a potential lottery anomaly, we postulate that a) the lottery preference of investors is not linked as closely to idiosyncratic skewness and volatility as previously thought[6], calling for a revision of Kumar (2009)'s definition of a "small probability of extreme returns" and b) the (T)MAX Strategy is ill-equipped to exploit a lottery anomaly in a market whose investors require a high compensation to take on idiosyncratic skewness risk relative to their demand for lottery-like assets.

5.2 Potential explanations for the TMAX Strategy puzzle in the mutual funds market

At this stage, it is important to put this thesis' research in the mutual funds market into context. As the literature review established, the profitability of the MAX Strategy in the stock market has been proven beyond reasonable doubt, across different time periods and markets, and after being subjected to numerous robustness checks. Even though the TMAX Strategy is still in its early steps, Lin et al. (2021) also provide convincing empirical evidence of the profitability of the TMAX Strategy in the stock market. The mutual funds data has expressly been sampled for the returns to represent the weighted average return of the portfolio holdings, free of other external influences. Consequently, the lack of significant returns or the presence of significant losses of the TMAX Strategy in the mutual funds market both provide clear evidence that professional money managers are capable of avoiding falling into the (T)MAX effect 'trap', i.e. succumbing to the low subsequent performance of lottery-like assets. To see why this conclusion is permissible, let us assume a situation where a fund manager whose fund is ranked in the High decile portfolio in month $t-1$ does not rebalance the portfolio holdings until the end of month t (at least). Due to the convincing evidence of the presence of a TMAX effect in the stock market, this fund will experience a relatively lower return in month t. In this case, we should have observed statistically significant profitability of the TMAX Strategy. The fact that we could not indicates that fund managers close or reduce the positions in lottery-like stocks such that the funds' performance does not succumb to the low subsequent performance of these assets. This central result not only confirms our initial hypothesis (1b), but also previous research by Agarwal et al. (2021) that found that fund managers have a tendency to avoid lottery-like assets if they have the opportunity to.

[6] In particular, the lottery anomaly exists even in any subset of cryptocurrencies that have similar levels of idiosyncratic skewness and volatility.

Still, there remain intriguing results that warrant further investigation, namely the presence of a (marginally) significant reverse TMAX effect under value weights, the inconsistency between insignificant average raw returns and significant abnormal returns, as well as the lack of robustness of the reverse TMAX effect to alternative specifications of lottery-like demand.

5.2.1 Lack of persistence of the TMAX discount

The latter intriguing observation is probably the clearest indication that the significant results we observed in the mutual funds market are either due to the specific setting and/or due to the influence of other factors, but not convincing evidence of a lottery anomaly.

Moreover, and as alluded to in the methodology, the inconsistency between the insignificant average raw returns and significant abnormal returns guides to a potential cause of these conflicting results: the lack of persistence of the TMAX discount. It is possible that the (reverse) TMAX strategy was very profitable during one specific time period, and generated quasi-zero returns during the rest of the sample period, thereby generating significant abnormal returns but, averaged over the whole period, no significant difference between the Low and High decile portfolios.

To investigate this hypothesis, we start by plotting the cumulative returns of the TMAX Strategy and compare it to the cumulative returns of the market portfolio as defined by Fama and French (1996, 2015), from 1985 to 2022. We have shown that the TMAX Strategy is close to being a market-neutral strategy; thus, it makes little sense to compare the raw returns of the TMAX Strategy and the market portfolio. Instead, the risk-adjusted returns are used as a basis for comparison. To compute returns of the TMAX Strategy that can be compared risk-wise to the market portfolio's, we calculate the strategy's Treynor ratio in each period, defined as:

$$TR_{TMAX_t} = \frac{R_{TMAX_t} - R_{f_t}}{\beta_{TMAX}}$$

Where the numerator is the excess return of the TMAX Strategy in period t, and the denominator the TMAX Strategy's *beta*.

First, we compare the TMAX Strategy and the market portfolio's cumulative performance. As both the raw and risk-adjusted returns indicate an underperformance of the TMAX strategy, the corresponding graph should corroborate this observation.

