Cryptocurrencies As an Asset Class? *An Empirical Assessment*

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KEY FINDINGS

- There is only a mild, and not significant, correlation between returns on cryptocurrencies and returns on traditional asset classes on a daily basis.
- Past returns significantly drive trading volume, consistent with the idea that short-term market activity is primarily driven by sentiment.
- Macroeconomic factors such as the term structure of interest rates and inflation expectations do not seem to affect market activity in either the short or the long term.

ABSTRACT: *This article empirically investigates some of the key features of cryptocurrency returns and volatilities, such as their relationship with traditional asset classes, as well as the main driving factors behind market activity. The main empirical results suggest that while there is a mild relationship between returns on cryptocurrencies and commodities, and precious metals in particular, the relationship does not translate into volatility spillover effects. Consistent with existing theoretical models in which trading activity is primarily driven by investor sentiment, we show that trading volume is driven by past returns. On the other hand, macroeconomic factors do not seem to affect market activity in either the short term or the long term.*

TOPICS: ***Currency, exchanges/markets/clearinghouses****

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The explosive growth of peer-to-peer exchanges and Blockchain technology has spurred the emergence of cryptocurrencies as a significant component of financial markets.[1] At the time of writing, there are about 1,000 actively quoted cryptocurrencies. The best-known is Bitcoin, which has been classed as a commodity in the United States, and therefore is covered by the Commodity Exchange Act, along with gold and oil, according to the Commodity Futures Trading Commission (CFTC).[2]

In this article, we use a large panel of prices, traded volumes, and market capitalization on actively quoted cryptocurrencies to

[1] A Blockchain is an open and distributed ledger that records all transactions, called blocks, which are sequentially linked and secured in a verifiable and permanent way using cryptography. Each block contains a link to a previous block, that is, a hash pointer, a time stamp to identify the timing of the transaction, and the transaction data.

[2] Bitcoin was introduced in 2008 in a white paper by Satoshi Nakamoto, a still unverified entity. He introduced Bitcoin as a decentralized, peer-to-peer electronic cash system that does not need central authorities or trusted third parties to operate.

empirically investigate their relationship with standard asset classes. In addition, we investigate the risk-return trade-off of individual cryptocurrencies, to shed some light on the underlying investment properties. Finally, we make use of regression analysis, a Granger causality, and a panel Vector Autoregressive (PVAR) model to investigate the driving forces behind market activity.

Given the novel and emergent status of cryptocurrency markets, understanding the properties and the relationship between cryptocurrencies and global asset classes is relevant to a broad audience—from market participants seeking different sources of returns and diversification, to regulators wishing to better understand the trading motives and market structure when designing policy regimes, and to academics searching for new insights into the economics of cryptocurrencies. Indeed, even though emerging rapidly, the literature on cryptocurrency markets is still largely underdeveloped compared to that of traditional asset classes.

The empirical analysis is based on a panel of 300 cryptocurrencies with daily prices, trading volume, and market capitalization expressed in US dollars, aggregated from more than 150 exchanges between January 1, 2017, and March 30, 2019. The data are aggregated on a volume-weighted basis across exchanges in order to mitigate the risk that manipulation on a single exchange could affect the overall reliability of the results. Indeed, Gandal, Hamrick, Moore, and Oberman (2018) and Li, Shin, and Wang (2018) documented the existence of diffuse market manipulation strategies such as pump-and-dump schemes on a high-frequency, within-exchange, basis. Still, it is hard to believe that all the exchanges could be affected at the same time in an economically meaningful manner, especially given that the exchanges are mostly disconnected from one another and present quite different trading conditions (see, e.g., Makarov and Schoar 2018).

The main results show that there is no significant relationship between returns on cryptocurrencies and global proxies of traditional asset classes, except for a mild correlation with the returns on precious metals. These results are consistent with the conventional wisdom that cryptocurrencies may be useful for diversification purposes, being uncorrelated with other asset classes, although they cannot be thought of as a traditional asset class. In addition, the empirical analysis demonstrates that there are no spillover effects between cryptocurrencies and standard asset classes, at least as far as realized volatility measures are concerned.

Delving further into the dynamics of market activity, the empirical results provide evidence that trading volume is influenced by past returns and volatility. These results are consistent with existing empirical evidence on equity markets that shows a positive and significant correlation between stock returns and trading volume (see, e.g., Karpoff 1987; Gallant, Rossi, and Tauchen 1992; Schwert 1989; Campbell, Grossman, and Wang 1993; and Llorente, Michaely, Saar, and Wang 2002). In addition, the results are consistent with some of the existing research in the cryptocurrency space, which shows that trading activity is driven by investor sentiment (see, e.g., Drobetz, Momtaz, and Schroder 2019 and Li and Yi 2019).

On the other hand, other macroeconomic factors, such as inflation expectations, the yield curve, and real exchange rates, do not have a significant role, consistent with earlier findings by Yermack (2013) that show that Bitcoin is not driven by major macroeconomic events.

Literature Review

This article contributes to two strands of literature. First, it adds to recent literature that aims to understand the investment properties of cryptocurrencies. Yermack (2013) and Dyhrberg (2016) investigated the hedging properties of Bitcoin within the context of a diversified portfolio and reached opposite results. In particular, Yermack (2013) argued that Bitcoin is uncorrelated with the majority of fiat currencies and is much more volatile, and therefore of limited usefulness for risk management purposes and diversification. Krueckeberg and Scholz (2018) investigated both the cross-sectional correlations and the correlation with other asset classes of a relatively small set of cryptocurrencies, as well as the market stability issues. Liu and Tsyvinski (2018) looked at the top three cryptocurrencies in terms of market capitalization and investigated their relationship with US equity, bonds, and some of the main currencies. Similar to them, this study looks at the relationship between cryptocurrencies and standard asset classes. But it also looks at a much broader cross-section, the risk-return trade-off of cryptocurrencies, and the determinants of market activity at the individual level. Also, it compares cryptocurrencies to global proxies of traditional asset classes, rather than US-based assets. This is more consistent with the global nature of cryptocurrency investments.

Secondly, this article contributes to a growing literature that aims at understanding the economics of cryptocurrency markets. The existing studies in economics related to Bitcoin and cryptocurrencies mostly focus on the operational features of cryptocurrencies, such as the likelihood of exchanges defaulting (e.g., Moore and Christin 2013), the possibility of mining manipulation and illegal uses of bitcoins (e.g., Eyal and Sirer 2014 and Foley, Karlsen, and Putnicns 2018), the reconstruction of transaction networks (e.g., Kondor, Posfai, Csabai, and Vattay 2014), the efficiency of a decentralized public ledger for conducting financial transactions (e.g., Evans 2014 and Dwyer 2015), and the implications for central banks and monetary policy (e.g., Bordo and Levin 2017).

A few theoretical models and discussions have been proposed to study the equilibrium pricing mechanism and the development of a decentralized market place. Chiu and Koeppl (2017) developed a general equilibrium monetary model to investigate the optimal design of a cryptocurrency system based on a Blockchain. They showed that a standard "proof-of-work" protocol generates a welfare loss of 1.4% of consumption. Such loss can be lowered substantially by financing mining rewards through money supply growth rather than by increasing transaction fees. Similarly, Huberman, Leshno, and Moallemi (2017) investigated the fee structure and showed it might be the outcome of an equilibrium of a congestion queuing game derived from the throughput limited by the infrastructure. Bolt and van Oordt (2016) developed an economic framework to analyze the exchange rate of virtual currencies. Finally, Sockin and Xiong (2018) provided a theoretical framework to assess the fundamental value of a cryptocurrency. In particular, they showed that when aggregate demand is unobservable, the trading price and volume of cryptocurrencies serve as important channels for aggregating private information and for facilitating coordination on equilibrium prices.

