

Pro forma modeling of cryptocurrency returns, volatilities, linkages and portfolio characteristics

Cryptocurrency
forecast models

145

Rama K. Malladi

*Department of Accounting, Finance, Economics, and Business Law,
California State University Dominguez Hills, Carson, California, USA*

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Abstract

Purpose – Critics say cryptocurrencies are hard to predict and lack both economic value and accounting standards, while supporters argue they are revolutionary financial technology and a new asset class. This study aims to help accounting and financial modelers compare cryptocurrencies with other asset classes (such as gold, stocks and bond markets) and develop cryptocurrency forecast models.

Design/methodology/approach – Daily data from 12/31/2013 to 08/01/2020 (including the COVID-19 pandemic period) for the top six cryptocurrencies that constitute 80% of the market are used. Cryptocurrency price, return and volatility are forecasted using five traditional econometric techniques: pooled ordinary least squares (OLS) regression, fixed-effect model (FEM), random-effect model (REM), panel vector error correction model (VECM) and generalized autoregressive conditional heteroskedasticity (GARCH). Fama and French's five-factor analysis, a frequently used method to study stock returns, is conducted on cryptocurrency returns in a panel-data setting. Finally, an efficient frontier is produced with and without cryptocurrencies to see how adding cryptocurrencies to a portfolio makes a difference.

Findings – The seven findings in this analysis are summarized as follows: (1) VECM produces the best out-of-sample price forecast of cryptocurrency prices; (2) cryptocurrencies are unlike cash for accounting purposes as they are very volatile: the standard deviations of daily returns are several times larger than those of the other financial assets; (3) cryptocurrencies are not a substitute for gold as a safe-haven asset; (4) the five most significant determinants of cryptocurrency daily returns are emerging markets stock index, S&P 500 stock index, return on gold, volatility of daily returns and the volatility index (VIX); (5) their return volatility is persistent and can be forecasted using the GARCH model; (6) in a portfolio setting, cryptocurrencies exhibit negative alpha, high beta, similar to small and growth stocks and (7) a cryptocurrency portfolio offers more portfolio choices for investors and resembles a levered portfolio.

Practical implications – One of the tasks of the financial econometrics profession is building pro forma models that meet accounting standards and satisfy auditors. This paper undertook such activity by deploying traditional financial econometric methods and applying them to an emerging cryptocurrency asset class.

Originality/value – This paper attempts to contribute to the existing academic literature in three ways: Pro forma models for price forecasting: five established traditional econometric techniques (as opposed to novel methods) are deployed to forecast prices; Cryptocurrency as a group: instead of analyzing one currency at a time and running the risk of missing out on cross-sectional effects (as done by most other researchers), the top-six cryptocurrencies constitute 80% of the market, are analyzed together as a group using panel-data methods; Cryptocurrencies as financial assets in a portfolio: To understand the linkages between cryptocurrencies and traditional portfolio characteristics, an efficient frontier is produced with and without cryptocurrencies to see how adding cryptocurrencies to an investment portfolio makes a difference.

Keywords Cryptocurrency, Pro forma, IAS 32, Panel-data, Pooled OLS, Fixed effects, Random effects, VECM, Fama-French, Factor analysis, GARCH

Paper type Research paper



JEL Classification — G11, G17

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1. Introduction

Cryptocurrencies evoke polarizing responses from researchers and industry participants. Supporters claim that cryptocurrencies provide a store of value (Bisnoff, 2020; Fidelity, 2020; Salzman, 2020) and are a game-change in accounting practice (Cai, 2021; Psaila, 2017). Opponents believe they are scams, prone to hacking and theft and a financial bubble (Imbert, 2017; Suberg, 2018; Takemoto & Knight, 2014).

A cryptocurrency has three characteristics: (1) it is a digital medium of exchange that uses strong cryptography to secure financial transactions; (2) creation of additional currency units is controlled and not in the hands of any single entity; (3) assets transfers can be verified [1]. Cryptocurrencies have evolved over the last decade. An anonymous person, Nakamoto (2008), is the brain behind the first and the most popular cryptocurrency – BTC, popularly abbreviated as BTC. Other cryptocurrencies have emerged following the success of BTC [2]. As of January 2022, a total of 8,700 cryptocurrencies with a combined marketcap of \$2.2 trillion are supporting \$90 billion daily transactions [3]. BTC is the biggest cryptocurrency with a market capitalization (or currency in circulation) of United States dollar (USD) 888 billion and a market share of 40%.

In comparison, \$2.2 trillion of USD currency notes are in circulation (cryptocurrencies are equal to the USD market) [4]. Ethereum is second on the list, with a market capitalization of \$443 billion [5]. The combined marketcap of the top six cryptocurrencies is more than 72%, and that of the top 20 is more than 90% of the overall marketcap. BTC's marketcap is larger than the combined marketcap of the next 25 cryptocurrencies. In a nutshell, the cryptocurrency market is large and heavily concentrated.

The success of cryptocurrencies is attributed to the blockchain, the backbone of cryptocurrencies. There are five key features of blockchain: (1) Immutability: since multiple copies of a blockchain are kept and managed by consensus across a peer-to-peer network, no one peer can alter past transactions; (2) Security: It is a fundamental cryptological law that is relatively easy to set a problem that is very, very difficult to solve. What is relatively easy for a network of computers to do is, in practice, impossible even for much larger networks to undo; (3) Verifiability: anyone in the world can check for themselves that the rules of the system are being followed; (4) Resilience: The distributed nature of the ledger makes it resilient. Even if many peers go offline, the information is still accessible. (5) Transparency: all transactions are broadcast to all peers, making the ledger transparent (Blockchain, 2019).

In addition to its original application in cryptocurrency, blockchain quickly became popular in other industries, including accounting. As a result, another concept, “triple-entry accounting,” reemerged. Although double-entry accounting has been used for more than 600 years, blockchain has led to the emergence of a promising triple-entry accounting method. Triple-entry accounting with blockchain, when properly implemented, can fundamentally improve accounting (Cai, 2021; Yuji, 1986).

One of the main criticisms of cryptocurrencies is price volatility. As an example, BTC market capitalization grew rapidly from less than \$1 billion in 2013 to more than \$325 billion in December 2017 (218% annualized gain), collapsed to \$56 billion in December 2018 (83% annualized loss) and recovered to \$231 billion in June 2019 (1,602% annualized gain) [6]. Such price volatility is not a characteristic of a major currency such as USD or GBP. As more publicly listed firms start accepting cryptocurrencies, the accounting profession has started focusing on the accounting standards of cryptocurrencies and suitable pro forma models since cash is categorized as a financial asset under the International Financial Reporting Standards (IFRS). Do cryptocurrencies meet the definition of cash? There is no clear answer to this question currently. However, it is prudent to be ready for a positive answer as many central banks contemplate currency-backed cryptocurrencies (Bech & Garratt, 2017; Boar, Holden, & Wadsworth, 2020).

Designed as a decentralized currency, BTC is not intended to become a reporting currency and instead complement fiat money. In the case of BTC, the accounting principle of faithful representation requires interpretation of the economic substance for financial reporting that varies with reporting entity (Tan & Low, 2017). International Accounting Standards Board's IAS32 specifies guidelines for financial instruments. The recognition, measurement and disclosure of financial instruments are the subjects of IFRS 9 or IAS 39 and IFRS 7, respectively. For a detailed overview of the IAS32, refer to Deloitte (2006) and IFRS (2021). Many deficiencies exist in the IFRS accounting of cryptocurrencies compared with the traditional IFRS framework. There is no agreement about a specific accounting model for accounting for cryptocurrencies (Shehada & Shehada, 2020). The novelty, ambiguity, and the lack of official guidance surrounding cryptocurrency transactions impose additional audit risks that should be considered during client acceptance and retention and planning audit procedures (Vincent & Wilkins, 2019).

There is vast and rapid innovation taking place in the cryptocurrency markets. There are mainly four types of cryptocurrencies (SoftwareTestingHelp, 2022):

- (1) Payment tokens are used for buying and selling goods and services on digital platforms without an intermediary, as in traditional finance and banking arenas. Of course, the majority of cryptocurrencies and tokens fall into this category. Examples of payment tokens: Monero, Ethereum and BTC.
- (2) Utility tokens are considered coupons or vouchers but essentially are digital units representing a value on the blockchain. In other words, the token provides certain access to a product or service run or operated by the token issuer. The holder gains the right to a product or service to an equivalent value of token but not ownership. Examples of utility tokens: Funfair, Basic Attention Token, Brickblock, Timicoin, Sirin Labs Token and Golem.
- (3) Security tokens are securitized cryptocurrencies that derive value from an external asset that can be traded under a financial regulation as security. They, therefore, are used for securitized tokenization of properties, bonds, stocks, real-estates, property and other real-world currencies. Examples of security tokens: Sia Funds, Bcap (Blockchain Capital) and Science Blockchain.
- (4) Exchange tokens are issued by and used in cryptocurrency exchanges, which are crypto marketplaces for buying, selling and swapping tokens. They are primarily used to facilitate exchange between other tokens or as gas utility payments. Examples of exchange tokens: Binance Coin or BNB token, Gemini USD, FTX Coin for FTX Exchange, OKB (OK Blockchain Foundation) for Okex exchange, KuCoin Token, Uni token, HT for Huobi exchange, Shushi, and Crypto.com Coin (CRO) for [Crypto.com](https://crypto.com).

The financial modeling and accounting of cryptocurrencies are yet to be fully explored. This paper attempts to contribute to the existing academic literature in three ways:

- (1) Pro forma models for price forecasting: five established traditional econometric techniques (as opposed to novel methods) are deployed to forecast prices. These five methods, namely pooled ordinary least squares (OLS) regression, fixed-effect model (FEM), random-effect model (REM), panel vector error correction model (VECM) and generalized autoregressive conditional heteroskedasticity (GARCH), are workhorses of financial econometricians. Applying traditional financial econometric techniques (as opposed to novel methods) to an emerging cryptocurrency asset class makes it easy for other researchers and policymakers to compare results across traditional asset classes and cryptocurrencies. This paper focuses on three main areas of interest to financial

pro forma modelers – returns, volatilities and linkages. These forecasting models can help finance and accounting professionals who deal with the IAS32 standards.

- (2) Cryptocurrency as a group: instead of analyzing one currency at a time and running the risk of missing out on cross-sectional effects (as done by most other researchers), the top six cryptocurrencies that constitute 80% of the market are analyzed together as a group using panel-data methods. By deploying panel data methods, well-established econometric techniques are applied to the cryptocurrency field. A major advantage of panel data is increased precision in estimation. This results from increased observations due to combining or pooling several data periods for each individual (Cameron & Trivedi, 2005). Panel data research methods are frequently used in empirical accounting research (De, 2008).
- (3) Cryptocurrencies as financial assets in a portfolio: More retail and institutional investors are adding cryptocurrencies to their existing portfolio basket with increasing popularity. The Public Company Accounting Oversight Board (PCAOB) lists digital assets as a key area of focus in its inspection outlook. Given the rapid public acceptance of cryptocurrencies, the PCAOB plans to increase its understanding of public accounting firms' client acceptance and continuance policies, resource deployment and planned audit procedures concerning cryptocurrency (PCAOB, 2018). So, it is essential to understand the linkages between cryptocurrencies and traditional portfolio characteristics. An efficient frontier is produced with and without cryptocurrencies to see how adding cryptocurrencies to an investment portfolio makes a difference.

The rest of the paper is organized as follows: the next section reviews the evolving and limited cryptocurrency literature. The section on data explains several data sources used in this study in detail. The methodology section describes the six statistical methods deployed in this paper, followed by the results and out-of-samples forecasts section, which elaborates on each method's findings. The final section presents conclusions and identifies the scope for further research.

2. The literature on cryptocurrencies

FinTech, a convergence area of finance and technology, can be a complex area to understand in detail. A well-rounded academic researcher needs to understand cryptography, network computing, distributed ledger, parallel processing, electronic exchanges, market microstructure, standard asset pricing, econometrics and business applications of technology. This is certainly a tall order. As a result, most researchers conduct research in silos or interdisciplinary teams. In the last five years, academic researchers from economics, finance and accounting disciplines have shown a greater interest in this area, mainly because of the growing and continued success of cryptocurrencies in the financial markets and greater adaptation by publicly-listed global firms.

Narayanan (2016) provides a comprehensive introduction to BTC, blockchain and the ecosystem around cryptocurrencies. A technical introduction to BTC, blockchain, security, network and privacy is also available (Antonopoulos, 2014; Conti, Sandeep Kumar, Lal, & Ruj, 2018; Tschorsch & Scheuermann, 2016). As of January 2022, the blockchain has 31 million verified users and processed more than \$1 trillion transactions from 80 million digital wallets in more than 200 countries [7]. It is worth noting that BTC runs on blockchain, one of the dominant digital ledger technologies (DLT). However, other DLTs, such as XRP Ledger, which powers Ripple, are not based on blockchain (Blockgeeks, 2018; Reiff, 2020; UK Government, 2016).

The cryptocurrency market is inefficient – based on long-term analyses, it is found that BTC market inefficiency has increased over time (Krückeberg & Scholz, 2020). One of the

reasons for this inefficiency is the conflicting view of cryptocurrencies. Some economists were skeptical of BTC in the beginning. [Cheah and Fry \(2015\)](#) probably articulated the skepticism the best when they stated that “we find empirical evidence that the fundamental price of BTC is zero.” [Yermack \(2015\)](#) noted that BTC behaved more like a speculative investment than a currency. [Böhme, Christin, Edelman, and Moore \(2015\)](#) were among the first to combine the economics, technology and governance aspects of BTC.

Accounting for cryptocurrency assets does not fit easily within the IFRS framework ([Grant Thornton, 2018](#)). In IFRS, effective 1 January 2018, there is no reference regarding cryptocurrencies. According to IAS 8.10, management shall use its judgment in developing and applying an accounting policy, in the absence of IFRS that specifically applies to a transaction, other event or condition ([Procházka, 2018](#)). There is no agreement about a specific accounting model for accounting for cryptocurrencies ([Shehada & Shehada, 2020](#)). There is so much ambiguity that professionals are unsure which IAS is applicable. Some argue that it will be appropriate to account for cryptocurrencies per IAS 38 “Intangible Assets” either at cost or revaluation. In limited circumstances, it may be appropriate for an entity to account for cryptocurrency assets per the guidance set out in IAS 2 “Inventories” for commodity broker-traders ([Grant Thornton, 2018](#)). AICPA issued a nonauthoritative recommendation treating cryptocurrencies as intangible assets ([AICPA, 2019](#)). The confusion around auditing standards and resulting audit risks are well-documented ([Vincent & Wilkins, 2019](#)).