Figure 5.2 not only shows the underperformance of the TMAX Strategy, but it also reveals that, had an investor implemented the TMAX Strategy at the beginning of 1985, he would have lost all of his investment by 1987, on a risk-adjusted basis. Over the same time period, an investment in the market portfolio would have generated a 56% return. It is worth remembering that the TMAX Strategy entails creating self-financing portfolios at the beginning of each month, therefore the term 'investment' might be ambiguous. However, whenever the TMAX Strategy yields a negative return, i.e. the short leg outperformed the long leg, this loss has to be financed at the rebalancing date, which can be considered an investment in the strategy. In light of this, it becomes clear how consistently bad the performance of such a strategy would be. Even though no initial investment is necessary to implement the TMAX strategy, by the loss-financing alone, an investor would have lost an amount equal to the long position in January 1985 after roughly one year and a half, when controlling for risk.

While this observation is relevant, it does not help in finding a time-dependency of the reverse TMAX effect that might explain the results under value weights. Therefore, we also compare the reverse TMAX Strategy's risk-adjusted cumulative performance, i.e. going long in the High decile portfolio and short in the Low decile portfolio, and the market portfolio's cumulative performance in Figure 5.3.

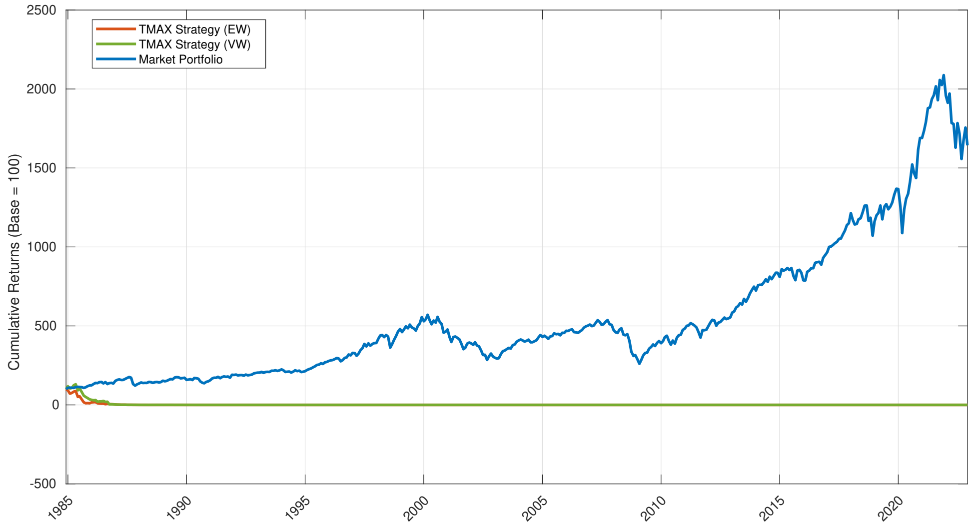

Figure 5.2: Cumulative returns of the TMAX Strategy vs Market Portfolio

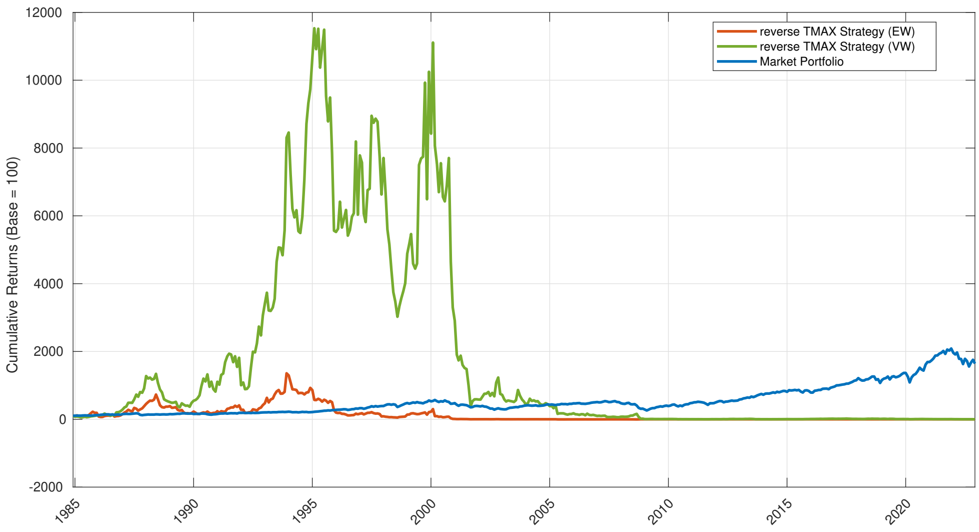

Figure 5.3: Cumulative returns of the reverse TMAX Strategy vs Market Portfolio

Figure 5.3 provides eye-opening results. It indicates that the reverse TMAX effect is concentrated in the time period from 1985 to 2000, and disappears afterwards. As a result, the reverse TMAX Strategy under value weights would have been extremely profitable until February 2000, where it would have generated a cumulative risk-adjusted return of roughly 11'000%, compared to a 584% cumulative return of the market portfolio. Even the reverse TMAX Strategy under equal weights would have outperformed the market portfolio on a risk-adjusted basis until 1996/1997, though the outperformance is significantly less pronounced than under value weights. Starting in February 2000, an underperforming spell of about two years starts and is so stark that all of the previous relative gains are lost by 2003, which perfectly coincides with the Dot-com crash. The reverse TMAX Strategy then recovers and outperforms the market again until 2005, before losing ground and converging to zero. After the Global Financial Crisis until the end of 2022, the cumulative return of the reverse TMAX Strategy is roughly zero.