Differently from them, this study utilizes a relatively granular dataset of prices and volumes aggregated over more than 150 exchanges worldwide over a time span of almost six years, in an effort to investigate the relationship between cryptocurrency returns and global proxies for traditional asset classes.

The structure of the article is the following. The next section describes the data. The third section represents the core of the study and reports the empirical results, and the final section concludes.

DATA

Prices and Trading Volume

The data sample refers to intraday prices and trading volume (both expressed in USD) of the top 300 cryptocurrencies from CryptoCompare, a website-based data provider that collects real-time data from more than 150 active exchanges. This dataset comprises more than 90% of the total market capitalization throughout the sample. We obtained data on an hourly basis for the sample period from December 2013 to March 2019. Recent work by Alexander and Dakos (2020) suggests that CryptoCompare data is among the most reliable for use in both academic and practical settings.[3]

The panel is unbalanced, meaning that the number of cryptocurrencies at the beginning of the sample is not the same as at the end. Exhibit 1 provides initial descriptive statistics for the top 20 cryptocurrencies, and also reports a set of descriptive statistics for the daily trading volume, expressed in $mln, and the daily returns in %. For ease of exposition, we report the statistics for the top 20 cryptocurrencies in terms of average market capitalization over the sample period. The first five columns report the descriptive statistics for the trading volume. The picture that emerges is rather clear. Bitcoin (BTC) and Ethereum (ETH) show the highest average trading volume, with transactions that amount to almost $2 billion and $1 billion respectively on a daily basis. Similarly, BTC and ETH show the highest volatility for market activity, with a standard deviation of trading volume that is an order of magnitude higher than other cryptocurrencies such Litecoin, NEM, Monero, and NEO.

The last five columns report the descriptive statistics for the daily returns. More mature cryptos, such as BTC and ETH, tend to show lower returns and volatility on a daily basis. Interestingly, all cryptos show

[3] The reliability of CryptoCompare has been proven by a number of relevant strategic partnerships, such as VanEck's indexes division (to price ETFs); Refinitiv, one of the world's largest providers of financial markets data and infrastructure; and Yahoo Finance (the popular platform uses CryptoCompare's data on more than 100 cryptocurrency quote pages).

Exhibit 1

A First Look at the Cryptocurrency Market

Name	Trading Volume (in $ mln)					Returns (%)				
	Mean	Median	StDev	Skew	Kurtosis	Mean	Median	StDev	Skew	Kurtosis
Binance Coin	58.07	40.002	61.975	3.125	20.424	1.273	0.082	9.963	2.728	22.276
Bitcoin	1,952.898	83.529	3,356.034	2.351	9.875	0.164	0.144	3.889	0.019	8.641
Bitcoin Cash	668.252	400.181	900.868	5.817	55.052	0.248	–0.545	9.265	1.584	11.337
Bitcoin Gold	47.427	11.376	126.627	7.52	77.626	–0.196	–0.509	10.242	2.483	33.093
Bitcoin SV	104.897	81.347	83.192	3.107	15.257	0.712	–0.618	13.026	2.28	18.123
Cardano	126.342	56.975	207.924	4.066	23.954	0.625	–0.432	10.97	5.508	58.682
Dash	50.958	0.869	85.386	2.54	14.942	0.652	–0.215	9.949	10.637	248.482
EOS	681.047	615.336	639.17	1.837	8.805	0.685	–0.27	11.079	6.079	86.482
Ethereum	1,059.541	345.801	1396.144	1.744	6.959	0.568	–0.104	7.229	0.277	16.378
Ethereum Classic	169.43	129.966	210.319	2.72	13.591	0.621	–0.196	12.731	16.877	425.897
IOTA	67.056	28.605	156.047	7.154	70.859	0.261	–0.303	8.678	0.858	7.617
Litecoin	204.495	6.013	427.919	4.858	46.531	0.224	0	6.069	1.849	20.378
Monero	23.542	2.49	49.009	4.343	30.195	0.474	–0.099	7.661	1.623	14.963
NEM	12.372	1.359	29.183	5.315	41.139	0.761	–0.02	9.768	5.055	72.886
NEO	103.892	75.551	139.779	4.682	43.31	0.814	–0.342	10.894	3.224	31.149
OmiseGO	51.505	36.797	51.6	4.997	44.785	0.56	0	9.265	2.198	17.304
Qtum	191.577	131.067	258.92	4.516	28.959	0.294	–0.234	9.739	2.333	18.11
Stellar	36.631	0.136	86.915	6.331	71.988	0.557	–0.357	8.862	3.913	38.458
TRON	241.168	156.378	363.083	5.596	47.857	1.129	–0.262	13.209	4.014	32.079
XRP	236.339	1.303	697.512	6.904	64.264	0.385	–0.319	8.007	7.484	145.562

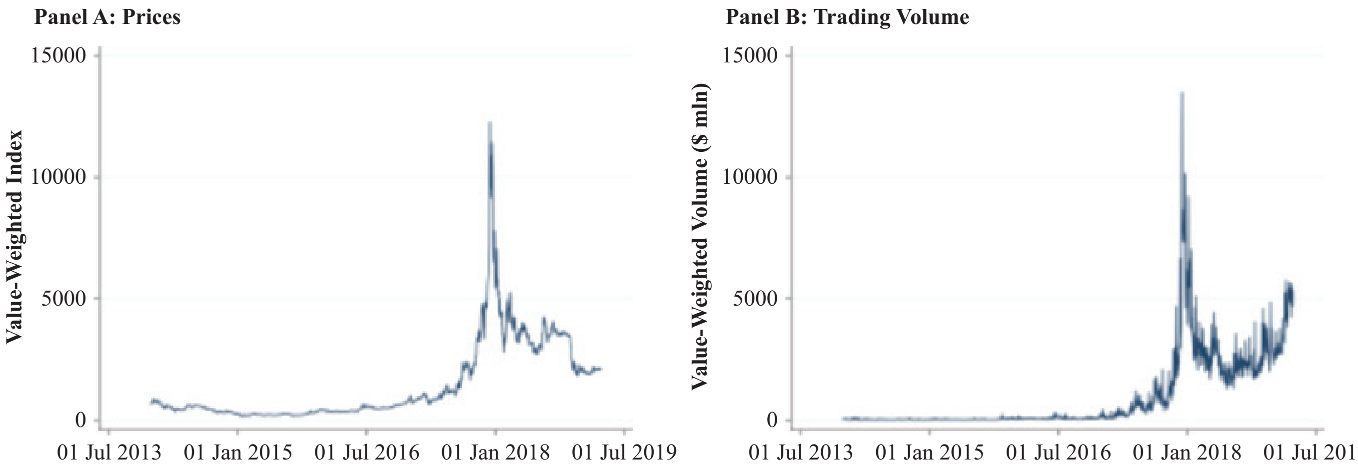
Notes: This exhibit reports a set of descriptive statistics for the top 20 cryptocurrencies in the sample in terms of average market capitalization. In particular, the table reports the trading volume expressed in $ mln and the daily returns in %. The data are aggregated over more than 150 exchanges worldwide, where the aggregation is based on the amount of trading in each exchange on a given day. The sample period is from December 2013 to March 2019, daily.

positive skewness and a high level of excess kurtosis over the sample period. This shows that a simple buy-and-hold strategy fully invested in cryptos is more likely to experience large gains vis-a-vis large losses, despite the fact that the latter can be substantial. The massive kurtosis that characterizes the distribution of daily returns shows that a simple Gaussian framework cannot capture the time-series variation of cryptocurrency returns. Non-normality has been shown by academic research to be a critical feature for the econometric modeling of cryptocurrency returns. Daily data are converted into monthly observations to mitigate the noise that characterizes the highly volatile daily cryptocurrency returns.