One way to improve the understanding of cryptocurrencies is by building better predictive models and testing them with real-world data. The finance and accounting community takes years to accept a new financial product. For example, Swaps took more than eight years after the Financial Accounting Standards Board (FASB) issued new accounting rules for derivatives and hedging transactions ([Kawaller, 2007](#)). The quality of financial statement information plays a unique role in determining credit spread ([Griffin, 2008](#)). The initial academic studies centered around BTC’s return, volatility and linkages with gold since BTC is sometimes called digital gold ([Popper, 2015](#)). Financial asset return predictability is of great interest in the financial literature ([Golez & Koudijs, 2018](#)). The investment asset universe has been extended to include cryptocurrencies ([Shin, 2016](#)). So, naturally, financial researchers focused on cryptocurrency price forecast models for wide-ranging applications such as investment ideas, risk management, or pro forma modeling. The next three subsections summarize cryptocurrency return, volatility and linkages (to other financial markets) with an eye on pro forma modeling. A detailed explanation of the underlying econometric techniques is provided in the methodology section.

2.1 Pro forma factors influencing cryptocurrency returns

There have been several studies on cryptocurrencies’ prices and returns. Many researchers found cryptocurrency returns hard to explain by commonly-used economic or financial variables. [Liu and Tsyvinski \(2018\)](#) established that the risk-return tradeoff of cryptocurrencies (BTC, Ripple and Ethereum) is distinct from stocks, currencies and precious metals. Cryptocurrencies have no exposure to the most common stock market and macroeconomic factors. They found that cryptocurrency returns can be predicted by factors specific to cryptocurrency markets, such as the momentum effect. Since their study was conducted in a nonpanel setting, they did not account for cross-sectional effects across multiple currencies. [Aalborg, Molnár, and de Vries \(2019\)](#) studied several financial variables and Google searches to conclude that none of the considered variables could predict BTC returns. [Malladi, Dheeriyaa, and Martinez \(2019\)](#) have studied BTC return predictability using stock markets and gold and accurately forecasted the direction of returns but missed the magnitude of returns. [Brauneis and Mestel \(2018\)](#) observed that cryptocurrencies become less predictable/inefficient as liquidity increases.

Some researchers have used technical analysis to explain cryptocurrency returns: [Huang, Huang, and Ni \(2019\)](#) used big data and technical analysis and found that fundamentals hardly drive BTC returns. They constructed a classification tree-based model for return prediction using 124 technical indicators. They provided evidence that the proposed model had strong out-of-sample (OSS) predictive power for narrow ranges of daily returns on BTC. Cryptocurrencies have very high unconditional volatility and are subject to sudden, massive price swings. As the search for determinants of cryptocurrency returns goes on, researchers have found broad themes, such as market forces of supply and demand, the arrival of additional information, trust, speculators ([Ciaian, Rajcaniova, & Kancs, 2016](#)), price clustering at round numbers ([Urquhart, 2017](#)), persistence ([Caporale, Gil-Alana, & Plastun, 2017](#)), mining difficulty and block size ([Adjei, 2019](#)), market stress and herding ([Raimundo Júnior, Palazzi, Tavares, & Klotzle, 2020](#); [Youssef, 2020](#)) and investor attention ([Subramaniam & Chakraborty, 2020](#)).

Instead of analyzing one currency at a time and running the risk of missing out on cross-sectional effects (as done by most other researchers), the top six cryptocurrencies that constitute 90% of the market are analyzed together using panel data methods in this study. Daily returns are analyzed using pooled OLS and panel data (random and fixed effects) methods ([Baltagi, 1995](#); [Gujarati & Porter, 2009](#)).

2.2 Pro forma factors influencing cryptocurrency volatilities

Volatility possesses several stylized facts, which make it inherently more forecastable. As such, volatility prediction is one of the most important and, at the same time, more achievable goals for anyone allocating risk and participating in financial markets ([Marra, 2015](#)). ARCH and GARCH models have been applied to a wide range of time series analyses, but finance applications have been particularly successful ([Engle, 2001](#)). Financial market volatility is an important input for investment, option pricing and financial market regulation ([Poon & Granger, 2003](#)). [Andersen, Bollerslev, Christoffersen, and Diebold \(2006\)](#) provide a comprehensive theoretical overview of volatility forecasting.

The workhorse of financial volatility modeling is the Autoregressive Conditional Heteroskedasticity (ARCH) family, initially conceptualized by [Engle \(1982\)](#) and generalized as a GARCH by [Bollerslev \(1986\)](#). Engle's ARCH class of models spurred a virtual "arms race" to develop better procedures for modeling and forecasting time-varying financial market volatility. More than 135 GARCH models are documented in [Bollerslev, Watson, and Russell \(2010\)](#). Volatility forecasting in finance is a highly-researched topic with detailed surveys ([Andersen et al., 2006](#); [Bollerslev, Chou, & Kroner, 1992, 1994](#); [Engle, 2001](#); [Satchell & Knight, 2011](#)).

Since this paper aims to keep things simple so that most readers in the accounting and finance area can follow and compare results, a plain-vanilla GARCH (1,1) model is used for volatility forecasting. In support of this rationale, after comparing 330 ARCH-type models in terms of their ability to describe the conditional variance, [Hansen and Lunde \(2005\)](#) found no evidence that more sophisticated models outperform a GARCH(1,1). The GARCH(1,1) is the simplest and most robust family of volatility models ([Engle, 2001](#)). The GARCH(1,1) model forecasts both the direction and the magnitude of BTC volatility, and forecasting volatility is more precise than returns ([Malladi et al., 2019](#); [Malladi & Dheeriyaa, 2021](#)).

2.3 Linkages between cryptocurrencies and other financial assets

Many linkages exist between cryptocurrencies and other financial assets. BTC was originally termed digital gold, so researchers initially focused on links between cryptocurrencies, gold and national currencies. [Dyhrberg \(2016a\)](#) classified BTC as something in between gold and the USD using GARCH models. Later on, the search for the linkages to other financial assets started. BTC is a hedge against the Financial Times Stock Exchange Index ([Dyhrberg, 2016b](#)). BTC lowered

portfolio risk because of its low correlation with financial assets involving gold, oil and equities (Guesmi, Saadi, Abid, & Ftiti, 2019). After studying four cryptocurrencies, Klein, Pham Thu, and Walther (2018) found that Gold and BTC behave in opposite ways – Gold acts as a safe-haven asset in times of market distress. However, they show that BTC acts as the exact opposite and positively correlates with downward markets.

Tiwari, Adewuyi, Albuлесcu, and Wohar (2020) provide evidence of significant risk contagion among major cryptocurrencies' price returns, both in bull and bear markets. Bouri *et al.* (2017) showed that BTC could serve as an effective diversifier for most cases, using daily and weekly data and Engle's dynamic conditional correlation model (2002). Dyhrberg (2016a) found that BTC can be an ideal tool for risk-averse investors as a buffer against negative shocks to the market, whereas Dyhrberg (2016b) found that BTC can serve as a hedge against market-specific risk.

Prior studies have not used panel-based econometrics to study linkages. Since cryptocurrency returns may be cointegrated, the panel-based VECM of Engle and Granger (1987) and Johansen (1991) is used in this study. Finally, Fama and French (2015) five-factor analysis is used to uncover linkages between the stock market and cryptocurrency returns.

3. Data

This study covers cryptocurrencies' (price, return, volume and volatility), stock returns (the US, other developed markets and emerging markets), bond yields (short, intermediate and long-term), gold prices (since BTC was originally labeled as digital gold) and volatility index (VIX) – a broad indicator of financial market uncertainty. The VIX is also known as the investor fear gauge (Whaley, 2000) and is computed as the expected price fluctuations in the S&P 500 index options over the next 30 days. These variables cover the major asset classes often used to create investor portfolios.

Eight data sources are used in this study: (1) daily cryptocurrency price in USD and volume from Coindesk [8]; (2) daily S&P 500 stock index values from Yahoo Finance [9]; (3) Morgan Stanley Capital International (MSCI) world daily stock index [10] covering large and mid-cap stocks of 23 developed markets; (4) MSCI emerging markets daily stock index [11], covering large and mid-cap stocks of 26 emerging markets; (5) daily US bond yields of the 3-month T-bill, 10-year and 30-year T-bonds [12]; (6) daily gold prices from the World Gold Council [13]; (7) daily VIX from Chicago Board of Options [14]; (8) Fama-French factors [15].

The analysis window is from 12/30/2013 (the earliest date when BTC price and volume data is available) to 08/01/2020 (including eight months of the COVID-19 pandemic period). Summary statistics of all variables in this study are shown in Table 1, characteristics of six major cryptocurrencies are provided in Table 2, correlations in Table 3 and daily return distributions are plotted in Figure 1. Cryptocurrencies trade round the clock, so their data are available on all seven days of the week. However, stocks, bonds, gold and VIX data are available only on US trading days. Consequently, VIX dates (from the CBOE trading days) are used as a baseline, and weekend data for cryptocurrencies are removed from the dataset. As a result, 1,654 daily data is compiled from 12/30/2013 (the earliest date when price and volume data is available for BTC) to 08/01/2020 (most recent). Daily returns are computed using the $\ln(P_t/P_0)$ formula, where P_t is today's closing price, and P_0 is the previous trading day's closing price. Five-day (or calendar week) cryptocurrency volatility is computed as the standard deviation of the last five daily returns $\times \sqrt{5}$.

Table 1 summary shows that BTC price is an order of magnitude larger than the rest. BTC and Litecoin have been around the longest ($N = 1,654$), whereas Chainlink and Cardano are relatively new ($N \sim 700$). Cryptocurrencies are very volatile: the standard deviations of daily returns are several times larger than those of other financial assets. All cryptocurrencies have lost more than 37.5% in a single day and gained more than 21.2% on another day. In contrast,

Table 1.
Summary statistics of
all variables in
the study

	<i>N</i>	Mean	Median	Min	Max	StdDev	Skew	Kurtosis
<i>Cryptocurrency price (\$ USD)</i>								
Litecoin	1,654	\$41.04	\$23.29	\$1.16	\$358.34	\$52.02		
Bitcoin	1,654	\$3822.83	\$1221.94	\$178.10	\$19497.40	\$3971.55		
Ethereum	1,244	\$204.46	\$169.93	\$0.43	\$1366.77	\$228.89		
XRP	1,243	\$0.26	\$0.22	\$–	\$3.38	\$0.33		
Chamlink	709	\$1.47	\$0.56	\$0.15	\$8.64	\$1.52		
Cardano	702	\$0.12	\$0.07	\$0.02	\$1.08	\$0.15		
<i>Cryptocurrency daily transaction volume (\$USD, billions)</i>								
Litecoin	1,654	0.84	0.06	–	6.96	1.43		
Bitcoin	1,654	6.51	0.34	0.003	63.33	10.72		
Ethereum	1,244	3.54	1.49	–	26.51	4.94		
XRP	1,243	0.68	0.27	–	9.42	0.93		
Chamlink	709	0.10	0.01	–	1.48	0.18		
Cardano	702	0.13	0.08	0.002	1.71	0.18		
<i>Cryptocurrency five-day volatility of daily returns</i>								
Litecoin	1,654	11.6%	9.1%	0.0%	54.3%	9.0%		
Bitcoin	1,654	8.5%	6.9%	0.5%	43.4%	6.1%		
Ethereum	1,244	13.2%	11.4%	0.7%	62.8%	8.7%		
XRP	1,243	11.8%	8.8%	0.1%	147.3%	12.8%		
Chamlink	709	17.4%	13.5%	1.4%	92.6%	12.8%		
Cardano	702	15.3%	12.1%	1.2%	109.0%	13.3%		
<i>Cryptocurrency (Daily returns)</i>								
Litecoin	1,653	0.04%	–0.11%	–37.53%	49.59%	6.64%	0.93	12.79
Bitcoin	1,653	0.16%	0.12%	–41.96%	21.19%	4.71%	(0.64)	10.75
Ethereum	1,243	0.41%	–0.11%	–48.22%	34.21%	7.13%	0.10	8.41
XRP	1,242	0.26%	–0.36%	–61.63%	102.74%	8.06%	2.44	37.36
Chamlink	708	0.52%	–0.05%	–57.94%	84.14%	9.78%	1.16	15.03
Cardano	701	0.26%	–0.25%	–42.16%	110.31%	9.39%	3.72	41.67

(continued)

	<i>N</i>	Mean	Median	Min	Max	StdDev	Skew	Kurtosis
<i>Financial asset classes (daily returns)</i>								
S&P500	1,654	0.034%	0.058%	-12.765%	8.968%	1.129%	(1.06)	25.94
MSCI World	1,654	0.020%	0.062%	-10.280%	8.351%	0.964%	(1.56)	27.88
MSCI EM	1,654	0.005%	0.034%	-7.321%	5.810%	0.980%	(0.75)	8.97
3M T-Bill	1,653	0.002%	0.001%	0.000%	0.007%	0.002%	0.56	1.74
10Y T-Bond	1,653	0.006%	0.006%	0.002%	0.009%	0.002%	(0.87)	3.88
30Y T-Bond	1,653	0.008%	0.008%	0.003%	0.011%	0.001%	(1.04)	4.35
Gold	1,654	0.027%	0.000%	-5.152%	5.133%	0.856%	0.10	6.72
VIX index								
VIX index	1,654	16.45	14.2	9.14	82.69	7.66		
Note(s): The first four panels in this table show cryptocurrency price, return, daily volume and five-day volatility. The last panel shows other financial asset classes in the study (i.e. stocks, bonds, gold and VIX)								

Table 1.