Considering this information, we divide the sample period into two sub-periods, one from 1985 to January 2000, and another from February 2000 until the end of the sample, to investigate whether the profitability of the TMAX Strategy significantly differs between the two sub-periods. The results can be found in Table 5.5.

	JAN 1985- JAN 2000		FEB 2000 - DEC 2022	
	EW	VW	EW	VW
Panel A: Raw returns of the TMAX-sorted portfolios				
Low	0.351	0.421	0.360	0.284
	(1.17)	(1.28)	(1.30)	(1.31)
2	0.688**	0.671*	0.183	0.271
	(2.37)	(1.77)	(0.82)	(1.15)
3	0.871***	1.044***	0.349	0.518
	(3.02)	(3.16)	(1.20)	(1.56)
4	0.839***	1.003***	0.159	0.306
	(2.77)	(2.91)	(0.70)	(1.06)
5	0.843***	1.022***	0.211	0.167
	(2.84)	(2.89)	(0.92)	(0.72)
6	1.068***	1.320***	0.283	0.363*
	(3.61)	(4.01)	(1.24)	(1.70)
7	0.846***	0.981***	0.308	0.376
	(2.85)	(2.87)	(1.33)	(1.57)
8	1.024***	0.994**	0.387	0.336
	(3.43)	(2.40)	(1.62)	(1.45)
9	0.734**	0.809**	0.521**	0.460*
	(2.35)	(2.20)	(2.06)	(1.84)
High	1.170***	1.737***	0.241	0.287
	(3.45)	(4.41)	(0.83)	(1.01)
Panel B: Profitability of the TMAX Strategy				
Low - High	-0.819*	-1.316**	0.119	-0.003
	(-1.81)	(-2.56)	(0.30)	(-0.01)
FF5 alpha	-1.309***	-1.736***	0.001	-0.001
	(-5.49)	(-5.58)	(0.16)	(-0.22)

Table 5.5: Sub-period analysis of the TMAX Strategy

The results from Table 5.5 corroborate what Figure 5.3 already hinted at: the TMAX Strategy's profitability is time-dependent and lacks persistence. The reverse TMAX effect is significantly less strong, and insignificant under both equal and value weights after January 2000. Even more, the effect reverses and the traditional TMAX effect can be observed under equal weights from February 2000 to December 2022, albeit not statistically significant. Interestingly, even the reverse TMAX strategy generates significant raw (and abnormal) returns in the sub-sample period 1985-2000, which has not been the case when considering the whole time period.

Most importantly, Table 5.5 allows us to reconcile the previously observed conflicting results between the analysis of the raw and abnormal returns. From 1985 to January 2000, both the raw and abnormal returns are statistically significant, under both weights; on the other hand, from February 2000 until the end of 2022, neither the raw nor the abnormal returns are statistically significant, no matter the weighting scheme used.