Although the sample is relatively short, it is reasonably representative of the development of the cryptocurrencies market. Exhibit 2 reports both a value-weighted price index (left panel) and a value-weighted index of aggregate trading volume (right panel) expressed in millions of US dollars. Notably, the sample includes a variety of market phases—the early development of Bitcoin and a few competing cryptocurrencies such as Litecoin and Ripple in early 2013, the dramatic increase in valuations that made headlines for the whole cryptocurrency market, and the substantial market drop in the summer of 2017, where almost every cryptocurrency suffered massive losses. The sample also includes a variety of institutional market changes, such as the Chinese ban on exchanges, the introduction of futures contracts, and the apparent market consolidation toward the end of the sample.

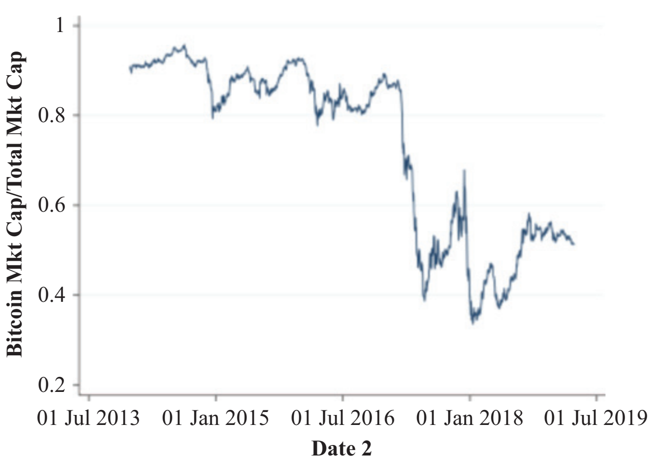
Exhibit 3 shows the market capitalization of Bitcoin (BTC) over the total market capitalization of the cryptocurrency market. It is easy to see that until late 2016 the market was widely dominated by BTC, with a market value well above 80% of the total market capitalization. Exhibit 3 illustrates that the sample under investigation is fairly representative of the development of the cryptocurrency market. By the same token, the market structure of cryptocurrencies has only developed since late 2016. In this respect, the market micro-structure

EXHIBIT 2
Cryptocurrency Prices and Trading Volume



Notes: The left panel of this exhibit shows a value-weighted index of the cryptocurrency prices calculated based on the top 300 cryptocurrencies. The right panel shows a value-weighted index of trading volume (in $ mln). The sample period is from December 2013 to March 2019.

EXHIBIT 3
Bitcoin Market Capitalization over Total Market Capitalization



Notes: This exhibit shows the market capitalization of Bitcoin as a fraction of the total market capitalization. The sample period is from December 2013 to March 2019.

is in full development, as shown by a higher number of equally relevant exchange platforms at the end of the sample. Such an increasing number of exchange platforms could be the result of an endogenous growth process led by increasing profits due to the compounding effect of rising prices and market activity.

Exhibit 4 shows that returns can be quite high on a daily basis. However, volatility is sizeable as well—raising the question of whether returns may be that high on a risk-adjusted basis.

Exhibit 5 shows the cross-sectional distribution of the Sharpe ratios for each of the 300 cryptocurrencies in the sample. Clearly, returns are much lower in risk-adjusted terms, with a median Sharpe ratio equal to 0.702 on an annual basis. Adjusting for market risk, the returns become even smaller. We measure market risk as the daily return on the value-weighted price index shown in Exhibit 2, where the weights depend on the market capitalization of each cryptocurrency in the sample on a given day.

Exhibit 6 shows the cross-section of intercepts obtained from a CAPM-like regression in which the dependent variable is the daily returns on a given cryptocurrency, and the independent variable is the daily returns on the market index as explained above. Given that the sample comprises more than 90% of the total market capitalization, these intercepts are akin to a Jensen's alpha.

The estimates show that the median Jensen's alpha in the cross-section is around four basis points on a daily basis—far lower than the raw returns shown in Exhibit 1. This possibly means that after controlling for market risk, the returns on cryptocurrencies are not as high as one might think. The right panel of Exhibit 6

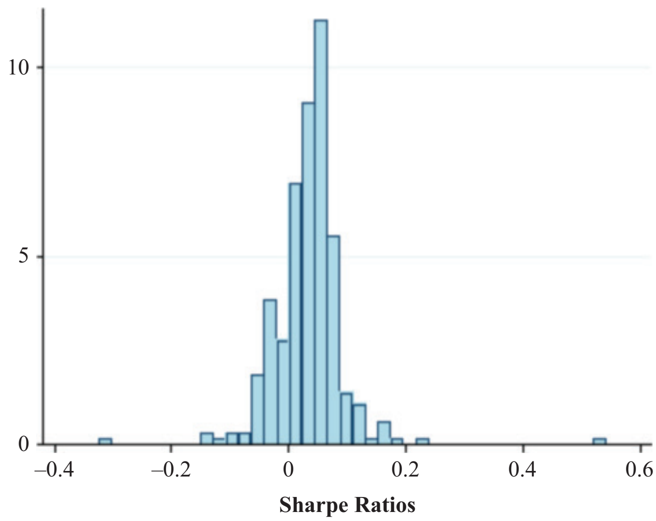
EXHIBIT 4

Cryptocurrencies and Traditional Asset Classes

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
Panel A: Daily Returns													
Treasury	–0.114									–87.72			
	(0.744)									(55.94)			
Treasury Developed		–0.0645								86.85			
		(0.738)								(59.21)			
Corporate Bond			–0.368							0.288			
			(0.586)							(0.662)			
Real Estate				–0.230							0.146		
				(0.182)							(0.544)		
REIT					–0.229						–0.351		
					(0.157)						(0.468)		
Commodity						–0.056						–0.049	
						(0.099)						(0.103)	
Precious Metals							–0.063					–0.054	
							(0.152)					(0.156)	
Long-Term Vol								–0.016					–0.086
								(0.021)					(0.070)
Short-Term Vol									–0.007				0.061
									(0.018)				(0.058)
Obs.	1,541	1,541	1,541	1,541	1,541	1,541	1,541	1,541	1,541	1,541	1,541	1,541	1,541
Adj R^2	0.000	0.000	0.0001	0.0010	0.0013	0.000	0.0001	0.001	0.0002	0.004	0.0013	0.000	0.002
Panel B: Monthly Returns													
Treasury	–1.742									–479.0			
	(3.011)									(251.1)			
Treasury Developed		–1.574								474.4			
		(2.991)								(250.5)			
Corporate Bond			2.315							4.530			
			(1.617)							(2.843)			
Real Estate				0.270							2.831		
				(0.754)							(3.931)		
REIT					0.0986						–2.460		
					(0.707)						(3.702)		
Commodity						0.740						0.800*	
						(0.472)						(0.441)	
Precious Metals							–0.697					–0.818	
							(0.687)					(0.684)	
Long-Term Vol								–0.117					–0.587
								(0.101)					(0.602)
Short-Term Vol									–0.085				0.418
									(0.094)				(0.537)
Obs.	64	64	64	64	64	64	64	64	64	64	64	64	64
Adj R^2	0.005	0.0037	0.026	0.002	0.000	0.036	0.016	0.015	0.010	0.167	0.013	0.059	0.024

*Notes: This exhibit reports the results of a time-series regression where the dependent variable is the log-returns on a value-weighted index of cryptocurrency prices (see Exhibit 2) whereas the independent variable is a set of returns on a traditional asset class. Standard errors are double-clustered across time and individuals. Panel A: reports the results for the daily returns, whereas Panel B: shows the results for returns that are aggregated on a monthly basis. The sample period is from December 2013 to March 2019. Statistical significance is distinguished with ***, **, and *, for the 1%, 5%, and 10% level respectively.*

EXHIBIT 5
Sharpe Ratios



Notes: This exhibit shows the annualized Sharpe ratio of the cryptocurrencies in the sample. The Sharpe ratio is based on the unconditional mean and standard deviation of the returns for the top 300 cryptocurrencies in terms of market capitalization. The sample period is from December 2013 to March 2019.

plots the distribution of market betas, and indeed there is considerable exposure to the market in the cross-section, that is, the average beta is only slightly below the theoretical threshold of one, with a substantial fraction of market betas lying above one.

