

The Effect of US Monetary Policy Shock on Cryptocurrency Returns

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Abstract

I explore the effect of US monetary policy shocks on the returns of digital assets since the creation of Bitcoin. A pool of 100 cryptocurrencies are separated into three categories. The monetary policy shocks are measured with two different futures contracts, Fed fund futures and 10-Year bond futures, around a FOMC meeting announcement. With the use of a panel fixed effect model, I find that changes to both futures prices around FOMC meeting have differing effects on the returns of digital assets. In particular, my results suggest that digital assets with deeper integration of blockchain, like digital assets under the dApp category, are more vulnerable to shocks from the long-term forward guidance of FOMC whereas assets with top level blockchain infrastructure, like digital assets under the Currency category, shows no significant effect from either of the monetary policy shocks.

Introduction

In this thesis, I explore the effect of US monetary policy shock on returns of various cryptocurrencies, or digital assets, since the creation of Bitcoin. Monetary policy shocks have been studied in numerous works through various topics, but a broad study incorporating various cryptocurrencies has been missing. Economic fundamentals suggest that as interest rate goes up, returns on risk-free assets grow and this will deter investors away from other investments including cryptocurrencies. This reduction in demand should be reflected in price and therefore, the return. However, the effect of US monetary policy shocks on returns of digital assets isn't very well documented as digital assets are still in their infancy phase.

Throughout the past ten years, many researchers and economists have developed new economic fundamentals regarding this unique classification of assets and continue to build upon the field of literature. Earlier works look at the underlying mechanisms behind the production and maintenance of cryptocurrencies. As more scholars are focusing on the use of cryptocurrencies in the real financial markets (Pieters 2016; Pieters and Vivanco 2017; Demir et al. 2018), economists are interested in the market factors that would affect the valuation and the return of cryptocurrencies even though cryptocurrencies fundamentally have a large speculative

component (Cheah and Fry 2015). However, a large portion of the literature focuses solely on Bitcoin and leaves several other cryptocurrencies behind. Recent increase in blockchain technology has greatly increased the types of digital assets available today. Unlike Bitcoin and its related store-of-value digital assets, these other classifications of digital assets exhibit unique characteristics that are unequally affected by various factors. Because of this, further specification between the three different categories, Currency, Protocol, and dApp, can provide more useful information. Successfully defining these categories is crucial for a thorough understanding as previous literature has emphasized that each category responds differently to certain shocks (Corbet, Larkin, et al. 2017).

1. Currency: most notable digital asset under this category is Bitcoin. As the digital asset market expanded, many new peer-to-peer currencies similar to Bitcoin has emerged. Majority of these alternative coins, or “alt coins”, make minor improvements to Bitcoin source code to improve transaction speed, fees, and ease of use. For the purpose of this study, these are assets whose primary functions are store-of-value or a medium of exchange.
2. Protocol: most notable digital asset under this category is Ethereum. For the purpose of this study, these are digital assets that utilize blockchain to perform a specific data task. These include any form of identification, data management, data manipulation, and contracts.
3. dApp: the term dApp stands for decentralized application and most notable asset is XRP. The term dApp refers to any application where the back-end code is run on a decentralized peer-to-peer network. For the purpose of this study, I define dApp as any

decentralized application built on a blockchain platform. Most easily understood example is a decentralized storage application.

Because dApp has its blockchain element embedded into its decentralized platform away from the user-end, I call this blockchain position the bottom level in the infrastructure level. Currency, on the other hand, has its blockchain element very close to the user-end and therefore, its blockchain position is at the top level. Protocol will lie in the middle between the two levels.

This upcoming research will add onto this currently growing depth of literature on digital assets and cryptocurrencies. For the purpose of this study, cryptocurrencies and digital assets are analogous and used interchangeably. Unlike existing literature, I use variations to measure monetary policy shocks and in doing so, I can measure the direct magnitudes of the shocks on the digital asset exchange rates (Corbet, McHugh, et al. 2017; Corbet, Larkin, et al. 2017; Sovbetov 2018; Polasik et al.). Also, the volatility-level effect of monetary policy shock has been studied previously but direct return-level study with a large pool of digital assets has not been conducted (Corbet, Larkin, et al. 2017). By comparing this effect between the three categories through interaction terms, the varying magnitudes of the effects among the three categories can be highlighted. The remainder of the thesis will be organized as follows. First, brief overview of the literature in cryptocurrency will take place. It will then follow with data and methodology. Results will be presented and will be concluded with a discussion and a conclusion.