Table 2.
Cryptocurrencies in
this study (sorted by
marketcap)

Name	Symbol	MCap (\$bil)	Coin price	Supply(mil)	Volume(\$bil)	%MCap	%Vol
Bitcoin	BTC	215.68	\$11,686.11	1,84,56,006	22.88	60.9%	24.7%
Ethereum	ETH	43.86	\$391.24	11,21,11,584	12.03	12.4%	15.4%
XRP	XRP	12.84	\$0.29	44,86,26,46,997	2.10	3.7%	3.1%
Chainlink	LINK	4.98	\$14.23	35,00,00,000	1.04	1.4%	2.4%
Cardano	ADA	3.89	\$0.15	25,92,70,70,538	0.28	1.1%	0.4%
Litecoin	LTC	3.73	\$57.24	6,52,03,610	1.97	1.1%	1.6%

Note(s): This table shows the top six cryptocurrencies by marketcap (MCap) in August 2020
Out of the top 10, Tether is pegged to the USD
Bitcoin Cash and Bitcoin SV are linked to the BTC price
Binance Coin is a token and cannot be mined. So, these four cryptocurrencies are removed from the top 10, thus
yielding the top six to study

gold has neither lost more than 5.15% nor gained more than 5.13% in a single day. In addition, cryptocurrencies exhibit positive skewness and higher kurtosis.

In Table 2, six cryptocurrency profiles are summarized. Collectively, they constitute more than 80% of the overall marketcap of \$349 billion. These six cryptocurrencies support more than \$40 billion of the overall \$88 billion daily transactions.

Table 3 summarizes the correlations between variables in this study. Cryptocurrency daily returns are uncorrelated with other financial assets (i.e. stocks, bonds and gold), a highly desirable property of a good hedge in a portfolio. The volume of cryptocurrency transactions is positively correlated with the VIX. Daily returns of gold and cryptocurrencies are uncorrelated.

Figure 1 shows the histogram of daily returns and their summary statistics. Chainlink has the largest average (0.515%) and widest dispersion (8.554% between the 3rd and 1st quartile). BTC has the smallest distribution of 3.467%. It is interesting to note that all currencies have a positive mean return.

Figure 2 shows the market share of each currency by global transactions as measured in USD: 62.1% of the daily international cryptocurrency transactions were conducted using BTC, 26.3% by Ethereum and 6.9% by Litecoin. The other three currencies (XRP, Chainlink and Cardano) have a negligible market share. Ethereum has gained prominence only since 2016. Before 2016, BTC and Litecoin were popular cryptocurrencies.

4. Methodology to uncover pro forma model factors

This section explains the econometric methods behind the pro forma models in detail. Pro forma models need inputs, and the methods in this section uncover the factors driving cryptocurrency prices, returns and volatilities. A modular approach is followed for this analysis using six well-established financial econometric methods. Each of the six methods is described in its own subsection below. The first four methods focus on the forecastability of prices and returns and the fifth on volatility. The most commonly used control variables (i.e. volume, volatility and VIX) are included to compare results with other studies. Fama-French’s five-factor analysis is shown in the sixth subsection to discover similarities between cryptocurrencies and stock market factors. The results from these six methods, OSS forecasts and the cryptocurrency portfolio’s efficient frontier are shown in the next (i.e. results) section.

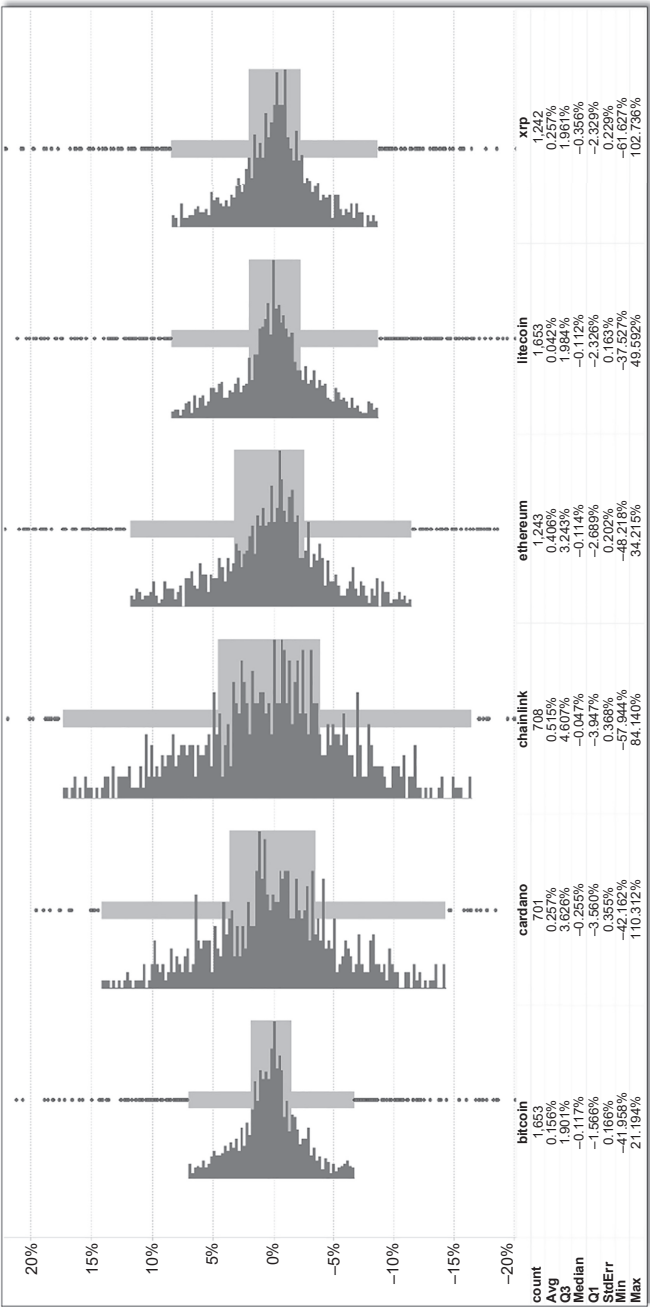
In the first method, cryptocurrency returns are studied with a pooled OLS regression model – neglecting the time-series and cross-sectional effects. In the second and third methods, the time-series and cross-sectional results are analyzed using two of the most commonly-used panel data regression models: (1) the fixed-effect model (FEM) and (2) the random-effect model (REM). Many econometrics textbooks cover these three methods

Bitcoin, N = 1654										Litecoin, N = 1654									
RET	R_SP500	R_WORLD	R_EM	R_GOLD	R_3M	R_10Y	R_30Y	VOLM	VOLT	RET	R_SP500	R_WORLD	R_EM	R_GOLD	R_3M	R_10Y	R_30Y	VOLM	VOLT
R_SP500	0.07	1.00								R_SP500	0.05	1.00							
R_WORLD	0.01	(0.17)	1.00							R_WORLD	0.01	(0.17)	1.00						
R_EM	0.03	(0.06)	0.71	1.00						R_EM	0.02	(0.06)	0.71	1.00					
R_GOLD	(0.00)	0.05	(0.03)	0.03	1.00					R_GOLD	0.01	0.05	(0.03)	0.03	1.00				
R_3M	0.00	(0.00)	0.00	(0.01)	0.01	1.00				R_3M	0.01	(0.00)	(0.00)	(0.01)	0.01	1.00			
R_10Y	(0.02)	0.00	(0.01)	(0.03)	(0.06)	0.38	1.00			R_10Y	(0.00)	0.00	(0.01)	(0.03)	(0.06)	0.38	1.00		
R_30Y	(0.01)	0.01	(0.01)	(0.02)	(0.06)	0.05	0.92	1.00		R_30Y	0.00	0.01	(0.01)	(0.02)	(0.06)	0.05	0.92	1.00	
VOLM	0.02	(0.01)	(0.00)	(0.01)	0.03	0.33	(0.51)	(0.67)	1.00	VOLM	0.06	(0.01)	(0.01)	(0.01)	0.04	0.42	(0.44)	(0.59)	1.00
VOLT	(0.03)	(0.04)	(0.01)	(0.02)	0.04	0.09	0.06	0.01	0.18	VOLT	0.11	(0.02)	0.00	(0.00)	0.01	0.12	0.15	0.11	0.09
VIX	(0.06)	(0.17)	(0.14)	(0.14)	0.03	(0.12)	(0.50)	(0.53)	0.51	VIX	(0.06)	(0.17)	(0.14)	(0.14)	0.03	(0.12)	(0.50)	(0.53)	0.35
Ripple (XRP), N = 1243										Ethereum, N = 1244									
RET	R_SP500	R_WORLD	R_EM	R_GOLD	R_3M	R_10Y	R_30Y	VOLM	VOLT	RET	R_SP500	R_WORLD	R_EM	R_GOLD	R_3M	R_10Y	R_30Y	VOLM	VOLT
R_SP500	0.06	1.00								R_SP500	0.05	1.00							
R_WORLD	0.00	(0.17)	1.00							R_WORLD	0.01	(0.17)	1.00						
R_EM	0.05	(0.06)	0.71	1.00						R_EM	0.05	(0.06)	0.71	1.00					
R_GOLD	0.05	0.05	(0.03)	0.03	1.00					R_GOLD	0.08	0.05	(0.03)	0.03	1.00				
R_3M	0.00	(0.00)	(0.01)	(0.01)	0.01	1.00				R_3M	(0.06)	(0.00)	(0.00)	(0.01)	0.01	1.00			
R_10Y	(0.00)	0.00	(0.01)	(0.03)	(0.06)	0.38	1.00			R_10Y	(0.02)	0.00	(0.01)	(0.03)	(0.06)	0.38	1.00		
R_30Y	(0.00)	0.01	(0.01)	(0.02)	(0.06)	0.05	0.92	1.00		R_30Y	0.00	0.01	(0.01)	(0.02)	(0.06)	0.05	0.92	1.00	
VOLM	0.06	0.00	0.00	0.00	0.04	0.42	(0.30)	(0.47)	1.00	VOLM	(0.01)	(0.02)	(0.02)	(0.02)	0.03	0.32	(0.51)	(0.67)	1.00
VOLT	0.16	(0.02)	(0.00)	0.00	(0.01)	0.04	0.19	0.17	1.00	VOLT	0.07	(0.04)	0.01	0.01	0.02	0.20	0.02	0.09	(0.10)
VIX	(0.05)	(0.17)	(0.14)	(0.14)	0.03	(0.12)	(0.50)	(0.53)	0.33	VIX	(0.06)	(0.17)	(0.14)	(0.14)	0.03	(0.12)	(0.50)	(0.53)	0.50
Chainlink, N = 709										Cardano, N = 702									
RET	R_SP500	R_WORLD	R_EM	R_GOLD	R_3M	R_10Y	R_30Y	VOLM	VOLT	RET	R_SP500	R_WORLD	R_EM	R_GOLD	R_3M	R_10Y	R_30Y	VOLM	VOLT
R_SP500	0.09	1.00								R_SP500	0.09	1.00							
R_WORLD	0.00	(0.25)	1.00							R_WORLD	0.01	(0.25)	1.00						
R_EM	0.07	(0.13)	0.73	1.00						R_EM	0.08	(0.13)	0.73	1.00					
R_GOLD	0.01	0.24	(0.09)	(0.01)	1.00					R_GOLD	0.07	0.25	(0.09)	(0.01)	1.00				
R_3M	(0.01)	(0.02)	(0.02)	(0.04)	(0.04)	1.00				R_3M	(0.07)	(0.02)	(0.02)	(0.03)	(0.04)	1.00			
R_10Y	(0.02)	0.00	(0.02)	(0.03)	(0.08)	0.79	1.00			R_10Y	(0.05)	0.00	(0.02)	(0.03)	(0.08)	0.79	1.00		
R_30Y	(0.02)	0.01	(0.01)	(0.02)	(0.08)	0.80	0.99	1.00		R_30Y	(0.04)	0.01	(0.01)	(0.02)	(0.08)	0.80	0.99	1.00	
VOLM	0.09	(0.02)	(0.01)	(0.01)	0.03	(0.70)	(0.79)	(0.80)	1.00	VOLM	0.11	(0.02)	(0.01)	0.03	(0.01)	(0.26)	(0.10)	(0.10)	1.00
VOLT	0.11	(0.01)	0.03	0.00	0.00	(0.10)	0.14	0.16	(0.06)	VOLT	0.26	(0.02)	0.01	(0.01)	(0.04)	(0.13)	0.10	0.11	0.26
VIX	(0.06)	(0.17)	(0.12)	(0.14)	(0.59)	(0.58)	(0.60)	0.57	(0.01)	VIX	(0.06)	(0.17)	(0.12)	(0.14)	(0.04)	(0.58)	(0.60)	0.09	(0.03)

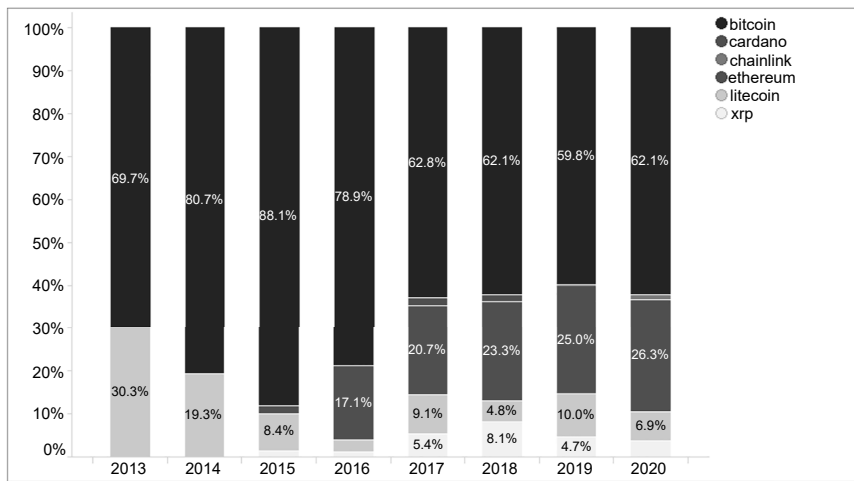
Note(s): Negative numbers are shown in (). Daily correlations > 0.1 are highlighted. "R_" in headings means daily return

Table 3.
Daily return
correlations of
cryptocurrencies and
other financial assets

Figure 1.
Daily price return
(RET) and distribution
of six major
cryptocurrencies



Note(s): The top panel in this figure plots a histogram of daily returns from 12/31/2013 to 08/01/2020 of six major cryptocurrencies. The bottom panel shows the daily return statistics for each cryptocurrency



Note(s): In 2020, 62.1% of the daily global cryptocurrency transactions were conducted using BTC, 26.3% by Ethereum, and 6.9% by Litecoin. XRP, Chainlink, and Cardano have a negligible market share. Ethereum has been prominent only since 2016. Before 2016, BTC and Litecoin were popular. Legend is shown on the right-hand side of the figure

Figure 2.
Daily transaction
market share by
currency and year

(Baltagi, 1995; Cameron & Trivedi, 2005; Gujarati & Porter, 2009; Wooldridge, 2010). Collinearity is less likely in a panel data setting since its cross-section adds much variability (Ranjan & Agrawal, 2011; Baltagi, 1995). In panel data analysis, R -square or adjusted R -square is low. Generally, R -square is low in cross-sectional data compared to time series data due to the heterogeneity of cross-sections. Besides, R -square is low in financial data as financial data is not normally distributed. A low R -square does not mean we have a biased or inconsistent estimator (Wooldridge, 2010). Joint estimation of multiple cryptocurrency returns is done using simultaneous equations. The main advantage of joint estimation is the gain in efficiency that results from incorporating correlation in unobservable across equations (Cameron & Trivedi, 2005).