The return pattern of the TMAX Strategy over the sample period makes it significantly loss-making overall, when considering the effectively implemented strategy. The underperformance in the first sub-period is so strong that even the 23 years of close-to-zero returns that follow do not change the final outcome. Therefore, the abnormal (negative) returns are significant under both weights in Table 4.6, since the Fama-French five-factor model uses the effective TMAX Strategy return vector as the dependent variable. However, when comparing the average returns of the High and Low decile portfolios over the whole sample period in a Welch t-test, we cannot reject the null hypothesis of zero mean return, since, when relying only on the standard errors and average returns, the difference is not significant. This goes to show how crucial it is to use a Welch t-test, and not a one-sample t-test on the effectively implemented TMAX strategy to investigate lottery-like preferences. The one-sample t-test is more biased when the effect is not across the whole sample period.

5.2.2 Fama-French Model lack-of-fit

A subsidiary reason for why the TMAX Strategy may generate significant negative abnormal returns while the raw returns are insignificant could be the lack-of-fit of the Fama-French five-factor model. Although from an econometrical standpoint, we can reject the null hypothesis under the F-test for this model, from an economic standpoint, the risk factors that explain the returns of the TMAX Strategy are probably too different from the ones considered in the Fama-French five-factor model. Such a situation could result in a significant alpha simply because of an economic lack-of-fit rather than as an indication of an anomaly.

To support this idea, please refer to Table 4.6. Besides the market factor, none of the other four factors from the model are statistically significant. Moreover, as reported previously, the regressions' R^2 are relatively low compared to the standard set by previous research.

This argument can explain part of the mentioned inconsistency, besides the lack of persistence. That being said, this argument should be seen as a call for further research on which risk factors affect the TMAX Strategy rather than a scientific explanation of the initially observed inconsistency in raw and abnormal returns.

5.2.3 The 1990s, a period of performance – fund flow virtuous cycle?

The question remains on why the reverse TMAX Strategy had such success (especially) in the 1990s until the Dot-com crash (and not afterward). To answer this question, we briefly revisit the history of the mutual funds market in the U.S. and Europe in the 1990s and link it to the relationship between fund flows and performance.

In the 1990s, the mutual funds market grew rapidly around the world; in the United States, from 1 to 7 trillion AUM[7], influenced by capital market development, investor confidence in market integrity, liquidity & efficiency, and financial system orientation (Fernando et al., 2003; Klapper, 2004). In the early 2000s, 93% of mutual funds were actively managed. Since then, and especially since after the Global Financial Crisis, a trend towards passive funds can be observed; in 2020, only 63% of all mutual

[7] https://www.ici.org/doc-server/pdf%3Aper06-03.pdf

funds remained actively managed.[8] Compared to a 32% CAGR of actively managed fund AUM in the 1990s, AUM only grew at a 4-5% CAGR since then.

This turning point affecting the actively managed fund industry may be the root cause of the disparate profitability of the TMAX Strategy since it significantly affected (and affects) the industry's fund flows. The "smart money" hypothesis suggests a positive relationship running from past fund flows to future performance (Gruber, 1996; Zheng, 1999; Keswani & Stolin, 2008; Yu, 2012; Muñoz, 2019). In addition, past performance is an important factor in the allocation decision of mutual funds investors, i.e. investors reward past 'winners' with additional funds (Chevalier & Ellison, 1997; Sirri & Tufano, 1998; Fant & O'Neal, 2000; Huang et al., 2007; Agarwal et al., 2021).

How does this performance–fund flow relationship relate to the (reverse) TMAX effect? As Table 4.2 clearly shows, the one-month lagged return increases monotonically with TMAX. While the funds in the lowest TMAX-sorted portfolio have an average lagged return of -0.996%, the ones in the highest decile portfolio have an average lagged return of 10.285%. Therefore, the reverse TMAX strategy disposes of a clear link to past performance.[9]