Literature Review

In order to successfully create an applicable and an original study, a thorough examination of the existing literature must take place to identify and establish a base of knowledge that is needed for the analysis. According to the very recent St. Louis Fed's report on cryptocurrency, the main purpose behind the initial development of cryptocurrencies was to

develop an electronic transaction system with cash-like characteristics (Berentsen and Schar 2018). Recent surge in popularity within the public has peaked the interests of many economists and researchers regarding the different aspects of this rudimentary classification of digital assets (Kristoufek 2013; van Wijk 2013; Kristoufek 2015; Bouoiyour 2015).

Early literature looks at the underlying mechanisms behind production and maintenance of cryptocurrencies. Cryptocurrencies' unique production function allowed for a new and unique classification of assets and currently, new digital assets are being created in more specific, functional classifications. Cryptocurrencies have been further examined and is compared to traditional fiat money and store-of-value such as gold (Dyhrberg 2016; Baur et al. 2017). Simultaneously, researchers are curious about the pricing and the valuation of cryptocurrencies. Many literatures look at effects of various elements on return and volatility of cryptocurrencies as well. The rest of the review will discuss some of the points above.

1. Technology behind Cryptocurrencies

Since the creation of Bitcoin in 2009 by Nakamoto, the technology behind this emerging cryptocurrency known as blockchain has gained massive traction and has been a focal point of research for many scholars. Blockchain is a technology underlying the distributed public records or a ledger that keeps track of all transactions and or digital events between the participating members for Bitcoin (Nakamoto 2008; Crosby 2015; Peck 2017). It is simply a growing list of blocks that are linked using cryptography. The first ever cryptocurrency, Bitcoin, utilizes this technology to create a purely peer-to-peer electronic cash (Nakamoto 2008). The initial piece of literature published by Nakamoto prior to the public release of Bitcoin outlines many of the basic principles behind cryptocurrencies. Later publication from Bohme et al. (2015) dives deeper and provides a detailed account for the components of cryptocurrencies such as the blockchain

technology, transactions and fees associated with them, wallet, and mining. Both literatures confirm that the utilization of one-way hash function onto a chain of hash-based proof-of-work prevents the problem of double spending. Dwyer (2015) provides a better account of the innate double-spending problem and how the blockchain network can overcome this. The network processes are as follows. Each transaction is timestamped and broadcasted to all nodes. These nodes then individually collect new transactions into a block. These nodes then compute the proof-of-work associated with its block. This proof-of-work is then broadcasted back to all nodes and checked to see if all the transactions are valid. They use the accepted block's hash to create the next block in the chain and this is again broadcasted and repeated. The complex nature and the irreversibility of the one-way hash function and the rigorous process involved in creating a proof-of-work associated with each block prevents the double spending problem as long as the majority of nodes are honest (Dwyer 2015). The limitation of supply created by the production mechanism associated with mining combined with the innate properties of the technology creates an equilibrium with a positive value associated with the digital asset (Dwyer 2015). This conclusion drawn by Dwyer has been cited and supported by later literatures (Corbet, McHugh, et al. 2017; Corbet, Larkin, et al. 2017; Peck 2017). Blockchain is now being utilized in much greater scope than ever before. New digital assets with unique functions associated with blockchain and innovative decentralized platforms based off of blockchain are continuously being created. Constant improvement in the technological sector has further improved blockchain's potential.

2. Characteristics of Cryptocurrencies

One of the first explored topic for cryptocurrencies, specifically Bitcoin, was to determine a classification for this digital asset. Glaser et al. (2014) asks this question and

provides empirical insight on whether consumers are drawn to Bitcoin as a mean for a medium of exchange or store-of-value. They conclude that uninformed consumers are treating Bitcoin as means of alternative investment rather than a medium of exchange. Dyhrberg (2016) further tests this claim using an asymmetric GARCH model. He finds that Bitcoin can be classified as something between gold and traditional currencies and that Bitcoin could be used as a risk management tool in financial markets (Dyhrberg 2016). However, a follow-up replication study could not reliably replicate these results (Baur et al. 2017). This extension states that alternative statistical methods provide a different and a more reliable result. Bauer et al. (2017) claims that the return characteristics of Bitcoin are neither between gold and US dollar nor anywhere close to gold or US dollar but instead resembles a highly speculative asset. These contradicting results require more research to clarify the characteristics of cryptocurrencies. The liquidity of Bitcoin is also discussed amongst scholars. Bitcoin remains fairly liquid in terms of its ability to exchange for currency (Dyhrberg 2016), but according to Bohme et al. (2015), the delay between transactions can span up to an hour which greatly impedes its liquidity. Transaction speed is determined by how much you are willing to pay for the transaction fee, but this issue of liquidity has been reduced greatly as the range of fees have dropped significantly from \$30~50 to \$0.09~0.30 in recent times.