The fourth method, the VECM, deals with potential endogeneity, simultaneity and causality between cryptocurrency returns. A panel-based VECM is used due to cointegration (Engle & Granger, 1987; Johansen, 1991). In the fifth method, the volatility modeling of cryptocurrencies is conducted using the GARCH model. The final (sixth) method concludes the analysis with a five-factor Fama and French (2015) analysis to understand the factor exposures of cryptocurrency returns. The efficient frontier (Markowitz, 1952; Merton, 1972) is also shown for completeness. Each of these six methods is briefly explained in the subsections below.

4.1 Pooled OLS regressions

An unbalanced panel is created by the cryptocurrency variable as the cross-section and date as frequency. There are four advantages of using panel data methods over a cross-section or time series data (Baltagi, 1995; Gujarati, 2012; Gujarati & Porter, 2009; Yavas & Malladi, 2020): (1) since panel data relate to individual currencies, over time, there is bound to be heterogeneity in these units. Panel data estimation can take such heterogeneity explicitly into account by allowing for individual-specific variables; (2) by combining time series of cross-section observations, panel data give more informative data, more variability, less

collinearity among variables, more degrees of freedom and more efficiency; (3) by studying the repeated cross-section of observations, panel data are better suited to study the dynamics of change and (4) panel data can better detect and measure effects that simply cannot be observed in pure cross-section or pure time-series data.

In short, panel data can enrich empirical analysis in ways that may not be possible if we use only cross-section (i) or time (t). The number of observations between 12/31/2013 and 08/01/2020 varies between 1,654 dates for BTC and 702 for Cardano. Considering six cryptocurrencies (cross-section), a $6 \times 1,654$ ($i \times t$) unbalanced long panel is created.

Granger and Newbold (1974) posit that spurious regression problems occur with nonstationarity in data, leading to unreliable correlations within regression analysis. A stationary series can be defined as one with a constant mean, constant variance and constant autocovariance for each given lag. The price and log price of cryptocurrencies is nonstationary. Whereas daily return, RET , is stationary. So, RET is the regressand, Y , in the analysis. Similarly, suppose a regressor is nonstationary (example: gold price or log of gold price). In that case, it is converted using the first-difference method (example: $\log(\text{gold price})_t - \log(\text{gold price})_{t-1}$) to a stationary series. Stock index levels, the log of gold price, the log of cryptocurrency price and treasury yields are all first-difference stationary, $I(1)$. The VIX, cryptocurrency volume and cryptocurrency volatility are stationary, $I(0)$. The Dickey and Fuller (1979) method tests the stationarity of individual time-series data. However, the literature suggests that panel-based unit root tests conducted in this paper have higher power than unit root tests based on individual time series (Im, Pesaran, & Shin, 2003; Levin, Lin, & James Chu, 2002).

The pooled OLS regression equation to estimate cryptocurrency daily return, RET_{it} , is shown in Equation (1). The ten regressors (X) were used previously in separate studies without a panel. All symbols and definitions in this study are included in the Appendix, Table A1.

$$RET_{it} = \beta_0 + \beta_{1-3}(R_{Stock})_{it} + \beta_{4-6}(\Delta Yield)_{it} + \beta_7(R_{Gold})_{it} + \beta_8(Volm)_{it} + \beta_9(Volt)_{it} + \beta_{10}(VIX)_{it} + \mu_{it} \quad (1)$$

where RET_{it} , the dependent variable, is the daily cryptocurrency return of i on day t , i : cryptocurrency (between 1 and 6) and t : day (between 1 and 1,654),

R_{Stock} : daily stock index returns: S&P 500 (1), MSCI Emerging Markets (2), MSCI World (3),

$\Delta Yield$: daily change in Treasury yields: 3-month TBill (4), 10- and 30-year TBonds (5, 6),

R_{Gold} : daily gold return (7), $Volm$: daily volume of transactions in \$ billions (8),

$Volt$: volatility (standard deviation of last five days' daily return) (9), VIX : daily VIX (10).

It is assumed that the regressors are nonstochastic, or if stochastic, are uncorrelated with the error term, and the error term satisfies the usual classical assumption, $E(\mu_{it}) \sim N(0, \sigma^2)$.

Stepwise regression can be used in a panel data setting. Researchers often follow the stepwise regression method when deciding on the "best" set of explanatory variables for a regression model. This method introduces the X variables from Equation (1), one at a time. This procedure is known as step-wise forward regression (Gujarati & Porter, 2009).

4.2 Fixed-effect model (FEM)

We capture the heterogeneity among the cryptocurrencies with a fixed-effect regression model (Baltagi, 1995; Greene, 2003; Gujarati & Porter, 2009). In a FEM model, each cryptocurrency, i , is

allowed to have its own time-invariant (hence the name fixed effect) intercept, β_{0i} , instead of β_0 , which is the same for all i in Equation (1), while continuing to assume that the slope coefficients are constant across firms. The FEM equation is shown below:

$$RET_{it} = \beta_0 + \beta_{1-3}(R_{Stock})_{it} + \beta_{4-6}(\Delta Yield)_{it} + \beta_7(R_{Gold})_{it} + \beta_8(Volm)_{it} + \beta_9(Volt)_{it} + \beta_{10}(VIX)_{it} + \mu_{it} \quad (2)$$

4.3 Random-effect model (REM)

If we relax the assumption in Equation (2) that β_{0i} is time-invariant and substitute it with a random variable with a mean value of β_0 (no i subscript) such that

$$\beta_{0i} = \beta_0 + \varepsilon_i \quad (3)$$

$$RET_{it} = \beta_0 + \beta_{1-3}(R_{Stock})_{it} + \beta_{4-6}(\Delta Yield)_{it} + \beta_7(R_{Gold})_{it} + \beta_8(Volm)_{it} + \beta_9(Volt)_{it} + \beta_{10}(VIX)_{it} + w_{it} \quad (4)$$

where, $w_{it} = \mu_{it} + \varepsilon_i$, ε_i is a random error term with mean 0 and variance, σ_ε^2 .

The resulting model in Equation (4) is called the REM, or the error components model (ECM) because the composite error term, w_{it} , consists of two error components: ε_i , which is the cross-section or individual-specific error component, and μ_{it} , which is the combined time series and cross-section error component. The question of which model (FEM vs REM) is preferred relies on the assumed correlation between the individual, cross-section specific, error component, ε_i and the regressors. If it is assumed that ε_i and the regressors (X) are uncorrelated, REM may be appropriate, whereas if ε_i and the regressors are correlated, FEM may be appropriate. In panel data studies, researchers routinely deploy both the FEM and the REM models for estimation, and they select one of the two estimation models based on the Hausman (1978) test.

4.4 Panel vector error correction model (VECM)

Simultaneous equation models help us distinguish between endogenous and exogenous variables. Sims (1980) argued that there should be no distinction between endogenous and exogenous variables, and all variables should be treated as endogenous – a key idea behind the development of the vector autoregressive (VAR) model followed by the vector error correction (VEC) model. In empirical accounting research, panel data methods are frequently used (De, 2008). However, VECM models are not commonly used.

Cryptocurrency returns may be cointegrated. It means there can be a long-term or equilibrium relationship between the returns. The VEC has cointegration relations built into the specification to restrict the long-run behavior of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. The cointegration term is the error correction term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments. The error correction mechanism (ECM), first used by Sargan (1964) and later popularized by Engle and Granger (1987), corrects for disequilibrium.

Granger representation theorem states that if two variables, Y and X , are cointegrated, their relationship can be expressed as ECM (Gujarati & Porter, 2009). The panel-based VECM of Johansen (1991) is used for this purpose. A P th order VECM is shown in Equations (5) and (6). The VECM is a special form of the VAR for $I(1)$ cointegrated variables (Hill, Griffiths, & Lim, 2018).

$$\Delta LPRICE_t(p) = \alpha_1 + \sum_{j=1}^p \beta_j \Delta LPRICE_{t-j} + \sum_{j=1}^p \gamma_j \Delta X_{t-j} + \delta_{1t} \quad (5)$$

$$\Delta X_t(p) = \alpha_2 + \sum_{j=1}^p \theta_j LPRICE_{t-j} + \sum_{j=1}^p \varphi_j \Delta X_{t-j} + \delta_{2t} \quad (6)$$

where, X_t is a regressor at time t , δ are stochastic error terms, called impulses or innovations or shocks. $E(\delta_t) = 0$, $E(\delta_t, \delta_{t-k}) = 0$ for any nonzero k . $\Delta LPRICE_t$ is the same as RET_t .

Granger causality: The [Granger \(1969\)](#) approach to whether X causes Y is to see how much of the current Y can be explained by Y 's past values and then see whether adding lagged X values can improve the explanation. One suspects that feedback and causality occur simultaneously in many realistic economic situations. The Granger causality test has been used extensively to test the direction of causality between variables. [Kao and Chiang \(2000\)](#) augmented [Dickey and Fuller \(1979\)](#) and [Johansen's \(1991\)](#) methods to help in the detection of cointegration and creation of panel VECM model before conducting Granger causality tests. The causality test, shown in [Equations \(7\) and \(8\)](#) provide a useful way of describing the relationship between two (or more) variables when one is causing the other(s).

Let X_t and Y_t be two stationary time series with zero mean. A simple causal model is

$$X_t = \sum_{j=0}^m a_j X_{t-j} + \sum_{j=0}^m b_j Y_{t-j} + \varepsilon_t, \quad (7)$$

$$Y_t = \sum_{j=0}^m c_j X_{t-j} + \sum_{j=0}^m d_j Y_{t-j} + \eta_t \quad (8)$$

where, ε_t, η_t are uncorrelated white-noise series, i.e. $E[\varepsilon_t \varepsilon_s] = 0 = E[\eta_t \eta_s]$, $s \neq t$, and $E[\varepsilon_t \varepsilon_s] = 0$ for all s and t .

The definition of causality in [Equations \(7\) and \(8\)](#) imply that Y_t is causing X_t , provided some b_j is not zero. Similarly, X_t is causing Y_t , provided some c_j is not zero. If both events occur, there is a feedback relationship between X_t and Y_t .

4.5 GARCH volatility model

[Andersen \(2006\)](#) states that return volatility is, of course, central to financial economics. The trade-off between risk and expected return, where risk is associated with some notion of price volatility, constitutes one of the key concepts in modern finance – as such, measuring and forecasting volatility is arguably among the most important pursuit in empirical asset pricing finance and risk management. As described in detail by [Brownlees, Engle, and Kelly \(2011\)](#), realized volatility models often demonstrate excellent forecasting performance. In this subsection, we switch focus from the return to volatility forecasting, using the US stock price model of [Bollerslev, Engle, and Nelson \(1994\)](#).

Volatility is inherently unobserved or latent and evolves stochastically through time. Not only is there nontrivial uncertainty to deal with in financial markets, but the level of uncertainty is latent. The current interest in volatility modeling and forecasting was spurred by [Engle's \(1982\)](#) ARCH paper, which set out the basic idea of modeling and forecasting volatility as a time-varying function of current information. A useful generalization of the ARCH model is the GARCH model introduced by [Bollerslev \(1986\)](#) and [Taylor \(1986\)](#). GARCH models have become the workhorses of volatility modeling. A detailed summary of the GARCH models in financial econometrics is provided in [Engel \(2001\)](#). Many surveys on this

topic are also available (Andersen *et al.*, 2006; Bollerslev *et al.*, 1992, 1994; Engle, 2001; Satchell & Knight, 2011).

According to the GARCH model, $\sigma_{Ret(t)}^2$, the conditional variance at time t depends not only on the lagged squared error term, μ_{t-j}^2 , at time $(t-j)$, but also on the lagged variance term, $\sigma_{Ret(t-i)}^2$, at time $(t-i)$. A generalized GARCH(p, q) model with exogenous X variables is shown in Equation (9).

$$\sigma_{Ret(it)}^2 = \alpha_{i0} + \sum_{j=1}^p \beta_{ij} \sigma_{Reti(t-j)}^2 + \sum_{k=1}^q \alpha_{ik} \mu_{i(t-k)}^2 + f(X_{it}) \quad (9)$$

where, $\sigma_{Ret(t)}^2$ is the conditional variance of cryptocurrency i 's daily return, RET_{it} , at time t .

α (ARCH coefficient), β (GARCH coefficient), and $f(X_t)$ are positive to ensure a positive conditional variance. μ_t is i.i.d. with mean zero, $\mu_t \sim N(0, \sigma_{Ret(t)}^2)$, to allow for conditional heteroscedasticity $Var_{t-1}[\mu_t] = \sigma_t^2$. X_t exogenous variable(s) are presumed to effect $\sigma_{Ret(t)}^2$.