Consequently, the funds in the High decile portfolio attract the largest fund inflows, and according to the "smart money" hypothesis, they are expected to perform better in the future. In other words, the significant reverse TMAX effect in the 1990s might act as a proxy of the performance–fund flow relationship. Since the 1990s were clearly a period of extremely strong inflows in (actively managed) funds, the mentioned relationship might explain the significant reverse TMAX effect. On the same note, the reverse TMAX effect might have vanished with the significantly lower growth in this type of fund since the early 2000s. In addition, the relative performance of active and passive funds clearly shifted in favour of passive funds since the Global Financial Crisis, due to a reduction in "alpha opportunities". As alpha opportunities decrease, active strategies lose their effectiveness, and performance fails to persist (Busse et al., 2021). As a result, while the High TMAX-sorted decile portfolio might have comprised the best past performers in the mutual funds market overall in the 1990s, it might not have since, due to the relative performance deficit of active funds, resulting in a less pronounced inflow differential between the High and Low decile portfolios from 2000 to 2022, reducing the performance–fund flow effect and thereby, the effect it has on the TMAX Strategy's profitability. The 'pure', true TMAX effect is therefore more likely to be observable in the sub-period from 2000 to 2022 than before.

5.3 TMAX Strategy - theoretically more sound but impractical?

Some of the observations that have been made during this thesis raise an important economic question regarding the TMAX Strategy: is this investment strategy not lacking in practicability what it makes up in terms of theoretical robustness compared to the MAX Strategy, especially when applied to other markets than the stock market (e.g., the cryptocurrency and mutual funds markets)? Three drawbacks of the TMAX Strategy will be briefly discussed in this section: time-series correlation of cross-sectional TMAXs, liquidity issues, and transaction costs.

Coming back to what has been explained in the methodology, it is important to note that these issues do not undermine in any way the theoretical findings of the (reverse) TMAX effect, i.e. the lottery-

[8] `https://web-assets.bcg.com/ba/c8/5b65e9d643abac4fa8e6820e86f4/bcg-global-asset-management-2022-from-tailwinds-to-turbulence-may-2022-r.pdf`

[9] N.B.: Both the "smart money" effect and the effect of investors' allocation decisions on the basis of past returns are different from a pure momentum effect (cf. the just-mentioned papers). While we use lagged returns as a qualitative illustration to support our hypothesis, a more formal empirical investigation of the effect of the performance-fund flow relation on the TMAX Strategy's profitability, that goes beyond the scope of this thesis, is welcomed to make more robust conjectures.

like preference of investors, only the practical implementation of any investment strategy that aims to exploit the related lottery anomaly.

5.3.1 Time-series correlation of cross-sectional TMAXs

The major caveat of the TMAX Strategy relative to the MAX Strategy is the possibility of empty long and/or short portfolios. In this research's cryptocurrency sample, the TMAX Strategy could not be implemented on roughly one-third of the rebalancing dates in normal times as no cryptocurrency's MAX ranked in either the first and/or the tenth decile in $t-1$, leaving the corresponding long-short portfolio empty (as Table 4.8 reports, this ratio increased to nearly two-thirds during speculative bubbles); the total number of weeks during which the TMAX Strategy lacked the characteristics for practical implementation amount to two and a half years. Although this issue was alleviated in the mutual funds market, the TMAX Strategy could still not be implemented for one year in total in that particular market.

This issue stems from the TMAX ranking process. While the MAX Strategy compares MAX through the cross-section of assets, the TMAX Strategy benchmarks the MAX on the own historical distribution of an asset's MAX. By construction, each MAX-sorted decile portfolio comprises the same number of assets at each rebalancing date, while each TMAX-sorted decile portfolio's size is dependent on the individual TMAX ranks in the investment universe.

Evidently, as the empty portfolio occurrences in this research have shown, not only returns between assets are correlated, but also extreme returns, resulting in time-series correlation of cross-sectional TMAX. In other words, asset A's extreme return rank in month t is correlated to asset B's extreme return rank relative to their respective historical distributions of extreme returns. A much larger investment universe is therefore required in order to implement the TMAX Strategy effectively, relative to the MAX Strategy. In this thesis, a mutual funds sample of 2'308 was not sufficient to completely eliminate this issue; even in Lin et al. (2021), out of the 11'562 stocks that formed the investment universe, only 11 ranked at one stage in the first decile of their MAX's historical distribution, which gives an order of magnitude of the required investment universe to persistently implement this investment strategy.