In the past 5 years, the “traditional” application of blockchain, or creation of digital assets mimicking Bitcoin, has shifted from what we have seen previously in other similar cryptocurrencies. Bitcoin, like many of the similar store-of-value digital assets, falls under the Currency category. More digital assets are now under the smaller category of Protocol and dApp instead of the typical Currency category. Protocol refers to digital assets that utilizes blockchain to perform a specific data task. These include Ethereum, a “smart contract” mechanism utilizing

blockchain, and Civic, a secure identification protocol utilizing blockchain. dApp refers to digital assets that base its entire platform on blockchain. These include XRP and XLM which are both payment platform hosted on a decentralized blockchain. Corbet and Larkin's (2017) study divided the top 100 cryptocurrencies into, previously mentioned, three categories, Currency, Protocol, and dApp, depending on its function and the underlying mechanism behind each digital asset. Categorization shown in this particular study highlights the difference in the effect of US monetary policy shock on the volatility of these digital assets between the three categories. The different cryptocurrencies have unique functions and mechanisms, which ultimately are affected by various market factors in unequal magnitudes. This suggests that studies that use prices of various cryptocurrencies should implore a strategy to distinguish the different categories of digital assets in their model. Clearly, there are many factors that might influence the pricing of digital assets that are common to other assets, but some of the confounding results presented above need further examination and replication to clarify the nature of cryptocurrency prices.

Statistical characteristics of cryptocurrency returns have also been studied. One of the first comprehensive look at the fit of GARCH-type modeling has been done by Chu et al. (2017). After testing 12 different GARCH types, authors conclude that IGARCH and GJR-GARCH provide the best fit under five different criteria. Very recent publication from Shaw (2018), however, criticizes the method of Chu et al. (2017) and states that Chu misdiagnosing the distribution of GARCH innovations questions the reliability of Chu's tests. Another article states that SVR-GARCH is a better fit over GARCH, EGARCH, and GJR-GARCH (Peng et al. 2018). As shown in this section, the characteristics and classifications of cryptocurrency remains complicated without a clear consensus.

3. Valuation and Pricing of Cryptocurrencies

When it comes to valuation and pricing of digital assets, first thing that might come into mind is the production function associated with the cryptocurrencies. However, this becomes increasingly problematic due to each cryptocurrencies and digital assets having different methods of creation and maintenance. For Bitcoin, the supply of the currency depends on its own mining process. Whenever a block is verified and added to the blockchain, the miners responsible for that block are rewarded with Bitcoins. The size of the reward is halved every 210,000 blocks mined and currently it is at 12.5 Bitcoin per block added to the blockchain. The difficulty associated with this mining process is correlated with Bitcoin prices (Bedford Taylor 2017). These mineable cryptocurrencies have displayed bigger exposure to volatility spillover effects (Corbet, Larkin, et al. 2017). Early research looked at macroeconomic factors on Bitcoin pricing (van Wijk 2013). According to van Wijk, several of the financial indicators related to the US have a significant effect on the value of the cryptocurrency. Later studies refute some of these indicators, specifically the Dow Jones, exchange rate and the oil price (Ciaian et al. 2016). Total trading volume in the financial market seemed to have no significant effect on Bitcoin prices (Balcilar et al. 2017). Another interesting indicator of Bitcoin is the Wikipedia views on Bitcoin (Kristoufek 2013; Ciaian et al. 2016). Later studies include market beta and volatility to have a significant effect as well (Sovbetov 2018). Series of studies done by Corbet on cryptocurrencies, US and international monetary policy changes show levels of volatility spillover effects on many cryptocurrencies (Corbet, McHugh, et al. 2017; Corbet, Larkin, et al. 2017).