Traditional Asset Classes

Cryptocurrencies represent a global investment vehicle. Although trading activity is often country-specific (for example, Makarov and Schoar 2018 showed that cross-country arbitrage opportunities often are hard to exploit), the pricing mechanism is far from being tied to a specific country. As a result, a fair comparison between cryptocurrencies and traditional asset classes should be based on global benchmarks.

For this reason, the main empirical analysis compares the returns and volatility of cryptocurrencies with the returns and volatilities of global proxies for standard asset classes, such as equity, treasury, corporate bonds, commodities, real estate, and volatility. For the returns on global equity, we used the returns of the FTSE global all-cap value-weighted index, which summarizes the performance of about 7,400 large, mid, and small-cap stocks, and covered both developed and emerging markets. Global trends in sovereign bonds were proxied by using the Global Broad Market index provided by BofA-Merrill Lynch, which tracks the performance of investment-grade public debt issued in the major markets, including "global" bonds. The commodity market and precious metals were the S&P GSCI Commodity and S&P GSCI Precious Metals total return index.

In addition to more traditional asset classes, we considered global proxies for investment in real estate and volatility. We calculated the former as the returns on the MSCI World Real Estate prices and REITs index, which represents a free float-adjusted value-weighted index that captures both large and mid-cap representation across more than 20 developed markets around the world. We computed daily returns on equity volatility strategies from the S&P 500 VIX Short-Term and Long-Term Futures index, which replicates a constant rolling long position in either short-term, that is, nearby, or long-term VIX futures contracts.

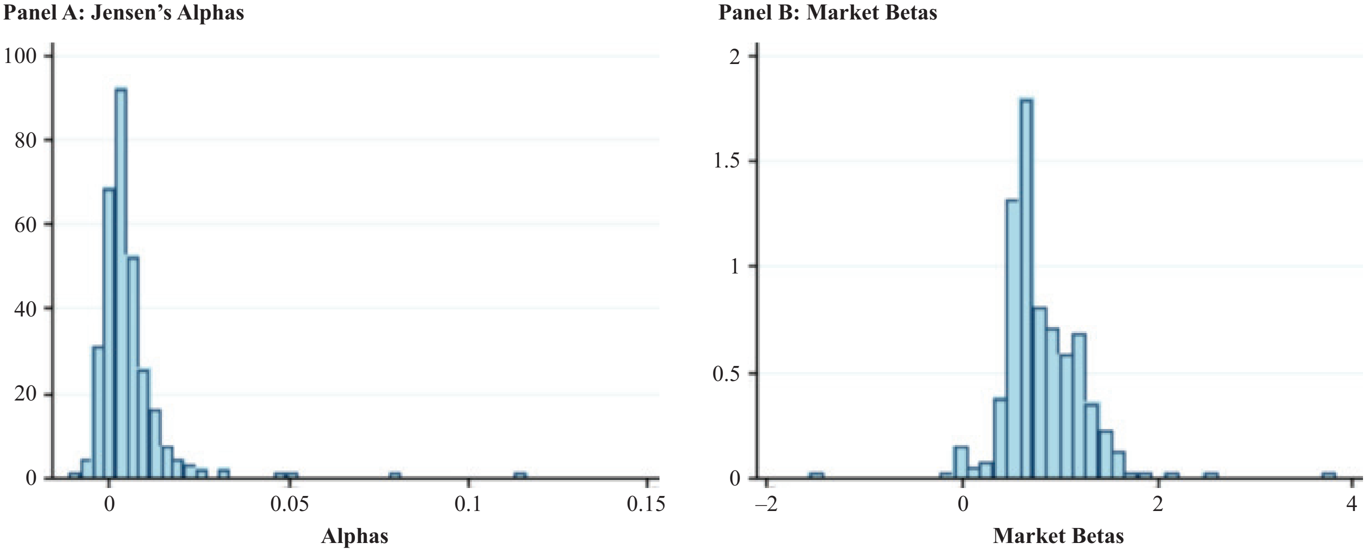
EMPIRICAL RESULTS

Exhibit 4 reports the estimates of a regression where the dependent variable is the log-returns on the value-weighted market index (see Exhibit 2), and the independent variables are the corresponding log-returns on traditional asset classes as outlined above. The lagged returns of the response and the explanatory variables, as well as the lagged values of the average traded volume, are included as additional control variables. We calculated returns daily and double-clustered standard errors across time and individuals.

Panel A shows the results for daily returns. The results indicated that there was no significant correlation between the daily cryptocurrency returns and the returns on other asset classes. None of the traditional investments seemed to show correlated returns with the cryptocurrency market. Panel B confirms this result when returns are aggregated on a monthly basis. With the exception only of commodity returns, which showed a borderline significant and positive correlation, none of the traditional asset returns was correlated with the returns on the cryptocurrency market. This was reflected in quite a small adjusted R^2, especially for daily returns.

Exhibit 4 shows the relationship between the aggregate cryptocurrency market and global proxies for

Exhibit 6
Alphas and Market Betas



Notes: This exhibit shows Jensen's alphas (left panel) and the market betas (right panel) for each of the top 300 cryptocurrencies in terms of market capitalization. The market betas are calculated by regressing the returns on a given cryptocurrency on the returns of a value-weighted index as shown in Exhibit 2. The sample period is from December 2013 to March 2019.

traditional asset classes. Although instructive, it is only indicative, as the substantial heterogeneity across different cryptos was diluted because of the value-weighted aggregation. We next addressed this issue by directly estimating a set of panel regressions with individual cryptocurrency fixed effects, which explicitly took into account the cross-sectional unobserved heterogeneity. In particular, we estimated a regression of the following form,

$$y_{it} = \alpha_i + \beta' x_t + \gamma' \text{Controls}_t + \epsilon_{it} \qquad (1)$$

where yit is the log-returns on cryptocurrency i at time *t*, *xt* is the log-returns on the traditional asset classes, Controlst is the set of control variables, α_i is the individual fixed effect, and eit is the idiosyncratic error term. Panel A of Exhibit 7 reports the estimate for daily returns. We included the lagged returns of both the response and the explanatory variables, as well as the lagged values of the average traded volume, as additional control variables. Standard errors were double-clustered across time and individuals.

None of the slope coefficients β' turned out to be significantly different from zero, that is, there seemed to be no relationship between the returns on single cryptocurrencies and traditional asset returns.

Panel B of Exhibit 7 shows the results aggregated on a monthly basis. Interestingly, precious metals were positively and significantly correlated with monthly returns on cryptocurrencies. Despite the fact that it was only borderline significant, such a relationship is consistent with some of the existing empirical evidence. By using a classic asymmetric GARCH modeling framework, Dyhrberg (2016) showed that several similarities exist between Bitcoin and gold, indicating the former may be useful for risk-averse investors to hedge their exposure on other asset classes. Again, Dyhrberg (2016) reinforced the idea that Bitcoin can be used as a hedge against negative shocks in the stock market.

The reason that gold and cryptos may share a "value storage" feature is intuitive: they both have a limited supply growth, and equilibrium prices primarily depend on aggregate demand. Over the past half-century, new gold mining supply added somewhere from 1% to 2% to the existing stock of previously mined gold. In the same spirit, the supply inflation rate for most cryptocurrencies is steadily decreasing. In both cases, the mining output is scarce, such that market prices largely depend on demand pressure.