At the end of the day, a trade-off has to be made. The TMAX Strategy can be implemented using only one asset, if one accepts a significant number of portfolio occurrences. The MAX Strategy cannot, but a smaller sample is necessary to persistently implement the investment strategy.

5.3.2 Liquidity issues

A consequence of the argument that a larger investment universe is required to consistently be able to implement the TMAX Strategy is liquidity issues, especially in the cryptocurrency market. In illiquid markets, the TMAX Strategy can less readily be adapted to include only liquid assets.

While the MAX effect can be exploited consistently with (only) 20 of the largest cryptocurrencies (cf. Grobys and Junttila (2021)), the same cannot be said for the TMAX effect with a sample of 80 cryptocurrencies (cf. this thesis). Even if an investor accepts investing, for example, in the risk-free asset or the market portfolio to forego the empty portfolio occurrences, he still faces significant liquidity issues in the cases where the TMAX Strategy can be implemented, given the strong positive correlation between size and liquidity in the cryptocurrency market.

On average, a \$1 additional investment in the High decile portfolio induces an increase of \$0.0282 in the underlying cryptocurrencies (cf. Amihud illiquidity measure in Table 4.1). Thus, a \$100 investment in the High decile portfolio incurs, on average, a \$2.82, or 2.82%, liquidity cost. Note that if a MAX Strategy investor used the same investment universe as this research, the liquidity issues would be similar (again, cf. Table 4.1, Panel C). The liquidity issues are therefore not purely related to the TMAX Strategy, but as explained, the MAX Strategy can more easily be adapted to avoid this issue.

5.3.3 Transaction costs

In the stock market (Lin et al., 2021), in the cryptocurrency market, and in the mutual funds market, the portfolio turnover is higher for the TMAX Strategy than for the MAX Strategy (cf. Table 4.1 & 4.2), implying higher transaction costs incurred through rebalancing.

The higher portfolio turnover indicates that the autocorrelation of MAX rankings when the historical distribution is used as the benchmark is lower than when the cross-section serves as the benchmark. Even though a low autocorrelation is welcomed in the realm of statistical tests, it is less desirable when the TMAX Strategy is implemented as an investment strategy.

As a consequence of the three drawbacks presented in this section, it is debatable whether the TMAX Strategy can actually better exploit the lottery anomaly in financial markets, even though it is theoretically more sound and produces, in most instances, a higher premium/discount than the MAX Strategy.

Conclusion

The present Master's thesis investigates Lin et al. (2021)'s TMAX Strategy in the cryptocurrency and mutual funds market. We observe statistically significant losses related to this investment strategy in the cryptocurrency market of 4.38% per week under equal weights, and 6.01% under value weights, on average. These findings extend previous research on a "MAX Momentum" effect in the cryptocurrency market by providing empirical evidence of a "TMAX Momentum" effect. In the mutual funds market, the TMAX Strategy generated an average loss of 0.82% (1.31%) from 1985-2000; since the early 2000s, no significant TMAX effect can be observed anymore.

This thesis establishes a clear link between cryptocurrency bubbles and the TMAX Strategy. During speculative bubbles, significantly more cryptocurrencies conform to lottery-like features than during normal times. As a result, the reverse TMAX Strategy is most profitable during times of irrational market frenzy as the market-wide presence of lottery-like cryptos exacerbates the TMAX Momentum effect. Akin to the chicken or the egg causality dilemma, further research should determine whether investors' lottery bias causes speculative bubbles or whether speculative bubbles cause a market-wide presence of lottery-like assets. This research establishes that the lottery bias at least boosts speculative bubbles as it generates further deviations from fundamental value. All in all, cryptocurrency bubbles and the lottery anomaly are inextricably linked. Additionally, prospect theory is relied upon to interpret the differing profitability of the TMAX Strategy depending on the state of financial markets (normal times, speculative bubbles, economic downturns).