Data

To develop the dataset, I selected the top 100 digital assets based on market cap from cryptocompare.com. The daily closing prices of these assets are obtained using a self-written python code and is included in the appendix. This tool gathers daily prices of various digital assets to my choosing and organizes it into a data table. The 100 different digital assets' closing prices from 1/28/2009~9/20/2017 were collected and divided into three different categories (currency, protocol, dApp). Out of the 100 digital assets, 43 digital assets were removed due to insufficient amount of observations (<90). These prices are represented in terms of log-returns.

To compare the differences between digital assets and other traditional stocks and currencies, additional data set consisting of Amazon, Apple and Microsoft stocks and GBP, CYN, EUR, and CAD exchange rate in USD were created. Stock data was obtained from Yahoo Finance in the form of daily closing price and currency exchange rates were obtained from investing.com in the form of daily closing price as well. The trade-weight US Dollar index was taken from the St. Louis Fed in the form of weekly data and S&P 500 index was taken from Yahoo Finance in the form of daily data.

This research aims to evaluate the effect of US monetary policy shocks on the return of various digital assets. To achieve this, a dataset of US monetary policy shock was constructed. The monetary policy shocks are measured through the change in price of two futures contracts around a FOMC meeting announcement. Both of these futures prices are in the form of daily tick prices and were obtained from CMEGroup. Due to the prices being in tick form, the average of all the trades within the minute were taken.

The first futures contract used to construct the US monetary policy shock is the Fed fund futures (FFF). Fed fund future prices can be used to represent real interest rate and the

expectation of future interest rate due to the nature of the contract. This information can reflect change in the expectation proxied by Fed fund futures prices. This surprise component will measure the unanticipated component of the Fed's decisions (Kuttner 2001). In order to obtain the desired component, manipulation of the prices is needed. First, we start with the equation that shows us the price of Fed fund futures:

$$f_{t,-10} = \frac{d(Realized) + (D-d)(Expected_{t,-10})}{D} \text{ where } D \text{ is the total amount of days in that particular}$$

month and d is the number of days remaining at that time. This equation can be reorganized into the following to isolate the expectation:

$$Expected_{t,-10} = \frac{D}{D-d} (f_{t,-10}) - \frac{d}{D-d} (Realized).$$

For the Fed fund futures surprise, the change in the expectation is the main focus:

$$FFF_t = Expected_{t,+20} - Expected_{t,-20}.$$

By using the same manipulation shown above, the expectation for 20 minutes after the announcement can be calculated. Combining these equations results in the equation that follows:

$$FFF_t = \frac{D}{D-d} (f_{t,+20} - f_{t,-10}) \text{ where } f_{t,+20} \text{ and } f_{t,-10} \text{ represent the prices of the futures.}$$

The second measure of monetary policy shock is from the 10-year treasury bond futures (TBF) as these reflect a future path for the monetary policy. According to previous research, 75-90% of the changes in this treasury bond futures prices are a response to future guidance of the FOMC announcement and therefore can be used to capture the future path of interest rates (Gürkaynak et al. 2005). This is measured as following: $TBF_t = tbf_{t,+20} - tbf_{t,-10}$ where tbf represents the prices of the futures.

Methodology

A panel fixed effect approach will be taken for this study. The standard model is as follows:

$$r_{i,t} = a_0 + a_1FFF_t + a_2TBF_t + \beta X_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t}$$

where i is a particular digital asset and ε is the residuals. I add individual fixed-effect (μ_i) to capture asset-specific elements as well as time fixed-effect (γ_t) to capture time-specific elements. FFF_t and TBF_t represent the monetary policy shocks as previously defined. $X_{i,t}$ are control variables in the same dimensions as $r_{i,t}$. These include Trade-Weighted US Dollar index in order to control for variations in price due to variations in dollar value. S&P 500 index is also included in this vector of control variables to account for variations attributed to stock market trends. This model will capture the effect of Fed fund futures and 10-year treasury bond futures surprises on the digital assets. To better understand the differing effects between categories, dummy variables will be created depending on the asset type and interaction terms will be added. The updated model is as following:

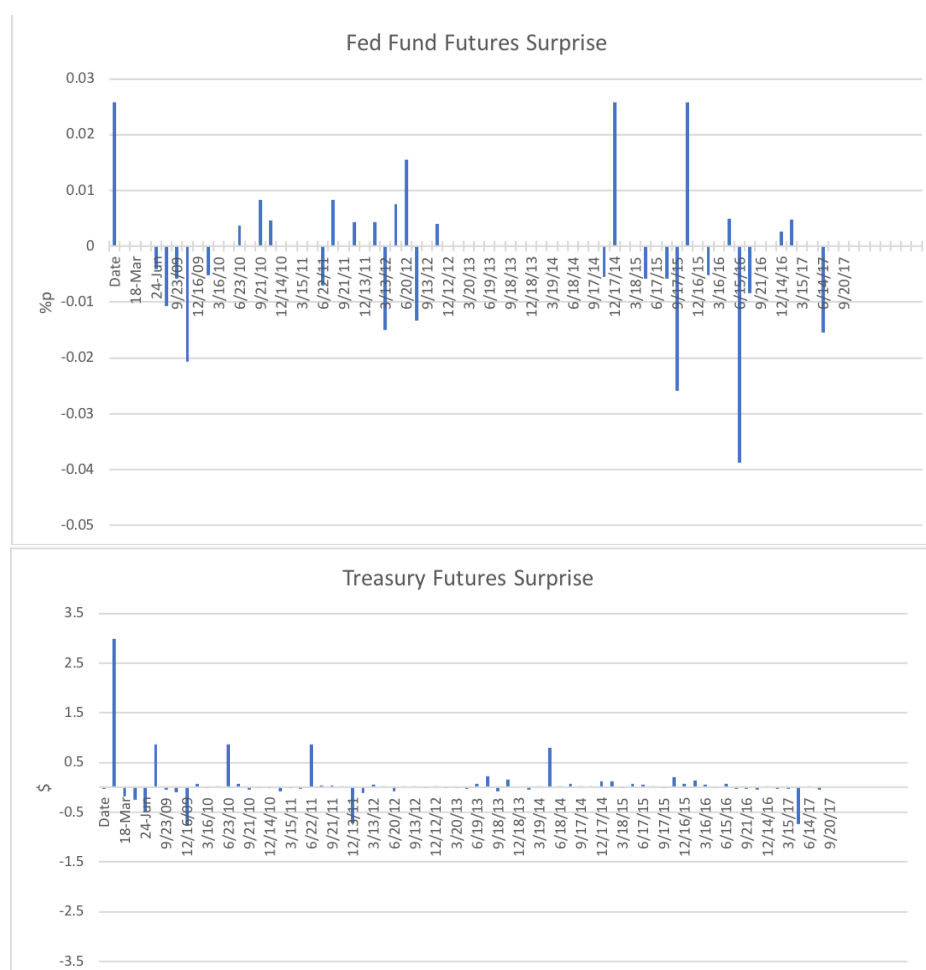
$$r_{i,t} = a_0 + a_1FFF_t + a_2TBF_t + a_3FFF_tProtocol + a_4FFF_tdApps + a_5TBF_tProtocol \\ + a_6TBF_tdApps + \beta X_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t}$$

This particular specification incorporates interaction terms in addition to the previous models. Terms Protocol and dApp are dummy variables with value 0 or 1 depending on the asset's category. This will capture the effects of the two futures surprises based on the category of the digital assets, Protocol and dApp, compared to the baseline group, Currency. a_1 represents the effect of Fed fund futures (FFF) surprises on Currency returns. a_2 represents the effect of 10-year treasury bond (TBF) surprises on Currency return. a_3 represents the additional effect of FFF surprises on Protocol compared to Currency. a_4 represents the additional effect of FFF surprises on dApp compared to Currency. a_5 represents the additional effect of TBF surprises on Protocol compared to Currency. a_6 represents the additional effect of TBF surprises on dApp compared to Currency. $a_1 + a_3$ represents the effect of FFF surprises and $a_2 + a_5$ represents the effect of

TBF surprises on Protocol returns. Lastly $a_1 + a_4$ and $a_2 + a_6$ represent the effect of FFF and TBF surprises on dApp.