EXHIBIT 7

Cryptocurrencies and Traditional Asset Classes: Panel Regressions

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
Panel A: Daily													
Treasury	–0.306									15.08			
	(1.320)									(59.90)			
Treasury Developed		–0.314								–15.19			
		(1.305)								(59.21)			
Corporate Bond			0.334							0.206			
			(1.223)							(1.375)			
Real Estate				0.235							0.887		
				(0.460)							(1.473)		
REIT					0.145						–0.582		
					(0.361)						(1.130)		
Commodity						0.198						0.159	
						(0.183)						(0.184)	
Precious Metals							0.372					0.333	
							(0.260)					(0.261)	
Long-Term Vol								–0.0845					–0.0658
								(0.0582)					(0.134)
Short-Term Vol									–0.0745				–0.0170
									(0.0520)				(0.102)
Obs.	55,277	55,277	55,277	55,277	55,277	55,277	55,277	55,277	55,277	55,277	55,277	55,277	55,277
Adj R^2	0.0016	0.0016	0.0016	0.0017	0.0017	0.002	0.0022	0.0042	0.0041	0.0017	0.0021	0.0020	0.0042
Panel B: Monthly													
Treasury	–1.199									–62.84			
	(2.298)									(126.9)			
Treasury Developed		–1.205								61.36			
		(2.281)								(125.9)			
Corporate Bond			1.984*							2.285			
			(1.085)							(1.715)			
Real Estate				0.342							3.556		
				(0.365)							(2.317)		
REIT					0.201						–3.073		
					(0.353)						(2.208)		
Commodity						0.341						0.349	
						(0.313)						(0.328)	
Precious Metals							1.160**					1.168**	
							(0.582)					(0.580)	
Long-Term Vol								–0.064					–0.256
								(0.062)					(0.720)
Short-Term Vol									–0.055				0.182
									(0.056)				(0.667)
Obs.	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323
Adj R^2	0.0247	0.0247	0.0318	0.0253	0.024	0.0270	0.035	0.026	0.026	0.0332	0.0302	0.038	0.0263

*Notes: This exhibit reports the results of a panel regression in which the dependent variable is the returns on each of the 300 cryptocurrencies in our sample, and the independent variable is a set of returns on a traditional asset class. Standard errors are double-clustered across time and individuals. Panel A: reports the results for the daily returns, whereas Panel B: shows the results for returns that are aggregated on a monthly basis. The sample period is from December 2013 to March 2019. Statistical significance is distinguished with ***, **, and *, for the 1%, 5%, and 10% level respectively.*

Gold and cryptocurrencies are similar in that they are both in limited supply, their prices can be highly volatile, and each can be seen as an alternative investment for those lacking faith in fiat currency and monetary policy. Yet investing in cryptos does not represent a safe bet per se; rather, it is a bet on the underlying Blockchain technology or project. To some extent this makes investments in cryptocurrencies more similar to investing in high-tech companies.

Volatility Spillovers

We next investigated volatility spillover effects between cryptocurrencies and traditional asset classes. A well-known monthly realized variance measure was obtained by summing squares of high-frequency log-returns (see, e.g., Christoffersen, Feunou, Jacobs, and Meddahi 2014 and the references therein)

$$RVar_{it} = \sqrt{\sum_{\tau=1}^{N} \gamma_{it}^2}, \tag{2}$$

where $\gamma T,it$ is the daily returns of cryptocurrency i in month t, and N is the number of days in the month. We first calculated volatility spillover effects between the aggregate cryptocurrency market (see Exhibit 2) and traditional asset classes. Panel A of Exhibit 8 shows the results of a regression where the dependent variable is the monthly realized variance for the aggregate cryptocurrency market, and the independent variable is the monthly realized of each of the other standard asset classes. Similar to the correlation between monthly returns, there was no evidence of strong and significant volatility spillover effects between markets. Panel B of Exhibit 8 shows the results from a panel regression of the form

$$RVar_{it} = \alpha_i + \beta' RDVar_{asset,t} + \gamma' \text{Controls}_t + \epsilon_{it}, \tag{3}$$

where $RVar_{it}$ is the realized volatility for crypto i, $RVar_{asset,t}$ the realized volatility on a given asset class, Controlst is the set of control variables, α_i is the individual fixed effect, and *tit* is the idiosyncratic error term. We used lagged values of the realized variances of cryptocurrencies and traditional asset classes as control variables and double-clustered standard errors across time and individuals.

Again, there was no significant spillover effect in volatilities between cryptocurrencies and traditional asset classes. As a whole, Exhibit 8 shows that risk in cryptocurrency markets does not correlate with risk in other asset classes. Interestingly, although it was not significant, the correlation between cryptocurrency volatility and the risk in other asset classes seemed to be largely negative.

Trading Volume, Volatility, and Returns

In this section we investigate the relationship among trading volume, volatility, and returns in cryptocurrency markets. A strong relationship between market activity and volatility has been documented in the literature as far as traditional asset classes. Economic theory suggests that variables such as trading volume, the number of transactions, or market liquidity should be tightly related to volatility, as returns movements are primarily due to the arrival of new information and the process that incorporates both public and private information in equilibrium prices (see, e.g., Glosten and Milgrom 1985 and Kyle 1985). Similarly, Kim and Verrecchia (1991) showed that the relationship between price changes and trading volume arises because the size of the trades is positively related to the quality of information in the presence of competition and asymmetric information among traders. Finally, Foster and Viswanathan (1993) and Holden and Subrahmanyam (1992) showed that the same type of positive correlation between volume and volatility can be generated in strategic models, although it might be attenuated by strategic playing of monopolist informed traders or market makers. On the empirical side, a significant part of the literature has documented a strong correlation between traded volume and return volatility in other asset classes. Among others, Gallant et al. (1992) and Andersen (1996) showed that a positive and significant correlation exists between market activity and returns volatility.

To investigate if there is any significant correlation between trading volume, returns, and volatility in cryptocurrency markets, we estimated a set of panel regressions where the dependent variable was change in trading volume (expressed in USD) and the independent variables were both contemporaneous and lagged values of returns and volatility across cryptocurrencies. Exhibit 9 reports the estimation results. We double-clustered standard errors across time and individuals, and

EXHIBIT 8
Volatility Spillovers

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
Panel A: Simple Regression													
Treasury	–286.0*									–9,880			
	(151.8)									(6,909)			
Treasury Developed		–270.9*								9,519			
		(148.4)								(6,768)			
Corporate Bond			–92.60*							–84.03			
			(54.26)							(66.29)			
Real Estate				–5.684							17.39		
				(8.169)							(20.95)		
REIT					–6.064						–20.09		
					(7.241)						(20.19)		
Commodity						–2.545						–1.320	
						(2.789)						(2.097)	
Precious Metals							–6.885					–5.122	
							(7.825)					(7.349)	
Long-Term Vol								0.0590					0.0085
								(0.0427)					(0.121)
Short-Term Vol									0.0520				0.0449
									(0.0395)				(0.112)
Obs.	64	64	64	64	64	64	64	64	64	64	64	64	64
Adj R^2	0.024	0.022	0.0269	0.0051	0.008	0.0091	0.0119	0.0164	0.0178	0.064	0.012	0.0136	0.0178
Panel B: Panel Regression													
Treasury	–10.40									–276.4			
	(6.316)									(180.5)			
Treasury Developed		–9.814								265.4			
		(6.181)								(187.0)			
Corporate Bond			–4.080*							–3.504			
			(2.222)							(2.403)			
Real Estate				–0.142							0.490		
				(0.362)							(1.133)		
REIT					–0.129						–0.489		
					(0.266)						(0.812)		
Commodity						–0.199						–0.200	
						(0.313)						(0.1862)	
Precious Metals							–0.229					0.0103	
							(0.229)					(0.224)	
Long-Term Vol								0.0018					0.0031
								(0.0012)					(0.0078)
Short-Term Vol									0.0015				–0.0011
									(0.001)				(0.0069)
Obs.	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323	6,323
Adj R^2	0.172	0.172	0.173	0.171	0.171	0.174	0.172	0.173	0.173	0.175	0.172	0.174	0.173