4.6 Fama-French five-factor analysis

Are cryptocurrencies analogous to stocks since cryptocurrency returns are more volatile than the traditional major currencies? The five-factor Fama and French (2015, 2017) model, an extension of the three-factor Fama and French (1993) model, helps answer this question by capturing average stock return effects. The five factors – the stock market risk, small vs big company, high vs low book to market, high vs low operating profitability and conservative vs aggressive investment effect. The original three-factor model did not include the last two factors. So, to better understand cryptocurrency returns, Fama-French five-factor analysis is performed using Equation (10). A few researchers have applied the five-factor analysis to cryptocurrencies (Li & Yi, 2019; Liu & Tsyvinski, 2018), albeit without panel data.

$$RET_{it} - R_{Ft} = \alpha_i + \beta_{Mi}(R_{Mt} - R_{Ft}) + \beta_{Si}SMB_t + \beta_{Hi}HML_t + \beta_{Ri}RMW + \beta_{Ci}CMA_t + \varepsilon_t \quad (10)$$

where R_F : daily risk-free rate, R_M : daily return on a value-weighted market portfolio,

five factors: β_M : market, β_S : size, β_H : value, β_R : profitability, β_C : investment style,

SMB : return difference between portfolios of small and big stocks,

HML : return difference between portfolios of high and low book to market stocks,

RMW : return difference between portfolios of robust and weak profitability stocks,

CMA : return difference between portfolios of conservative and aggressive stocks,

ε : zero-mean residual, and α : excess return (alpha).

5. Results, discussion and out-of-sample forecasts

This section summarizes the results based on the methodology described in section (4) and data gathered in section (3). Results are presented in the same order as the six methods described in the previous (i.e. methodology) section. The results from the six methods (i.e. pooled OLS, FEM, REM, VECM, GARCH and Fama-French) are produced sequentially in separate subsections. In addition, price forecasts from all methods are compared in the seventh subsection. The final subsection (8th) shows the efficient frontier with and without cryptocurrencies in a portfolio setting.

Table 3 shows that individual cryptocurrency daily returns are uncorrelated with stocks, bonds or gold – a highly desirable property of a good hedge in a portfolio setting. Other researchers have also found that cryptocurrencies are uncorrelated assets (Chan, Le, & Wu, 2019; Dyhrberg, 2016a, b; Guesmi *et al.*, 2019; Malladi *et al.*, 2019). The daily transaction volume of cryptocurrencies is positively correlated with the VIX, the investor fear gauge (Whaley, 2000) suggesting that investors gravitate towards cryptocurrencies when there is fear in the financial market. Daily returns of gold and cryptocurrencies are uncorrelated, disproving the claim that cryptocurrencies are digital gold (Popper, 2015) and backing assertions of other researchers such as Klein *et al.* (2018) that “Bitcoin is not the New Gold”.

5.1 Pooled OLS regression results

All 7,192 observations are pooled together in a pooled OLS, neglecting the panel data’s cross-section and time series nature. The regression coefficients (or betas) are assumed to be the same for all cryptocurrencies. Based on Equation (1), the pooled OLS regressions for all six cryptocurrencies together are shown below in Table 4. Panel (4.A) contains all variables in this study, and panel (4.B) shows only statistically significant regressors.

Panel A: All variables in the study					
Variable	Coefficient	Std. error	<i>t</i> -statistic	Prob	Significance
R _{SP500}	0.0139	0.1254	0.11	0.9115	
R _{EM}	0.5839	0.1197	4.88	0.0000	***
R _{World}	−0.2904	0.1200	−2.42	0.0155	**
R _{Gold}	0.3848	0.1038	3.71	0.0002	
ΔYield _{3m}	0.0880	0.0342	2.58	0.0100	**
ΔYield _{10Y}	0.0574	0.0606	0.95	0.3437	
ΔYield _{30Y}	−0.0175	0.0583	−0.30	0.7644	
ΔVIX	−0.0020	0.0007	−2.87	0.0041	***
ΔVolume	0.0046	0.0006	7.47	0.0000	***
ΔVolatility _{5d}	0.2242	0.0170	13.18	0.0000	***
Constant	0.0023	0.0008	2.78	0.0055	***
Observations			7,192		
R ²	0.0437		Adjusted R ²		0.0423

Panel B: Significant variables only					
Variable	Coefficient	Std. error	<i>t</i> -statistic	Prob	Significance
R _{EM}	0.5849	0.1196	4.89	0.0000	***
R _{World}	−0.2878	0.1197	−2.40	0.0162	**
R _{Gold}	0.3856	0.1022	3.77	0.0002	***
ΔYield _{3m}	0.0887	0.0341	2.60	0.0092	***
ΔYield _{10Y}	0.0409	0.0205	1.99	0.0461	**
ΔVIX	−0.0021	0.0004	−4.64	0.0000	***
ΔVolume	0.0046	0.0006	7.47	0.0000	***
ΔVolatility _{5d}	0.2242	0.0170	13.20	0.0000	***
Constant	0.0024	0.0008	2.79	0.0053	***
Observations			7,192		
R ²	0.0437		Adjusted R ²		0.0426

Note(s): Dependent variable: *RET*, the daily return of cryptocurrency. Panel (A) contains all variables in this study

C is a constant in the regression equation

Panel (B) contains only statistically significant terms (chosen by the stepwise least squares regression method)

Significance at the 10, 5 and 1% levels are indicated by *, ** and ***, respectively. The date range is from 12/31/2013 to 08/01/2020

Table 4.
Pooled OLS regression
results

One issue with the pooled OLS model is that it does not distinguish between cryptocurrencies. It does not tell us whether different explanatory variables (i.e. stocks, bonds, gold, VIX, volatilities and the volume of transactions) impact *RET* the same way for all the cryptocurrencies over time. By lumping together different cryptocurrencies at different times, we camouflage the heterogeneity (individuality or uniqueness) among the cryptocurrencies. The individuality of each cryptocurrency is subsumed in the error term of Equation (1), μ_{it} . Consequently, the error term may be correlated with some of the regressors in the model. If that is the case, the estimated coefficients may be biased and inconsistent (Gujarati & Porter, 2009).

The positive coefficients in panel (4.b) illustrate that cryptocurrency returns go up when emerging market stocks and gold perform well. Since emerging markets are part of the world index, the world index can be considered a control parameter: as shown in Table 3, the correlation between the world index and the emerging market index is 0.71. So, the negative coefficient on the world index can be overlooked as the control value. Gold and cryptocurrency returns move in tandem. For example, if cryptocurrency returns go up (or down) by 1%, gold returns go up (or down) by 0.3856%. The positive coefficients indicate that cryptocurrency returns increase when the bond yields (3-month and 10-year US treasuries) go up (signaling inflation).

The VIX coefficient is negative. Gold is a safe haven in extreme stock market conditions (Baur & Lucey, 2010). If cryptocurrencies were digital gold, the coefficient between *RET* and the VIX would have been positive. A negative coefficient between the VIX and *RET* does not support the claim that cryptocurrencies are digital gold, as Popper (2015) hoped. Removing R_{Gold} from the list of regressors does not alter the VIX coefficient sign. Moreover, suppose the regressand is R_{Gold} instead of *RET*. In that case, the VIX coefficient sign switches from negative to positive – indicating that the return on gold is positive during high volatility periods. So, the negative coefficient between the VIX and *RET* shows that cryptocurrencies are not a substitute for gold as a safe-haven asset. Klein *et al.* (2018) also found that gold and BTC behave oppositely during market downturns.

The volume coefficient is positive and significant, similar to findings in other studies, highlighting that trading volume has useful information to predict cryptocurrency returns (Bouri, Lau, Lucey, & Roubaud, 2019). A positive volatility coefficient is a desirable property for investors since the volatility is due to positive *RET* (instead of negative *RET*).

The individual effects of six cryptocurrencies are presented in Table 5. Only the VIX has a negative coefficient among all six individual cryptocurrencies. Volatility is a significant factor in five out of six cryptocurrencies, followed by the VIX (in four cryptocurrencies). Clearly, no other asset class among stocks, bonds and commodities can consistently explain the cryptocurrency returns. The absence of any relationship between the S&P500 index and the cryptocurrencies is worth noting. Coincidentally, the US has the highest BTC trading volumes globally (Thomson Reuters, 2017).

5.2 Fixed-effect model (FEM) results

The FEM results, based on Equation (2), are shown in Table 6. The $1,651 \times 6$ unbalanced panel is formed using six cross-sections (one for each cryptocurrency) and 1,651 daily returns.

As shown in panel (6.b), significant variables have the same sign and coefficients as those in Table 4b. So, the pooled OLS and FEM yield similar results for the eight significant factors: stock returns (emerging markets index and world index), gold returns, change in the bond yields (3-month and 10-year), VIX, cryptocurrency daily volume and volatility of cryptocurrency daily returns). The VIX coefficient continues to be negative, while all other coefficients are positive. The negative world index coefficient (control variable) can be overlooked because of the presence of the emerging market index. Reinforcing the pooled OLS method's finding, the negative VIX coefficient is undesirable for investors who believe that cryptocurrencies are digital gold or a safe-haven asset.

Bitcoin, $N = 1,653$, $R^2 = 0.0498$, adjusted $R^2 = 0.0486$					
Variable	Coefficient	Std. error	t -statistic	Prob	Significance
ΔVIX	-0.0018	0.0006	-3.11	0.0019	***
$\Delta Volume$	0.0033	0.0004	7.44	0.0000	***
$\Delta Volatility_{5d}$	-0.2003	0.0374	-5.36	0.0000	***
XRP, $N = 1,240$, $R^2 = 0.0733$, adjusted $R^2 = 0.0703$					
Variable	Coefficient	Std. error	t -statistic	Prob	Significance
R_{Gold}	0.7312	0.2572	2.84	0.0045	***
$\Delta Yield_{3m}$	0.1800	0.0904	1.99	0.0467	**
ΔVIX	-0.0022	0.0010	-2.11	0.0352	**
$\Delta Volume$	0.0184	0.0041	4.45	0.0000	***
$\Delta Volatility_{5d}$	0.2982	0.0405	7.37	0.0000	***
Chainlink, $N = 708$, $R^2 = 0.0807$, adjusted $R^2 = 0.0768$					
Variable	Coefficient	Std. error	t -statistic	Prob	Significance
R_{EM}	0.7187	0.3254	2.21	0.0275	**
ΔVIX	-0.0043	0.0014	-3.00	0.0028	***
$\Delta Volume$	0.2825	0.0508	5.56	0.0000	***
$\Delta Volatility_{5d}$	0.1998	0.0542	3.69	0.0002	***
Litecoin, $N = 1,653$, $R^2 = 0.0854$, adjusted $R^2 = 0.0843$					
Variable	Coefficient	Std. error	t -statistic	Prob	Significance
R_{SP500}	0.3295	0.1383	2.38	0.0174	**
$\Delta Volume$	0.0478	0.0044	10.84	0.0000	***
$\Delta Volatility_{5d}$	0.1310	0.0349	3.75	0.0002	***
Ethereum, $N = 1,241$, $R^2 = 0.0335$, adjusted $R^2 = 0.0319$					
Variable	Coefficient	Std. error	t -statistic	Prob	Significance
R_{Gold}	0.7680	0.2319	3.31	0.0010	***
$\Delta Yield_{3m}$	0.1926	0.0808	2.38	0.0173	**
$\Delta Volume$	0.0092	0.0016	5.70	0.0000	***
Cardano, $N = 701$, $R^2 = 0.1980$, adjusted $R^2 = 0.1945$					
Variable	Coefficient	Std. error	t -statistic	Prob	Significance
R_{EM}	0.8517	0.2909	2.93	0.0035	***
ΔVIX	-0.0048	0.0013	-3.79	0.0002	***
$\Delta Volume$	0.1451	0.0287	5.05	0.0000	***
$\Delta Volatility_{5d}$	0.4692	0.0456	10.29	0.0000	***

Note(s): Dependent variable: *RET*, the daily return of cryptocurrency
Only statistically significant terms (chosen by the stepwise least squares regression method) are shown for each currency
Significance at the 10, 5 and 1% levels are indicated by *, ** and ***, respectively. The date range is from 12/31/2013 to 08/01/2020

Table 5.
Individual OLS
regression results

One subtle difference between the pooled OLS and FEM methods is the coefficient of the three-month US treasury yields. It may be recalled that the slope coefficients across different cryptocurrencies remain the same in the FEM while the intercept varies. We next turn to the REM to allow for slope coefficient differences.

Panel (A), fixed-effect model (FEM), all factors					
Variable	Coefficient	Std. error	<i>t</i> -statistic	Prob	Significance
R_{SP500}	0.0135	0.1254	0.11	0.9143	
R_{EM}	0.5838	0.1197	4.88	0.0000	***
R_{World}	-0.2906	0.1200	-2.42	0.0155	**
R_{Gold}	0.3832	0.1038	3.69	0.0002	***
$\Delta Yield_{3m}$	0.0886	0.0342	2.59	0.0095	***
$\Delta Yield_{10Y}$	0.0579	0.0606	0.96	0.3390	
$\Delta Yield_{30Y}$	-0.0180	0.0583	-0.31	0.7572	
ΔVIX	-0.0020	0.0007	-2.88	0.0040	***
$\Delta Volume$	0.0046	0.0006	7.47	0.0000	***
$\Delta Volatility_{5d}$	0.2243	0.0170	13.19	0.0000	***
Constant	0.0023	0.0008	2.78	0.0055	***
Observations		7,192 observations in a panel of $1,651 \times 6$			
R^2	0.0441		Adjusted R^2		0.0421

Panel (B), fixed-effect model (FEM), significant factors only					
Variable	Coefficient	Std. error	<i>t</i> -statistic	Prob	Significance
R_{EM}	0.5848	0.1197	4.89	0.0000	***
R_{World}	-0.2879	0.1197	-2.41	0.0162	**
R_{Gold}	0.3839	0.1022	3.76	0.0002	***
$\Delta Yield_{3m}$	0.0894	0.0341	2.62	0.0087	***
$\Delta Yield_{10Y}$	0.0409	0.0205	1.99	0.0461	**
ΔVIX	-0.0021	0.0004	-4.64	0.0000	***
$\Delta Volume$	0.0046	0.0006	7.47	0.0000	***
$\Delta Volatility_{5d}$	0.2243	0.0170	13.21	0.0000	***
Constant	0.0024	0.0008	2.79	0.0052	***
Observations		7,192 observations in a panel of $1,651 \times 6$			
R^2	0.0441		Adjusted R^2		0.0424

Note(s): Dependent variable: *RET*, the daily return of cryptocurrency

Panel (A) contains all variables in this study

Panel (B) contains only statistically significant terms

Significance at the 10, 5 and 1 % levels are indicated by *, ** and ***, respectively. The date range is from 12/31/2013 to 08/01/2020

Table 6.
FEM results

5.3 Random-effect model (REM) results

The REM results are based on Equations (3) and (4) and are shown in Table 7. The coefficient signs in the REM remain the same as those of the FEM. However, the coefficient sizes vary – the REM reduces the coefficients of the emerging market stock return, gold return and the change in the three-month US Treasury yield while amplifying the coefficients of the changes in the VIX and volatility.