Results

Figure 1: US Monetary Policy Shocks

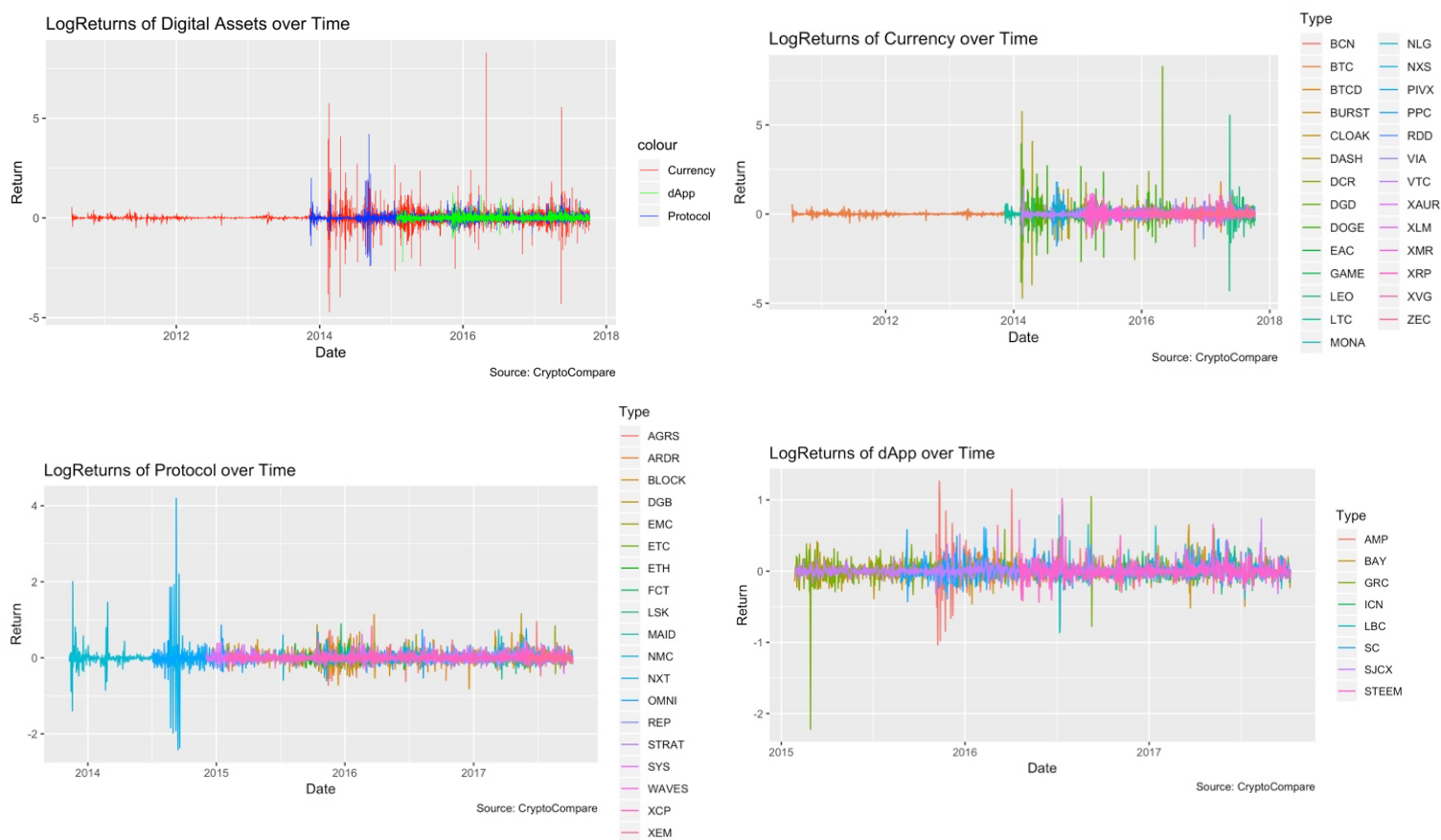


The two different types of measure for the US monetary policy shocks are first graphically presented through the two graphs that show the over-time snapshots of the shocks. The fed fund futures are used as a proxy to the interest rate change seen in the market. Because of this, the unit of measurement for FFF surprise is in % point change to the interest rate. This change in the expectation should reflect the short-term interest rate shock contained in the FOMC announcement. Treasury bond futures, however, are represented as a simple change in price, in USD, around the announcement time because the price change associated with the

treasury bond futures largely incorporate the forward guidance and the expectation of the future through the FOMC announcement (Gürkaynak et al. 2005).

Following is the graphical representation of all of the digital assets in the data set and it is further subdivided into corresponding groups.