*Notes: Panel A: reports the results of a time-series regression where the dependent variable is the realized variance of a value-weighted index of cryptocurrency prices (see Exhibit 2) whereas the independent variable is a set of returns on a traditional asset class. Panel B: reports the results of a panel regression with individual fixed effects in which the dependent variable is the realized variance on a given cryptocurrency, and the independent variable is the returns on one of the traditional asset classes. Standard errors are double-clustered across time and individuals. The sample period is from December 2013 to March 2019. Statistical significance is distinguished with ***, **, and *, for the 1%, 5%, and 10% level respectively.*

Exhibit 9

Trading Volume, Returns, and Volatility

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11
Rett	1.183***			1.319***					1.093***	1.139***	1.232***
	(0.117)			(0.0873)					(0.0975)	(0.0913)	(0.0805)
Rett-1		0.100		0.241***						0.261***	0.248***
		(0.149)		(0.0707)						(0.0841)	(0.0677)
Rett-2			–0.222*	–0.118*							–0.130**
			(0.132)	(0.059)							(0.0693)
RVart					0.234***			0.241***	0.217***	0.223***	0.169***
					(0.0640)			(0.0852)	(0.0380)	(0.0411)	(0.0481)
RVart-1						0.0407		0.0753		–0.0168	0.0658
						(0.0619)		(0.0732)		(0.0405)	(0.0480)
RVart-1							–0.0841*	–0.128***			–0.1121***
							(0.0482)	(0.0460)			(0.0331)
Obs.	6,323	6,022	5,720	5,720	6,323	6,022	5,720	5,720	6,323	6,022	5,720
Adj R^2	0.185	0.128	0.128	0.194	0.136	0.127	0.127	0.134	0.192	0.195	0.199

*Notes: This exhibit reports the results of a panel regression with individual fixed effects in which the dependent variable is the log-change in trading volume, and the independent variables are current and lagged returns and realized volatility. Standard errors are double-clustered across time and individuals. The sample period is from December 2013 to March 2019. Statistical significance is distinguished with ***, **, and *, for the 1%, 5%, and 10% level respectively.*

used lagged values of the changes in trading volume as a control variable.

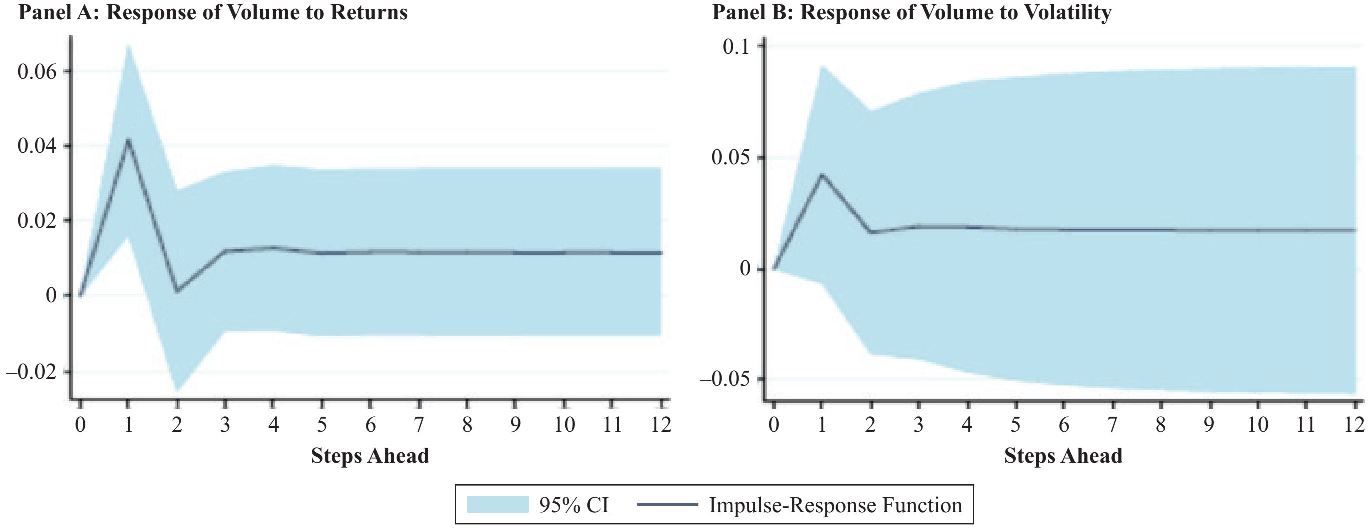
A few interesting aspects emerged. First, there was a significant contemporaneous relationship between changes in trading volume and returns, which held by controlling for both lagged returns as well as both contemporaneous and lagged realized variance. This result is consistent with Karpoff (1987), Gallant et al. (1992), and Schwert (1989), which showed a positive and significant correlation between daily stock returns and contemporaneous changes in trading volume. Similarly, Campbell et al. (1993) and Llorente et al. (2002) provided evidence that trading volumes tend to be higher when stock prices were rising. Bianchi and Dickerson (2018) demonstrated that in cryptocurrency markets, the interaction between current volume and returns can help to predict futures returns with a quite sizeable economic significance.

Second, lagged returns tended to have a positive effect on changes in trading volume, that is, lagged returns were positively correlated with future returns. Third, changes in trading volume and volatility, as proxied by Equation 2, were contemporaneously correlated after controlling for both current and lagged returns as well as lagged volatility. The significant and positive relationship between trading volume and volatility was consistent with some of the existing findings in the equity literature (see, e.g., Gallant et al. 1992 and Andersen 1996), in futures markets (see, e.g., Bessembinder and Seguin 1993 and Chang, Pinegar, and Schachter 1997). Interestingly, lagged volatility had a negative effect on future changes in trading volume. This was consistent with the conventional wisdom that higher uncertainty leads to lower transactions and less liquidity in the near future.

Although informative, the results provided in Exhibit 9 do not tell much as to how, and if, there is a significant effect of *today* returns and volatility changes on *future* average traded volume. To address this issue, we explored the transmission of structural macroeconomic shocks on traded volume by estimating the impulse response functions from a panel Vector Autoregressive (VAR) model. Unlike standard VARs, a panel VAR allows one to explicitly account for dynamic individual inter-dependencies with minimal restrictions. Shocks identification can then be performed by explicitly considering the heterogeneity presents in potentially highly interdependent markets. More specifically, just like standard VARs, all variables were assumed to be endogenous and interdependent. However, we added a cross-sectional dimension to the econometric specification, which gave panel VARs three characteristic features: first, lags of all endogenous variables of all units entered the model for cryptocurrency i, that is, dynamic inter-dependencies. Second, the reduced-form error terms were allowed to

Exhibit 10

Response of Volume to a Change in Returns or Volatility



Notes: This exhibit shows the response of the average monthly change in trading volume to a one-unit shock to past returns (left panel) and past realized volatility (right panel). The dark blue line represents the average impulse response, and the light-blue shaded area represents the 95% credibility intervals, which are obtained by implementing a double non-parametric bootstrap scheme. The latter is a combination of temporal re-sampling and cross-sectional re-sampling (see Kapetanios, 2008 for more details). The sample period is from December 2013 to March 2019.

be correlated in the cross-section of cryptocurrrency returns, that is, static inter-dependencies. Third, the model intercepts were allowed to be currency specific, that is, cross-sectional heterogeneity (see Canova and Ciccarelli 2013 for details).