The Hausman test is used to decide whether FEM or REM is a more appropriate model in this study. The Hausman test's null hypothesis is that the FEM and REM estimators do not differ substantially, while the alternative hypothesis is that they differ. The test statistic developed by Hausman has an asymptotic χ^2 distribution. If the null hypothesis is rejected, the conclusion is that the REM is not appropriate because the random effects are probably correlated with one or more regressors. The Hausman test results in Table 8 fail to reject the null hypothesis, for the estimated χ^2 value for five degrees of freedom is not significant (*p*-value of 0.641). As a result, we choose the REM over the FEM. We conclude that a REM explains the determinants of cryptocurrency daily returns better than the FEM.

So, based on the results so far, the five most significant determinants of cryptocurrency daily returns are: (1) daily stock returns on the emerging market; (2) daily return on gold;

Table 7.
REM results

Random-effect model (REM)					
Variable	Coefficient	Std. error	<i>t</i> -statistic	Prob	Significance
R _{EM}	0.4007	0.0829	4.83	0.0000	***
R _{Gold}	0.3507	0.1003	3.50	0.0005	***
ΔYield _{3m}	0.0856	0.0339	2.52	0.0117	**
ΔVIX	−0.0027	0.0004	−6.73	0.0000	***
ΔVolatility _{5d}	0.2319	0.0170	13.65	0.0000	***
Constant	0.0023	0.0008	2.70	0.0070	***
Observations	7,192 observations in a panel of 1,651 × 6				
<i>R</i> ²	0.0347	<i>Adjusted R</i> ²		0.0340	
<i>Effects specification</i>					
	<i>SD</i>	<i>Rho</i>			
Cross-section	0.0000	0.0000			
Idiosyncratic	0.0717	1.0000			

Note(s): Dependent variable: *RET*, the daily return of cryptocurrency
Only statistically significant factors are shown
Significance at the 10, 5 and 1% levels are indicated by *, ** and ***, respectively. The date range is from 12/31/2013 to 08/01/2020

Table 8.
Hausman test results to
select FEM or REM

Hausman test for the selection of FEM or REM				
Cross-section random-effect test comparisons				
Variable	Fixed	Random	Var(Diff.)	Prob
R _{EM}	0.4005	0.4007	0.00	0.8482
R _{Gold}	0.3490	0.3507	0.00	0.1252
ΔYield _{3m}	0.0862	0.0856	0.00	0.3543
ΔVIX	−0.0027	−0.0027	0.00	0.1137
ΔVolatility _{5d}	0.2320	0.2319	0.00	0.1421
Test summary	Observations	Chi-Sq. Statistic	Chi-Sq. d.f	Prob
Cross-section random	7,192	3.3863	5	0.641

Note(s): Dependent variable: *RET*, the daily return of cryptocurrency
Only statistically significant factors are shown
Significance at the 10, 5 and 1% levels are indicated by *, ** and ***, respectively. The date range is from 12/31/2013 to 08/01/2020

(3) changes in the daily yields of the three-month US treasury; (4) the daily change in the VIX and e) the daily change in the cryptocurrency volatility of daily returns. Barring the VIX, the remaining four factors move in the same direction as the daily cryptocurrency returns. All these five factors and their coefficients can be seen in [Table 7](#).

5.4 Panel vector error correction model (VECM) results

It is quite plausible to expect cointegration between the cryptocurrency returns. It means there can be a long-term or equilibrium relationship between their returns. If cointegration is detected between the cryptocurrency returns, the VECM is the preferred model described in [section 4.4](#). VECM model estimation is preceded by the panel unit root test and panel cointegration test, followed by the Wald test. The VECM results, based on [Equations \(5\) and \(6\)](#) are shown in [Table 9](#).

The Schwarz Criterion (SC) suggests a lag length of eight. Economically speaking, two variables will be cointegrated if they have a long-term or equilibrium, relationship between

them (Gujarati & Porter, 2009). The Kao (1999) panel cointegration test detects the existence of cointegration, and the Johansen Fisher panel cointegration test (Maddala & Wu, 1999) identifies three cointegrating terms, as shown in panel (9.a). The existence of three cointegrated times indicates that cryptocurrencies have a long-term equilibrium relationship with other commonly-used asset classes (i.e. stocks, bonds and gold).

VECM is conducted on levels as it automatically takes differences during estimation; seven lags and $LPRICE$ or $\log(price)$, instead of RET , are used in VECM analysis. Panel VECM cointegrated estimates are in panel (9.b). If a panel (9.b) coefficient is negative and significant, it signifies a long-run causal relationship between the independent variable to the dependent variable, $\log(price)$. Since the analysis is based on daily returns, the coefficients may be smaller. One can annualize them with the equation: $(1 + \text{coefficient})^{365} - 1$. Based on the significant coefficients, it is evident that other asset classes (i.e. stocks, bonds and gold) have a causal effect on cryptocurrency returns for up to five days (or one calendar week). Panel (9.c) shows much higher R^2 and adjusted R^2 for the VECM model than the OLS, FEM and REM regressions.

Detailed causality test results are computed using the VEC Granger causality and block exogeneity Wald test and presented in Table 10.

Panel (10.a) shows the causality of other variables on all six cryptocurrency daily returns, Ret . Barring cryptocurrency daily volume, all other variables have a causal effect on cryptocurrency returns. Panel (10.b) shows the same results as panel (10.a) but without BTC. The change in significance levels between panels (10.a) and (10.b) are highlighted. By comparing panels (10.a) and (10.b), one can see that 3-month treasury yields and emerging market stocks have a bigger impact on BTC than other cryptocurrencies.

Panel (10.c) shows the causality of all six cryptocurrency daily returns, Ret , on other variables, i.e. in the reverse direction of what is shown in panel (10.a). One would expect the causality of cryptocurrencies on other markets to be less significant since the cryptocurrency markets are smaller than the bond and stock markets. As expected, that is precisely what is shown in the panel (10.c). For example, changes in the 10-year treasury bond yield and the VIX have a causal effect on cryptocurrency returns. But not the other way round.

Similarly, panel (10.d) shows the same results as panel (10.c), but without BTC. The change in significance levels between panels (10.c) and (10.d) are highlighted. As one would expect, without BTC, the cryptocurrencies are too small to have a causal effect on the 10-year treasury yields, the VIX and the emerging market stocks. As expected, panel (10.d) causal effects (cryptocurrencies without BTC on other markets) are weaker than those in panel (10.c).

5.5 GARCH volatility model results

After analyzing returns in the past four subsections, let us focus on cryptocurrency volatilities. A generalized GARCH(p , q) model with exogenous X variables, as shown in Equation (9), is used for model estimation, and the results are shown in Table 11. The letter p refers to how many autoregressive lags, or ARCH terms, appear in the equation, while q refers to how many moving average lags are specified, which is often called the number of GARCH terms (Engle, 2001). Panel (11.a) contains the mean equation, and panel (11.b) shows the variance equation with an additional exogenous variable, daily transaction volume, denoted in Equation (9) as $f(X_{it})$.

The panel's daily return data is unbalanced (i.e. more rows for some cryptocurrencies than others). However, GARCH estimation requires the same number of data rows across all cross-sections. So, a common sample size of 706 observations is used for estimation. As a result, the start date of the analysis is 10/04/2017 instead of 12/31/2013. The end date remains as 08/01/2020. Based on the panel results (11.a), the GARCH(1,1) model indicates that cryptocurrencies' returns can be explained endogenously. Three out of six daily returns of cryptocurrencies (BTC, Cardano and XRP) have nothing to do with other asset classes (i.e. stocks, bonds and gold). Instead, the daily returns of these three cryptocurrencies can be

(a) Johansen Fisher panel cointegration test						
# Of cointegration	Fisher stat (trace)	Prob	Significance	Fisher stat (max- eigen)	Prob	Significance
None	472.5	0.0000	***	176.4	0.0000	***
At most 1	209.1	0.0000	***	153.3	0.0000	***
At most 2	80.9	0.0000	***	57.6	0.0000	***
<i>At most 3</i>	<i>34.5</i>	<i>0.0006</i>	***	<i>21.6</i>	<i>0.0420</i>	**
At most 4	16.7	0.1617		10.1	0.6040	
At most 5	9.4	0.6725		5.2	0.9503	
At most 6	6.5	0.8881		3.2	0.9940	
At most 7	5.6	0.9330		4.2	0.9793	
<i>Lags: 1 to 7, N = 7,206, linear deterministic trend</i>						
(b) VECM results for log(price), standard errors in (), <i>t</i> -statistics in []						
	Coefficient	Std. error	<i>t</i> -statistic	Prob	Significance	
LPRICE (−1)	0.0002	0.0000	3.8650	0.0001	***	
ΔYield _{30Y} (−1)	0.0045	0.0019	2.3803	0.0173	**	
ΔYield _{10Y} (−1)	(0.0033)	0.0013	(2.5542)	0.0106	**	
ΔLPRICE (−1)	0.0331	0.0122	2.7228	0.0065	***	
ΔLPRICE (−2)	0.0307	0.0121	2.5320	0.0113	**	
ΔLPRICE (−4)	0.0279	0.0121	2.3094	0.0209	**	
ΔYield _{30Y} (−2)	(0.1579)	0.0615	(2.5685)	0.0102	**	
ΔYield _{30Y} (−3)	(0.1351)	0.0616	(2.1938)	0.0283	**	
ΔYield _{10Y} (−2)	0.1593	0.0638	2.4954	0.0126	**	
ΔYield _{10Y} (−4)	(0.1088)	0.0638	(1.7054)	0.0881	*	
ΔYield _{3m} (−3)	(0.0997)	0.0361	(2.7579)	0.0058	***	
ΔYield _{3m} (−4)	0.0922	0.0363	2.5377	0.0112	**	
R _{Gold} (−2)	0.5357	0.1109	4.8296	0.0000	***	
R _{Gold} (−3)	(0.4137)	0.1118	(3.7001)	0.0002	***	
R _{Gold} (−5)	(0.4196)	0.1092	(3.8445)	0.0001	***	
ΔVIX (−2)	(0.0040)	0.0007	(5.3939)	0.0000	***	
ΔVIX (−4)	(0.0013)	0.0008	(1.7031)	0.0885	*	
ΔVIX (−5)	0.0013	0.0008	1.7151	0.0863	*	
R _{SP500} (−2)	(0.0003)	0.0001	(2.0064)	0.0448	**	
R _{SP500} (−3)	0.0004	0.0001	3.0052	0.0027	***	
R _{SP500} (−5)	(0.0004)	0.0001	(2.9706)	0.0030	***	
R _{World} (−1)	0.0006	0.0002	2.6606	0.0078	***	
R _{World} (−2)	(0.0004)	0.0002	(1.8938)	0.0583	*	
R _{World} (−4)	0.0008	0.0002	3.5133	0.0004	***	
R _{World} (−5)	(0.0002)	0.0001	(2.3825)	0.0172	**	
R _{EM} (−1)	(0.0005)	0.0001	(3.5521)	0.0004	***	
ΔVolatility _{5d} (−4)	(0.0881)	0.0180	(4.9056)	0.0000	***	
ΔVolatility _{5d} (−5)	(0.0306)	0.0179	(1.7071)	0.0878	*	
Constant	0.0018	0.0009	2.1340	0.0328	**	
(c) VECM equation stats						
	<i>N</i>	<i>R</i> ²		Adjusted <i>R</i> ²		
LPRICE	7,146	0.0527		0.0450		
ΔYield _{30Y}	7,142	0.1288		0.1216		
ΔYield _{10Y}	7,142	0.1013		0.0939		
ΔYield _{3M}	7,142	0.1951		0.1885		
R _{Gold}	7,146	0.1650		0.1582		
<i>(continued)</i>						

Table 9.
Panel cointegration
and VECM results

Table 9.

(c) VECM equation stats	N	R^2	Adjusted R^2
ΔVIX	7,146	0.1921	0.1855
R_{SP500}	7,146	0.2072	0.2007
R_{World}	7,146	0.9533	0.9529
R_{EM}	7,146	0.4843	0.4801
$\Delta Volatility_{5d}$	7,146	0.2270	0.2207
$\Delta Volume$	7,146	0.1724	0.1657

Note(s): Dependent variable: $\log(\text{price})$. Cointegration results are in panel (a), VECM results are obtained using seven lags and three cointegrated terms in panel (b) and VECM R^2 in panel (c). Three cointegrated terms identified in panel (a) are expanded in panel (b). Panel (c) shows a much higher R^2 for the VECM than the OLS, FEM and REM. Significance at the 10, 5 and 1% levels are indicated by *, ** and ***, respectively. The date range is from 12/31/2013 to 08/01/2020

explained endogenously by other cryptocurrencies. Of the remaining cryptocurrencies, three out of four significant factors that explain the daily return of Chainlink belong to other cryptocurrencies. Similarly, five out of six significant factors for Ethereum and Litecoin belong to other cryptocurrencies.

Notice the ARCH and GARCH betas in panel (11.b). The ARCH beta measures how volatility reacts to new information. The GARCH beta measures the persistence of volatility. Their sum is close to unity in many GARCH-based financial econometric models. It means that shocks to the conditional variance are highly persistent (Brooks, 2019; Engle, 2001). The underlying return process is mean-reverting when the coefficients sum up to less than one. As the sum gets closer to one, the mean reversion process becomes slower, i.e. shocks persist. As an illustration, for BTC, the sum of these two coefficients is 0.9685 (ARCH coefficient, α , of 0.1284 and GARCH coefficient, β , of 0.8401). This volatility persistence in Figure 3 shows actual, fitted and residual BTC volatility – In the 1st quarter of 2018, BTC prices crashed by more than 60%, leading to persistent volatility. Volatility persistence is found in all six cryptocurrencies.