Moreover, we are able to reconcile the findings on the lottery anomaly in the stock market with the ones in the cryptocurrency market in two major ways. First, conforming with previous research in the stock market, the TMAX Momentum effect is concentrated among underpriced cryptocurrencies. The results then differ in the subset of overpriced cryptocurrencies: no traditional TMAX effect can be observed. The main argument that is advanced in the literature for the profitability of the TMAX Strategy is the overpricing argument and the subsequent normalisation of this overpricing; however, the normalising of prices works only, as Lin et al. (2021) themselves show, when shorting activity in the related assets is high. As shorting activity in the cryptocurrency market is severely constrained due to liquidity and operational issues, we postulate that the overpricing argument does not hold when constraints on short selling are high.

Second, and arguably the biggest contribution to the research stream on lottery preference, this research fills the gap of a lacking explanation for the (T)MAX Momentum effect in the cryptocurrency market, notably, why research over research finds no evidence of a traditional (T)MAX effect knowing that cryptocurrencies exhibit significantly higher lottery-like features than, among others, stocks. We show that, when controlling for idiosyncratic skewness and volatility, the traditional TMAX effect *can* be observed through Fama-Macbeth regressions, i.e. that a higher MAX in $t-1$ is associated with significantly *lower* returns in t. This observation lays bare not only that a high idiosyncratic skewness risk premium has a strong negative effect on the profitability of the TMAX Strategy, but that the TMAX (and MAX) Strategy is ill-equipped to exploit the lottery anomaly in markets with high risk premia for idiosyncratic skewness and volatility. While lottery-like assets have, rationally, a higher expected return due to their higher (idiosyncratic) skewness, investors' lottery bias still suggests a lower future return of these assets due to overpricing. The direction of the 'total' effect depends on the magnitude of overpricing and the idiosyncratic skewness risk premium. The cryptocurrency market is emblematic in showing that these contradictory effects (risk premium for skewness and lottery bias), are a) directionally opposite (and not directionally aligned as argued by some rational choice theorists) and b) one *or* the other can explain the profitability of the TMAX Strategy: the lottery bias when the strategy is generating profits and risk premium for skewness when it is generating losses, as in the cryptocurrency market. Both explanations can coexist as one does not preclude the other; while we accept criticism for the (T)MAX Strategy's lacking ability to exploit the lottery anomaly (in some instances[1]), we firmly reject the idea that there is no lottery bias exhibited by (retail) investors. This thesis provides empirical evidence of why criticism might be justified and that the lottery bias is substantiated.

In the mutual funds market, we are able to confirm the initial hypothesis that professional money managers do not manifest a lottery-related bias when managing their funds, corroborating the findings of Agarwal et al. (2021). Before 2000, the results seem even to indicate that fund managers whose funds exhibit high lottery-like features in $t-1$ are able to use this characteristic to their advantage and generate relatively higher returns in t. The more reasonable conclusion, however, is to argue that a confounding factor confounds the interpretation of the data in the period from 1985-2000, the confounding factor potentially being a virtuous performance-fund flow cycle. More relevant for the out-of-sample profitability of the TMAX Strategy is that since the early 2000s, no TMAX effect is observable leading to the conclusion that the TMAX Strategy does not generate significant (abnormal) returns in the mutual funds market on average. Consequently, the lottery anomaly in the stock market is largely driven by retail investors.

While this study's findings offer valuable insights into both markets, it is important to acknowledge some inherent limitations to provide a comprehensive understanding. The profitability of the reverse TMAX Strategy (in the cryptocurrency market) is limited by times-series correlation of cross-sectional TMAXs, liquidity issues and transaction costs (see section 5.3 for more detail), in summary, by the lack of implementability in some periods. Also, the empty portfolio occurrences impact the hypothesis testing methodology (cf. Methodology for more detail) by creating a dissonance between TMAX Strategy and TMAX effect. Then, the reader should be aware of the cryptocurrency market's recency and its impact on statistical inference in the context of this research; in particular, the combination of sub-period analysis (normal times, bubbles, economic downturns) and empty portfolio occurrences limits the number of observations in each sub-sample, not to an extend that invalidates statistical inference, but nevertheless the robustness of the findings. Moreover, the lack of cryptocurrency data, in particular, a lack of extensive research on cryptocurrency anomalies (which curbs the empirical test for mispricing), on shorting activity (which curbs the conclusion relating to the overpricing argument), on gains/losses generated by investors (which curbs the analysis of the link between prospect theory and TMAX Strategy), constrains the analysis in that market. In the mutual funds market, investigating fund flows exceeds the scope of this research, but entails that the conclusions made regarding the performance-fund flow cycle still lack empirical validation.