The vector of endogenous variables contained the average monthly changes in trading volume, the realized returns and the realized volatility as from Equation 2. Exhibit 10 shows the impulse response function (IRF) of traded volume to past returns (left panel) and realized volatility (right panel). The dark line represents the average impulse response and the shaded area represents the 95% credibility intervals obtained by a double non-parametric bootstrap scheme, which is a combination of temporal re-sampling and cross-sectional re-sampling (see Kapetanios 2008 for details).

The left panel shows that a change in returns generated a positive short-term variation in the trading volume. On the other hand, the right panel shows that the future trajectory of trading volume did not directly depend on the level of volatility. As a whole, Exhibit 10 seems to suggest that trading activity in cryptocurrency markets is significantly affected by past performances rather than by risk. These results are consistent and complement earlier works on the effect of investors' sentiment on the time series of stock returns, such as Kothari and Shanken (1997), Neal and Wheatley (1998), Shiller (2000), and Baker and Wurgler (2000), among others.

Trading Volume and Macroeconomic Activity

Anecdotal evidence shows that the initial fuel for Bitcoin investments has been the compounding effect of the intentional devaluation of the Chinese Yuan (CNY) and the capital controls set by the Chinese central government. Both these factors spurred the demand of bitcoins by Chinese investors looking for a safe and anonymous way to send their money offshore.

In this section, we formally investigate the relationship between the traded volume and macroeconomic factors in an attempt to shed some light on the nature of trading activity in cryptocurrency markets. We consider four key factors in addition to a measure of market uncertainty and past performance of cryptocurrencies. The set of macroeconomic indicators comprises a measure of inflation expectations, the slope of the yield-curve, the VIX index (which measures near-term investors' expectations on market volatility and proxies aggregate market uncertainty), and the real effective exchange rate for the US dollar (USD REER). The real effective exchange rate is calculated as the weighted average of the US dollar relative to a basket of other major currencies, adjusted for inflation.[4]

We approximated the short-term expectations for future inflation by using the swap rate of the one-year inflation swap contracts for different countries. Under no-arbitrage, the fixed payment in an inflation swap contract approximates the expected value of inflation up to a risk-premium component which depends, among other factors, on inflation uncertainty and investors' risk aversion and preferences (see, e.g., Fama and Schwert 1977; Buraschi and Jiltsov 2005; Hordahl and Tristani 2007; and Chernov and Mueller 2012). Different measures of expected inflation can be obtained by using alternative approaches such as survey data (see, e.g., Evans 1998, Thomas 1999, and Schmeling and Schrimpf 2011), or econometric modeling (see, e.g., Stock and Watson 1999 and 2010. However, the advantage of inflation swaps is that they trade in active markets. This makes swap rates available at a high frequency and directly reflect expectations of actual market participants (see, e.g., Faust, Wright et al. 2013). In order to have an aggregate measure of expected inflation we extracted the first principal component of the weekly one-year swap rates for the United States, the Eurozone, and the United Kingdom. These represent the biggest and most liquid markets for inflation swaps. The first principal components accounted for about 70% of the cross-sectional variation in the swap rates.

In order to construct an aggregate measure of the yield spread, we took the differential between 10-year and 1-year government bond yield for the United States, the Eurozone, the United Kingdom, China, and Japan, and extracted the first principal component, which accounted for about 60% of the cross-sectional variation in the data.

Exhibit 11 reports the results of a set of panel regressions where the dependent variable was the monthly change in trading volume expressed in USD for a given cryptocurrency. The independent variables were the first-order differences of the first principal components of the inflation swap rates and the yield spreads. In addition, we included one-period changes in the VIX, the USD REER, the past returns for each currency, and

EXHIBIT 11

Trading Volume and Macroeconomic Factors

	M1	M2	M3	M4	M5
Inflation	–0.436				–0.445
	(0.342)				(0.358)
USD TW		–1.989			–3.325
		(1.872)			(2.023)
VIX			0.110		0.116
			(0.0895)		(0.0979)
Interest Rates				–0.0671	–0.0415
				(0.0586)	(0.0593)
Obs.	4427	4777	4771	4413	4413
Adj R^2	0.108	0.107	0.108	0.108	0.109

Notes: This exhibit reports the results of a panel regression with individual fixed effects where the dependent variable is the log-changes in trading volume and the independent variable is a set of proxies for macroeconomic conditions: market-based inflation expectations, the US dollar, aggregate market uncertainty, and the slope of the term structure. Standard errors are double-clustered across time and individuals. The sample period is from December 2013 to March 2019.

the lagged values of the dependent and the independent variables as additional control variables. Standard errors were double-clustered across time and individuals.

The empirical results showed that most macroeconomic indicators were not significantly correlated with market activity. For instance, global inflation expectations, as proxied by the first principal component on the inflation swap rates across major economies, did not affect market activity across cryptocurrency markets. Similarly, although with a positive slope, aggregate market uncertainty did not affect trading volume in the cryptocurrency space. These results held both considering macroeconomic factors in isolation as well as the factors jointly.

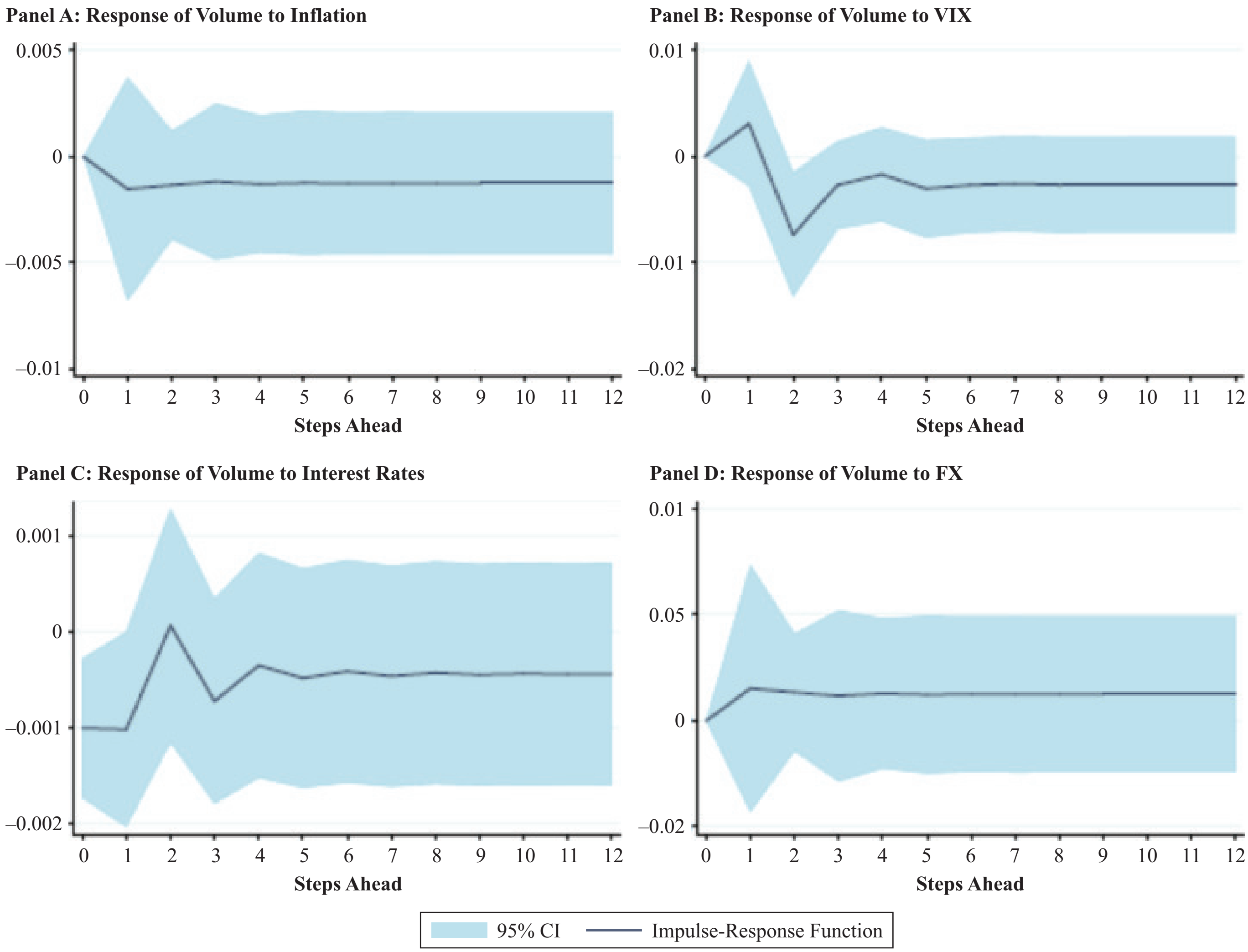
For the sake of completeness, we next investigated the longer-term relationship between changes in macroeconomic factors and trading volume via impulse-response functions. In addition to changes in trading volume, the vector of endogenous variables contains the one-period change in the first principal component of the yield spreads and the inflation swap rates across major economies, as well as the one-period change in the VIX index and the US dollar trade-weighted index.