5.6 Results of the Fama-French five-factor analysis

Because of the factor models (Fama & French, 1993, 2015) in finance, it is customary to conduct three- and five-factor analysis on asset returns and detect alpha (or excess return). Hence, the results of these two analyses are shown in Table 12 using Equation (10) and a panel data set made of $1,636 \text{ (days)} \times 6 \text{ (cross-sections)}$. Panel (12.a) shows three factors, and panel (12.b) shows all five factors. For a similar analysis, albeit in a nonpanel data setting, refer to Liu and Tsyvinski (2018).

These results provide the common stock factor exposures of the cryptocurrency returns. Notice both panels' negative and statistically significant alpha (error term in regression). The market beta (shown as MKT-RF) is positive and significant. As stock market returns go up, cryptocurrency returns also go up. Cryptocurrencies behave like small stocks (vs big stocks) due to positive and significant SMB factors. Furthermore, cryptocurrencies resemble growth stocks (vs value stocks) due to negative and statistically significant exposure to the HML factor.

Two new factors, RMW and CMA, are recently added to the popular three factors (Fama & French, 2015). The CMA factor, the difference between the returns of firms that invest conservatively and firms that invest aggressively, is not significant in the cryptocurrency universe. One would have expected a negative and significant CMA factor. The RMW factor, the difference between firms' returns with robust and weak operating profitability, is significant and negative – cryptocurrencies are more similar to firms with weak operating profitability. A combination of negative alpha, high beta, the similarity with small and

(a) Others to cryptocurrencies, all six cryptocurrencies				
Causal variable	Chi-square	df	Prob	Sig
R _{SP500}	36.7	7	0.0000	***
R _{EM}	16.4	7	0.0217	**
R _{World}	30.2	7	0.0001	***
R _{Gold}	47.6	7	0.0000	***
ΔYield _{3m}	19.9	7	0.0058	***
ΔYield _{10Y}	25.0	7	0.0008	***
ΔYield _{30Y}	42.5	7	0.0000	***
ΔVIX	43.0	7	0.0000	***
ΔVolume	3.2	7	0.8620	
ΔVolatility _{5d}	51.3	7	0.0000	***
All	373.3642	70	0.00001	***
(b) Others to cryptocurrencies, without bitcoin				
Causal variable	Chi-square	df	Prob	Sig
R _{SP500}	32.3	7	0.0000	***
R _{EM}	9.8	7	0.2027	
R _{World}	26.2	7	0.0005	***
R _{Gold}	34.3	7	0.0000	***
ΔYield _{3m}	13.6	7	0.0595	*
ΔYield _{10Y}	19.6	7	0.0064	***
ΔYield _{30Y}	34.2	7	0.0000	***
ΔVIX	31.4	7	0.0001	***
ΔVolume	4.0	7	0.7797	
ΔVolatility _{5d}	43.4	7	0.0000	***
All	296.7019	70	0.00001	***
(c) Cryptocurrencies to others, all six cryptocurrencies				
Causal variable	Chi-square	df	Prob	Sig
R _{SP500}	28.7	7	0.0002	***
R _{EM}	19.5	7	0.0068	***
R _{World}	34.8	7	0.0000	***
R _{Gold}	38.8	7	0.0000	***
ΔYield _{3m}	25.4	7	0.0006	***
ΔYield _{10Y}	13.2	7	0.0671	*
ΔYield _{30Y}	18.2	7	0.0111	**
ΔVIX	13.1	7	0.0697	*
ΔVolume	20.4	7	0.0047	***
ΔVolatility _{5d}	110.1	7	0.0000	***
<i>Lags: 1 to 7, N = 7,122</i>				
(d) Cryptocurrencies to others, without bitcoin				
Causal variable	Chi-square	df	Prob	Sig
R _{SP500}	20.9	7	0.0039	***
R _{EM}	13.8	7	0.0548	*
R _{World}	27.3	7	0.0003	***
R _{Gold}	25.4	7	0.0006	***
ΔYield _{3m}	22.5	7	0.0021	***
ΔYield _{10Y}	10.4	7	0.1696	
ΔYield _{30Y}	13.8	7	0.0546	*

Table 10.
Results of the VEC
Granger causality/
block exogeneity
wald test

(continued)

(d) Cryptocurrencies to others, without bitcoin					Cryptocurrency forecast models
Causal variable	Chi-square	df	Prob	Sig	
ΔVIX	9.1	7	0.2453		
$\Delta Volume$	22.6	7	0.0020	***	
$\Delta Volatility_{5d}$	114.0	7	0.0000	***	
<i>Lags: 1 to 7, N = 7,122</i>					
Note(s): Panel (a) shows the causality of other variables on all six cryptocurrency daily returns, <i>Ret</i>					
Panel (b) shows the same results as panel (a) but excludes BTC					
Panel (c) shows the causality of cryptocurrency daily returns, <i>Ret</i> , on other variables					
Panel (d) shows the same results as panel (c) but excludes BTC					
Highlighted rows show changes in significance between horizontal panels					
Significance at the 10, 5 and 1% levels are indicated by *, ** and ***, respectively					
The date range is from 12/31/2013 to 08/01/2020					

Table 10.

growth stocks and resembling firms with weak operating profitability are not encouraging signals for cryptocurrencies to become common and main-street investment vehicles.

5.7 Forecasting cryptocurrency prices (out-of-sample)

The usefulness of financial statement projections for corporate financial management is undisputed. Such projections, termed pro forma financial statements, are the bread and butter for much corporate financial analysis (Benninga, 2014). Pro forma modeling of cryptocurrency prices is a new topic. Most of these models fall into one of the two types: (1) based on machine learning (Derbentsev, Matviychuk, & Soloviev, 2020; McNally, Roche, & Caton, 2018); (2) based on econometric methods (Chu, Chan, Nadarajah, & Osterrieder, 2017; Dyhrberg, 2016a; Malladi & Dheeriyaa, 2021). In this paper, we followed the latter method. A detailed example of using time series methods to forecast cryptocurrency returns and volatilities can be seen in Malladi and Dheeriyaa (2021).

OOS forecasts demonstrate the usefulness of pro forma cryptocurrency methods developed so far in this paper. Since the REM method (using Equation 4) is found to be superior to the FEM method, we will use REM and contrast it with the other methods (pooled OLS using Equation (1) and panel VECM using Equations (5) and (6)). Readers interested in using VECM models for forecasting may refer to a hands-on course on macroeconomic forecasting [16].

To conduct OOS forecasts, one must split the data into two groups: a large part of the data (from 12/31/2013 to 05/31/2020) is used for training. Afterward, daily cryptocurrency prices are forecasted two days ahead during a two-month window (from 06/01/2020 to 08/01/2020). Producing long-horizon forecasts is difficult and error-prone in the financial markets. The results of the OOS forecast are shown in Figure 4.

One can see that the panel VECM model accurately forecasts the actual price for all six cryptocurrencies, further illustrating that cryptocurrencies exhibit simultaneity and endogeneity, which can be captured well by the panel-based error correction models such as the panel VECM.

5.8 Efficient frontier (with and without cryptocurrencies)

In this final subsection, the efficient frontier (Markowitz, 1952; Merton, 1972) is produced with and without cryptocurrencies with 500 optimal portfolios that offer the highest monthly return for a given level of risk or the lowest risk for a given level of return. Portfolios that lie below the efficient frontier are considered to be suboptimal. When portfolios consist of only traditional asset classes (US stocks, international stocks and gold), the commonly-seen

Table 11.
Results of the
GARCH(1,1) method
with exogenous
variable

(a) Mean equation												
Variable	R _{BTC} Coefficient	Sig	R _{Cardano} Coefficient	Sig	R _{Chainlink} Coefficient	Sig	R _{Ethereum} Coefficient	Sig	R _{Litecoin} Coefficient	Sig	R _{XRP} Coefficient	Sig
R _{BTC}	—		0.0798	*	0.2816	***	0.3779	***	0.4151	***	0.1280	***
R _{Cardano}	0.0955	***	—		0.0866	***	0.0672	***	0.0697	***	0.1242	***
R _{Chainlink}	0.0606	***			—		0.0726	***	(0.0468)	***		
R _{Ethereum}	0.3255	***	0.4494	***	0.5082	***	—	***	0.4265	***	0.3473	***
R _{Litecoin}	0.2015	***	0.2434	***			0.3673	***	—	***	0.1777	***
R _{XRP}			0.2899	***			0.1815	***	0.1029	***	—	
R _{Gold}												
REM									(0.1477)	*		
R _{SP500}												
R _{World}												
ΔYield _{3m}												
ΔYield _{10Y}							(0.0007)	**				
ΔYield _{30Y}					0.0020	**						
# Obs	706		706		706		706		706		706	

(b) Variance equation, $GARCH = C + ARCH\ beta * RESID(-1)^2 + GARCH\ beta * GARCH(-1) + volume\ beta * volume$												
Variable	Bitcoin Coefficient	Sig	Cardano Coefficient	Sig	Chainlink Coefficient	Sig	Ethereum Coefficient	Sig	Litecoin Coefficient	Sig	XRP Coefficient	Sig
C	0.0000	***	0.0000	***	0.0001	***	0.0000	***			0.0001	***
ARCH beta	0.1284	***	0.1880	***	0.1153	***	0.1885	***	0.1091	***	0.3825	***
GARCH beta	0.8401	***	0.8000	***	0.8723	***	0.7669	***	0.9157	***	0.6314	***
Volume beta	0.0000	***	0.0007	***					(0.0000)	*	0.0000	***

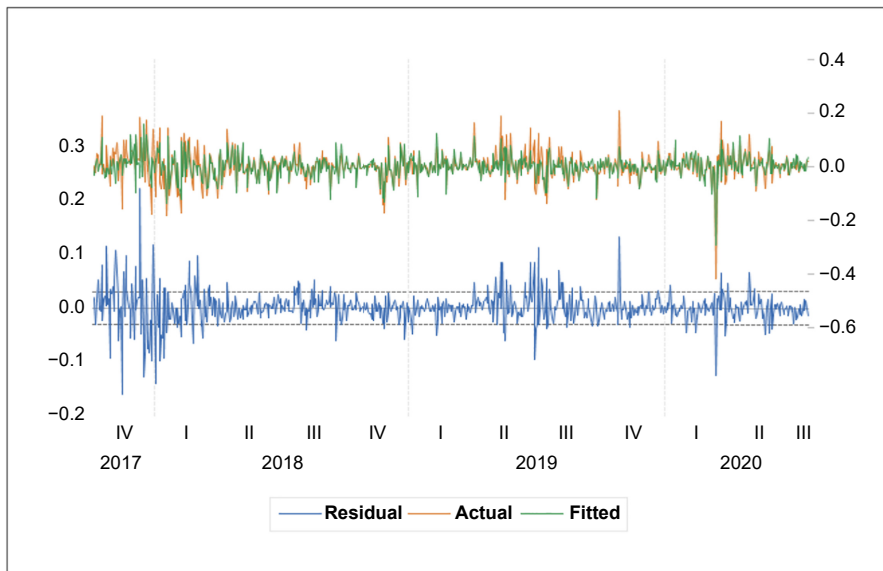
Note(s): Panel (a) shows the mean equation of daily returns of cryptocurrencies, stocks, bonds and gold. Significant terms are only shown

Panel (b) shows the volatility estimation containing the ARCH and GARCH coefficients

Due to the GARCH estimation requirement, data rows cannot be blank, so a common sample of 706 observations is used for estimation

So, the date range is from 10/04/2017 to 08/01/2020

Significance at the 10, 5 and 1% levels are indicated by *, ** and ***, respectively



Note(s): Using the GARCH(1,1) model results in Table (11), BTC volatility is fitted to the actual and shown in the top half of this graph. The GARCH(1,1) model estimates volatility well, i.e., actual vs. fitted curves are hugging each other. The residual curve shown in the bottom half is tested for robustness and contains neither serial correlation nor ARCH effects. Similar curves are produced for the other five cryptocurrencies but not included in the paper due to space constraints

Figure 3.
Actual, fitted and
residual graph of
bitcoin volatility

(a) Fama-French three factor analysis

Variable	Beta	Std. error	<i>t</i> -statistic	Prob	Sig
C, or alpha	(0.0022)	0.0009	(2.6)	0.0105	**
MKT_RF	0.0036	0.0007	5.1	0.0000	***
SMB	0.0073	0.0015	4.9	0.0000	***
HML	(0.0031)	0.0012	(2.6)	0.0093	***

(b) Fama-French five factor analysis

Variable	Beta	Std. error	<i>t</i> -statistic	Prob	Sig
C, or alpha	(0.0022)	0.0009	(2.5)	0.0131	**
MKT_RF	0.0036	0.0008	4.8	0.0000	***
SMB	0.0068	0.0015	4.4	0.0000	***
HML	(0.0026)	0.0015	(1.8)	0.0760	*
RMW	(0.0059)	0.0024	(2.4)	0.0147	**
CMA	0.0009	0.0031	0.3	0.7755	

Note(s): Dependent variable: $RET - R_f$. Panel (a) shows three-factor results

Panel (b) shows five-factor results

The results are based on a REM conducted in a $1636 \text{ (days)} \times 6 \text{ (cross-section)}$ panel setting

Significance at the 10, 5 and 1% levels are indicated by *, ** and ***, respectively. The date range is from 12/31/2013 to 08/01/2020