Besides the avenues for further research mentioned above, it would be of scientific interest to empirically test the impact of short selling (constraints) on the TMAX Strategy in the cryptocurrency market. Furthermore, given the observation of a traditional TMAX effect in the cryptocurrency market when controlling for idiosyncratic skewness and volatility, upcoming research might seek to elucidate how the lottery anomaly could be exploited in markets with high risk premia for these factors. Finally, to fill gaps in knowledge regarding the reverse TMAX effect prior to 2000 in the mutual funds market, future research endeavours may want to investigate on a broad, market level, the relationship between fund flows and TMAX Strategy, à la Agarwal et al. (2021).

[1] In particular, when the idiosyncratic skewness risk premium is high.

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Executive Summary [2]

This Master's thesis explores the profitability of the novel TMAX Strategy by Lin et al. (2021) in the cryptocurrency and mutual funds market. This investment strategy is considered a tool to investigate the documented lottery anomaly, which has previously been studied using the MAX Strategy by Bali et al. (2011). However, the TMAX Strategy subsumes the MAX Strategy and is theoretically more robust. The *raison d'être* of this thesis, therefore, is to investigate the lottery effect in these markets using the more robust of both investment strategies.

In the cryptocurrency market, this investment strategy generates statistically significant average raw losses of 4.38% per week under equal weights and 6.01% under value weights. This research thereby provides empirical evidence of a "TMAX Momentum" effect. Formally, going long (short) in the tenth (first) TMAX-sorted decile portfolio, i.e. in the cryptocurrencies whose MAX in week $t-1$ ranks higher (lower) than the 90th (10th) percentile of their historical distribution of MAX, generates statistically significant profits. This observation differs from the documented lottery anomaly in the stock market which predicts an underperformance, and not an outperformance, of lottery-like assets (i.e. assets that rank in the tenth TMAX-sorted decile portfolio).

The major contribution of this Master's thesis is that the study of the TMAX Strategy in the cryptocurrency market presented in this thesis fills the gap in knowledge of why lottery-like cryptocurrencies seem to outperform the rest of the market. Two phenomena that have already been documented in relationship with the lottery anomaly seem to be at the origin of this puzzle: mispricing and idiosyncratic skewness.

The mispricing explanation for the lottery anomaly interprets the effect as a normalisation of overpriced (lottery-like) assets. This argument strongly relies on shorting activity by arbitrageurs to work (cf. Lin et al. (2021)). As shorting activity in the cryptocurrency market is severely constrained due to liquidity and operational issues, we postulate that the overpricing argument does not hold when constraints on short selling are high. We further take comfort in this conclusion by showing that the TMAX Strategy's behaviour along the degree of mispricing in the cryptocurrency and the stock market is identical, except in the subset of the most overpriced assets, whose predicted price evolution heavily relies on shorting flows to hold.

Arguably the biggest contribution to the research stream of lottery-like preference is related to idiosyncratic skewness. Our findings in the cryptocurrency market suggest that the risk-based explanation of the lottery anomaly and the behavioural bias explanation can coexist, or, put differently, one explanation does not preclude the other since they measure different phenomena. The present study shows that the high risk-premium for idiosyncratic skewness in the cryptocurrency market drives the profitability of the reverse TMAX Strategy, but nevertheless, a higher TMAX is associated with a lower subsequent return. The direction of the 'total' effect depends on the magnitude of overpricing and the idiosyncratic skewness risk premium.

In the mutual funds market, we find a time-dependent disparity between the profitability of the TMAX Strategy; while the strategy generates significant losses prior to the early 2000s, no significant lottery effect can be observed after. A tentative explanation of the significant losses in the early part of the sample is linked to the fund flow-performance cycle in the mutual funds market of the 1990s. Overall, the observations suggest that professional money managers do not exhibit any bias for lottery-like assets, thereby confirming prior research by Agarwal et al. (2021), and linking the lottery anomaly to the investment behaviour of retail investors.

[2] Word count: 29'937 words