Exhibit 12 shows the estimation results. The dark line represents the average IRF and the shaded area represents the 95% credibility intervals obtained by a double non-parametric bootstrap scheme, which

[4] The weights were determined by comparing the relative trade balance of the US economy against each country within the basket.

EXHIBIT 12

Response of Volume to Macroeconomic Factors



Notes: This exhibit shows the response of the average monthly change in trading volume to a one-unit shock to a macro-financial factor. Top-left (-right) panel shows the response from a change in inflation expectations (VIX). Bottom-left (right) panel shows the response from a change in the slope of the term structure of interest rates (USD trade-weighted index. The dark blue line represents the average impulse response, and the light-blue shaded area represents the 95% credibility intervals, which are obtained by implementing a double non-parametric bootstrap scheme. The latter is a combination of temporal re-sampling and cross-sectional re-sampling (see Kapetanios 2008 for more details). The sample period is from December 2013 to March 2019.

is a combination of temporal re-sampling and cross-sectional re-sampling (see Kapetanios 2008 for details). The top-left (-right) panel shows the response of trading volume to a change in inflation market expectations (market uncertainty). With the only exception of a small reversal effect two months ahead consequent to a change in the VIX, neither inflation nor the VIX significantly affected market activity. The bottom panels show the change in trading volume due to a change in the slope of the yield curve (left panel) and the US trade-weighted index (right panel). Interestingly, a positive change in the slope of the term structure seemed to marginally lead to a small decrease in trading activity in cryptocurrency markets. The positive effect disappeared quickly after less than two months. On the other hand, changes in the USD index did not generate any significant change in trading volume in cryptocurrency markets.

CONCLUSION

Just as the value of a US dollar investment fluctuates based on countless factors—such as national interest rates, trade deficit with other countries, and government policy—cryptocurrencies trade at prices based on the perceived value of the platforms and projects with which they are associated. In this respect, instead of an investment in a country's economy, holding cryptocurrency can be seen as an investment in the network and the technology behind it.

In this article, we used a detailed data set of prices, traded volumes, and market capitalization for a large set of cryptocurrencies to empirically investigate their relationship with standard asset classes and the main driving factors behind market activity. The main empirical results suggest that, except for a mild correlation with precious metals, there is no significant relationship between returns on cryptocurrencies and more traditional asset classes. The same results apply for volatility spillovers. Also, while volatility correlates with traded volume, the latter is primarily driven by past returns. This is consistent with existing theoretical models in which trading activity is primarily driven by investors' sentiment. Finally, the empirical results provide evidence that macroeconomic factors do not significantly drive trading activity in cryptocurrency markets.

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ADDITIONAL READING

Cryptocurrency Risks

J. Benson Durham
The Journal of Investing
https://joi.pm-research.com/content/29/4/43

ABSTRACT: *Optimizations given historical data unsurprisingly produce sizeable allocations to Bitcoin (XBT). But further analyses of risks raise questions, even abstracting from expected returns. GARCH-based measures of dynamic XBT volatility and covariance suggest that optimal weights change over time. Also, quantile regressions indicate that conditional XBT returns with respect to the S&P 500 are modestly positively skewed. Yet benevolent symmetry is hardly stable or consistent along the distribution. Spectral analysis shows that the XBT volatility primarily owes to higher-frequency cycles. Nonetheless, XBT betas are substantially greater, and notably positive, over longer cycles compared with shorter cycles, which implies that XBT has been a much less effective strategic hedge. Dynamic principal components analysis indicates that individual coins' exposures to the "crypto market factor" have likely increased meaningfully enough over time to diminish diversification benefits.*

Cryptocurrency Survival Analysis

Jan Lansky
The Journal of Alternative Investments
https://jai.pm-research.com/content/22/3/55

ABSTRACT: *Cryptocurrencies are one of the greatest technological innovations. Cryptocurrencies are decentralized payment systems in which ownership is demonstrated cryptographically. An overview of ownership of payment units is stored in a data structure called blockchain. Of the thousands of cryptocurrencies, the best known are Bitcoin, Ethereum, Ripple, Litecoin, EOS, Cardano, NEO, Dash, and Monero. In the past, new cryptocurrencies were most often created by modifying the parameters of another cryptocurrency and by launching a new blockchain. Nowadays, new cryptocurrencies are most commonly created as applications on another existing cryptocurrency. Such cryptocurrencies are called tokens. Creating a new cryptocurrency is easy, but its value depends on users' willingness to pay for its units. If a cryptocurrency loses its users, it becomes worthless. In this article, we analyze over 2,500 cryptocurrencies that are or were previously traded on cryptocurrency exchanges. We have explored the probability that a cryptocurrency will not survive and will be delisted from exchanges. For the different categories of cryptocurrencies according to their previous trading time on exchanges, we have determined the conditional probability of delisting within 1 to 5 years. We found out that the new cryptocurrencies are the riskiest. With the increasing age of the cryptocurrency, the probability of its delisting decreases.*

Cryptocurrency and Blockchains: *Retail to Institutional*

Rand Low and Terry Marsh
The Journal of Investing
https://joi.pm-research.com/content/29/1/18

ABSTRACT: *A reduction in cost of traditional financial intermediation was one of the main motivations cited by Satoshi Nakamoto in a 2008 proposal for "… an electronic payment system based on cryptographic proof instead of trust." We begin here with some back-of-the-envelope calculations of these potential cost savings and benefits from the customer perspective. We then discuss the public blockchain ledger and various solutions to two important problems that are constraints on the public blockchain's trustless consensus, viz. "mining" costs in proof-of-work and governance issues. We speculate that foreseeable institutional implementations will often involve integration of permissioned blockchains with public blockchains. We then discuss exchanges for trading cryptocurrencies, the second component of the crypto blockchains, and in particular their "teething problems," along with the evolution of a subset of them into increasingly "industrial strength" entities. We suggest that with a more industrial strength infrastructure in place, self-executing smart contracts are virtually natural counterparts for more traditional passive investment products. We end with a discussion of Security Token Offerings (STOs) and the newer Initial Coin Offerings (ICOs): STOs are an interesting hybrid between the ICOs and traditional IPOs; they could conceivably pave the way to a long-time-coming "direct electronic IPO" market.*