Table 12.
Fama-French factor
analysis results

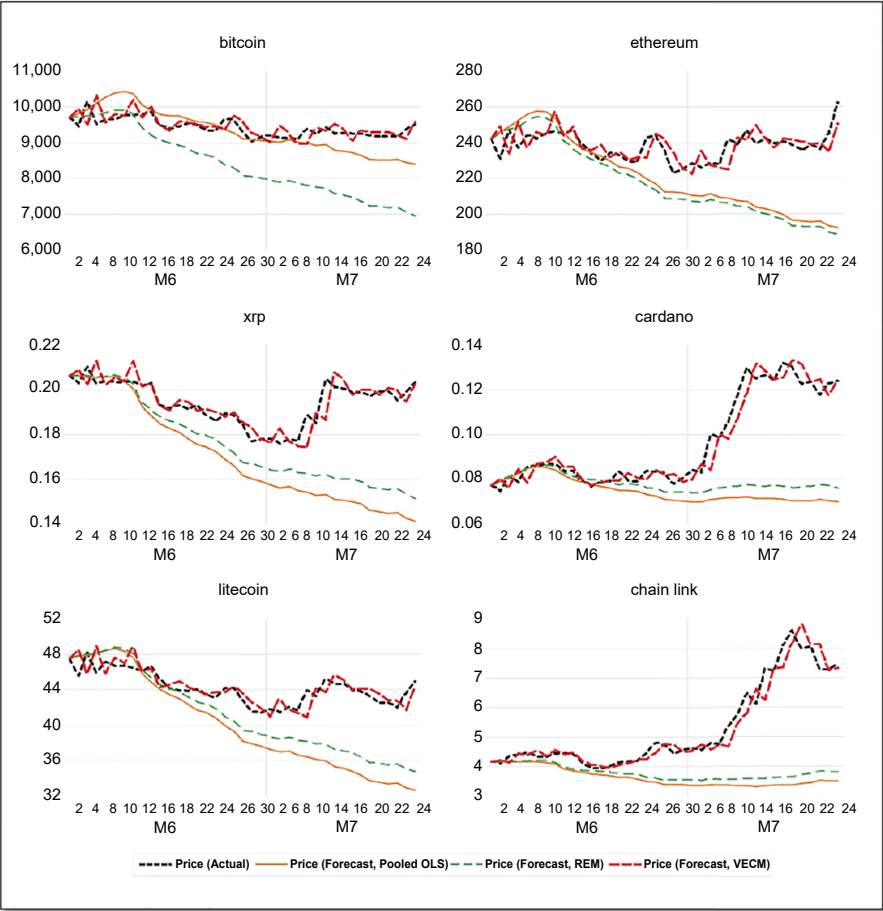


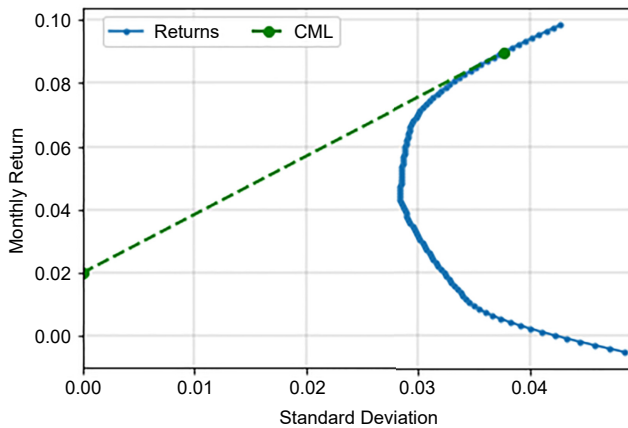
Figure 4.
Out-of-sample forecast
of six cryptocurrency
prices

Note(s): Actual versus forecasts based on pooled OLS, REM, and panel VECM. Forecast range: 06/01/2020 to 08/01/2020

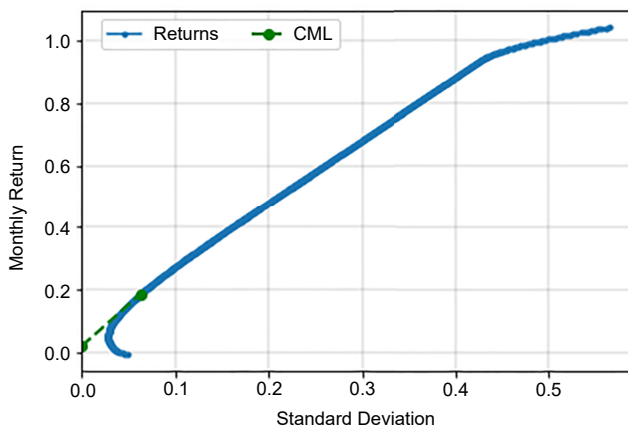
efficient frontier is shown in Figure 5a. However, as shown in Figure 5b, the inclusion of cryptocurrencies in a portfolio magnifies the risk (x -axis) and the return (y -axis) by order of magnitude. The tangency portfolio, intercept point of CML and the efficient frontier, is the most efficient portfolio. Including cryptocurrencies in a portfolio offers investors a larger tangency portfolio set, creating more portfolio choices. Since the risk-adjusted returns in Figure 5b resemble a levered portfolio, one can view a cryptocurrency portfolio similar to a levered portfolio made of traditional asset classes.

6. Conclusions

One of the tasks of the financial econometrics profession is building pro forma models that meet accounting standards and satisfy auditors. This paper undertook such an activity by deploying traditional financial econometric methods and applying them to an emerging cryptocurrency asset class. Vast and rapid innovation is taking place in the cryptocurrency



(a)



(b)

Note(s): The left panel (a) shows an efficient frontier based on monthly returns of SP500, Gold, MSCI_W, and MSCI_EM. The right panel (b) shows the efficient frontier with six cryptocurrencies (i.e., Bitcoin, Ethereum, XRP, Cardano, Litecoin, Chainlink). The return (on the y-axis) and risk (x-axis) in panel (b) are an order of magnitude larger than those in panel (a). The date range is from 12/31/2013 to 08/01/2020. A 2% annual risk-free rate is used to draw the capital market line (CML)

Figure 5.
Efficient frontier of
asset classes with and
without
cryptocurrencies

markets. More than 8,700 cryptocurrencies have been invented so far. Researchers need to understand such an emerging asset class. This paper attempts to create a bridge between the well-established econometric methods and an emerging cryptocurrency asset class. Six major cryptocurrencies (BTC, Ethereum, XRP, Chainlink, Cardano are Litecoin) are analyzed. Collectively, they constitute more than 80% of the overall market. These six cryptocurrencies are analyzed in a panel-data setting with the help of six econometric techniques (pooled OLS regression, the fixed-effect model, the random-effect model, VECM, GARCH and Fama-French factor analysis). The main findings of this analysis are as follows:

- (1) VECM produces the best out-of-sample price forecast of cryptocurrency prices.
- (2) Cryptocurrencies are unlike cash for accounting purposes: the standard deviations of cryptocurrency daily returns are several times larger than those of other financial assets. Such high volatility does not support the argument put forward by some accountants that cryptocurrency is similar to cash.
- (3) Cryptocurrencies are not a substitute for gold as a safe-haven asset.
- (4) The five most significant determinants of cryptocurrency daily returns are: the emerging markets stock index, S&P 500 stock index, return on gold, volatility of daily returns and the VIX. Pro forma models need to consider these five factors (in addition to others).
- (5) Their return volatility is persistent and can be forecasted using the GARCH model.
- (6) In a portfolio setting, cryptocurrencies exhibit negative alpha, high beta, similarity with small and growth stocks and resemble firms with weak operating profitability.
- (7) A cryptocurrency portfolio offers investors more choices and resembles a levered portfolio made of traditional asset classes.

Future research on cryptocurrency returns, volatility and portfolios can include more asset classes (hedge funds, private equity, etc.) and perpetual futures as factors and regime-switching models. Besides, accounting standards, regulation, technology and central monetary policies can be incorporated on top of the econometric analysis.

Notes

1. What Are cryptocurrencies?: <https://coinmarketcap.com/intro-to-crypto/what-are-cryptocurrencies/>
2. List of major cryptocurrencies by market capitalization, <https://coinmarketcap.com/all/views/all/>
3. List of all 8,700 cryptocurrencies: <https://coin.market/cryptos>
4. How much U.S. currency is in circulation?: https://www.federalreserve.gov/faqs/currency_12773.htm
5. The CoinDesk 20: <https://www.coindesk.com/coindesk20>
6. Bitcoin Market Capitalization, <https://coinmarketcap.com/>
7. Block chain by the numbers, <https://www.blockchain.com/about/index.html>
8. Cryptocurrency prices: <https://www.coindesk.com>
9. S&P 500 index (Adjusted close): <https://finance.yahoo.com/quote/^GSPC>
10. MSCI world index: <https://www.msci.com/documents/10199/149ed7bc-316e-4b4c-8ea4-43fcb5bd6523>
11. MSCI emerging markets: <https://www.msci.com/documents/10199/c0db0a48-01f2-4ba9-ad01-226fd5678111>
12. US treasury yields, FRED: <https://fred.stlouisfed.org>
13. Gold prices: <https://www.gold.org/data/gold-price>
14. VIX index: <http://www.cboe.com/vix>
15. Fama/French 5 Factors (2 × 3) [Daily]: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
16. IMF Macroeconomic Forecasting: <https://www.imf.org/en/Capacity-Development/Training/ICDTC/Courses/MFx>

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Appendix

Symbol	Name	Definition	Source
P_{it}	Price	Cryptocurrency price	coindesk.com
$LPRICE$	Natural log of price		
RET_{it}	Daily return	Daily return, $\ln[p(t)/p(t-1)]$ of i th cryptocurrency on day t ; also called $\Delta LPRICE$	
$\Delta LPRICE$	Difference in log price of cryptos, daily return	$\ln[p(t+1)/p(t)] = \ln[p(t+1)] - \ln[p(t)] = RET$	
R_{stock}	Daily change in index	Three indices are used: 1) S&P 500; 2) MSCI emerging markets; 3) MSCI World	yahoo.com ; msci.com
Δ_{yield}	Daily change in treasury yields	Three U.S. treasury yields: 1) 3-month T-Bill; 2) 10-year T-Note; 3) 30-year T-Bond	fred.stlouisfed.org
R_{Gold}	Daily gold return	Gold daily return, $\ln(pt/pt-1)$ of i th currency on day t	gold.org
$\Delta Volm$	Daily volume	Daily volume of crypto transactions in \$ billions	coindesk.com
$\Delta Volt$	Volatility of crypto	Volatility (standard deviation of last five days' daily return)	cboe.com
ΔVIX	Implied option volatility	Daily VIX	cboe.com
α	(a) Excess return (constant term); (b) ARCH coeff	Used in 2 places; (a) five-factor Fama-French factor analysis; (b) GARCH	(a) French website
β	(a) Five Fama-French factors; (b) GARCH coeff	Used in 2 places: (a) β_M :market, β_S :size, β_H :value, β_R :profitability, β_C :style; (b) GARCH	(a) French website
R_{Ft}	Daily risk-free rate	One-month treasury bill rate (from Ibbotson associates)	French website
R_{Mt}	Daily market return	Value-weight return of all CRSP firms incorporated in the US	French website
β_0 or C	Constant term in regression		
β_1	Regression coefficient	Regression coefficient of daily return on S&P 500	
β_2	Regression coefficient	Regression coefficient of daily return on MSCI EM	
β_3	Regression coefficient	Regression coefficient of daily return on MSCI World	
β_4	Regression coefficient	Regression coefficient of 3-month T-Bill yield daily change	
β_5	Regression coefficient	Regression coefficient of 10-year T-Note yield daily change	
β_6	Regression coefficient	Regression coefficient of 30-year T-Bond yield daily change	
β_7	Regression coefficient	Regression coefficient of daily gold return	
β_8	Regression coefficient	Regression coefficient of cryptocurrency change in daily volume	
β_9	Regression coefficient	Regression coefficient of cryptocurrency change in volatility of past 5 day returns	
β_{10}	Regression coefficient	Regression coefficient of change in daily VIX	
μ_t	Regression residual term in pooled OLS, FEM	$E(\mu_{it}) \sim N(0, \sigma^2)$	
w_t	Regression residual term in REM	$w_{it} = \mu_{it} + \varepsilon_i$, ε_i is a random error term with mean 0 and variance σ_ε^2	
ε_i	Random error term	ε_i is a random error term with mean 0 and variance σ_ε^2	

Table A1.
Variables used in
this study

(continued)

Table A1.

Symbol	Name	Definition	Source
σ_ε^2	Variance of the random error term	Used in w_t	
ε_t, η_t	Two uncorrelated white-noise	$E[\varepsilon_t \varepsilon_s] = 0 = E[\eta_t \eta_s], s \neq t$, and $E[\varepsilon_t \varepsilon_s] = 0$ for all s and t	
X_t and Y_t	Two stationary time series	X_t and Y_t are two stationary time series with zero mean	
$f(x_t)$	A positive term in GARCH	X_t exogenous variable(s) are presumed to effect	
$\sigma_{Ret(t)}^2$	Conditional variance of daily returns	Used in GARCH volatility model	

About the author



Dr Rama K. Malladi teaches financial modeling, corporate finance and investments at CBAPP. He has taught 26 finance and investment classes at the undergraduate, graduate and MBA levels. Dr Malladi received degrees from three continents – PhD in Finance from EDHEC Business School, a Grandes École in France, with Dr Frank Fabozzi as his dissertation adviser, MBA from the UCLA Anderson School of Management and Master of Technology in Electrical Engineering from the Indian Institute of Technology (IIT), Madras in India. Besides, he holds a Bachelor of Technology in Electrical and Electronics Engineering with a first-class distinction. He

has served in several leadership positions, including the President and Board of Governor of CFA Society Los Angeles. He earned Chartered Financial Analyst, Chartered Alternative Investments Analyst, Financial Risk Manager and Project Management Professional designations. Dr Malladi is a subject matter expert in the area of data and financial analytics. During the last 30 years of his career spanning the USA, Europe and Asia, he has led groups focusing on financial analytics, risk management and alternative investments. He has hands-on and managerial experience in this area and provided consultancy services to firms such as Starbucks (corporate headquarters), National Stock Exchange (corporate headquarters), Wachovia Securities, Toyota Financial Services (corporate headquarters), Deloitte Consulting, British Telecom (UK), British Gas (UK corporate headquarters), IBM (UK), Hewlett-Packard, Lockheed Martin, Tata Consultancy Services (corporate headquarters) and several others. One of his industry projects that used parallel computing technology has received the prestigious British Computer Society's annual national award, labeled as the "Oscars of the IT industry" by the Computing magazine in the late 90s. He has previously worked and lived in global financial and technology centers such as New York, San Francisco, Silicon Valley, Seattle, London, Paris, Nice, Zurich, Bombay and Bangalore. His research areas include asset management, alternative investments and risk management. Dr Malladi has published in peer-reviewed academic journals, such as *Applied Economics*, *Business Economics*, *Journal of Wealth Management*, *Review of Financial Economics*, *Journal of Asset Management*, *North American Journal of Economics and Finance* and others. His recent work on Cryptocurrencies and exchange-traded funds has received particular attention – he is invited to speak on this topic at the 94th annual conference of the Western Economic Association in San Francisco and subsequently at Fudan University, Shanghai, China. He is a resident of Anaheim Hills in Southern California for 25 years and lives with his wife and two daughters. Rama K. Malladi can be contacted at: rmalladi@csudh.edu

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