Figure 2: Graphs of Digital Asset Returns



Some characteristics of the digital asset as well as each category can be explored and highlighted. First, most cryptocurrencies tend to have greater variation in price throughout their respective infancy stages. Not only this, but the patterns of variation also vary amongst the three groups. Currencies exhibit greatest volatility whereas dApps exhibit the lowest volatility. As the blockchain position moves further down the infrastructural level, volatility of the given digital

asset generally goes down. This variation on some of the key statistics suggests that there are factors that apply unequal pressure depending on the blockchain position and its integration. This further incentivizes the introduction of interaction terms to separate the effects of each group.

Table 1: Regression Results of Digital Assets

	<i>Dependent variable:</i>			
	Log(return) (%)			
	(1)	(2)	(3)	(4)
FFF	-0.048 (0.372)	0.036 (0.385)	0.053 (0.477)	0.135 (0.538)
TBF	0.087** (0.037)	0.095*** (0.035)	0.053 (0.041)	0.062 (0.040)
FFF X Protocol			-0.013 (0.564)	-0.001 (0.567)
FFF X dApp			-0.646 (0.793)	-0.654 (0.802)
TBF X Protocol			0.071*** (0.022)	0.070*** (0.023)
TBF X dApp			0.084** (0.037)	0.084** (0.038)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01				

The regression table 1 includes 4 separate regressions. All regressions include individual fixed effects for each digital asset. Regression (1) and (2) include no interaction terms for the three categories. Regression (3) and (4) include the interaction terms for Protocol and dApp categories. Regression (2) and (4) include time fixed effects by year. The coefficients on the both fixed-effects and control variables are omitted. All coefficients' standard deviations have been clustered by time to account for within-time correlation and heteroscedasticity across the cryptocurrencies, *i*. A 1 dollar increase in TBF price will result in a 8.7% increase in return and

9.5% with the addition of time fixed-effects. A 1%p increase in interest rate will result in a -4.8% in return and 3.6% with the addition of time fixed-effects. The magnitude of these effects, in reality are quite minimal as realistic shocks will range anywhere from -0.05%~0.05%p change and \$-0.25~\$0.25 change in price.

To better understand how different groups might react to the same shock, we introduce interaction terms into the regression in (3) and (4). Once the interaction terms are included into the regression, the coefficients change significantly. For FFF surprise and Currency, we see 5.3% in return and 13.5% with time fixed-effects for 1%p increase in interest rate. Even though the sign of this coefficient is not according to the previous expectation, this is a very small value close to zero in real life scenarios as mentioned above and suggests that short-term interest rate shocks from the FOMC announcements have almost no effect on Currency. For FFF surprise and Protocol, we see an additional -1.3%p in return for (3) and 0.1%p in return for (4) for 1%p increase in interest rate. For FFF surprise and dApp, we see an additional -64.6%p in return and -65.4%p in return with time fixed-effects for 1%p increase in interest rate compared to Currency. Unlike the other two categories, these are very large coefficients that translate into a sizeable effect under real life scenarios. This suggests that short term interest rate shock in response to FOMC announcements have minimal effect on digital assets under Currency and Protocol but has an effect on dApp returns. However, it is worth noting that none of the coefficients under FFF surprises were significant. For TBF surprise and Currency, we see a 5.3% in return and 6.2% with time fixed-effects for \$1 increase in TBF price. Like FFF surprises, this effect is quite minimal under real life scenarios. For TBF surprise and Protocol, we see an additional 7.1%p in return for \$1 increase in TBF price in regression (3) and 7.0%p in regression (4). TBF surprises and dApp showed an additional 8.4%p in return for \$1 increase in TBF price in (3) and (4).

Protocol and dApp both showed coefficients with sizeable magnitudes in real life scenarios unlike Currency. This suggests Currency will show minimal effect to TBF surprises but both Protocol and dApp are sensitive to TBF surprises. We see significance for TBF surprises under Protocol and dApp categories in both (3) and (4) but not for any of the other coefficients.

Table 2: Regression Results of Traditional Stocks & Currencies

	<i>Dependent variable:</i>	
	Traditional Stocks (1)	Traditional Currencies (2)
FFF	-0.346*** (0.130)	-0.106*** (0.033)
TBF	0.002 (0.003)	0.004*** (0.001)
Observations	6,624	9,144
R ²	0.001	0.006
Adjusted R ²	0.001	0.005
F Statistic	3.979** (df = 2; 6619)	26.029*** (df = 2; 9138)

Note: *p<0.1; **p<0.05; ***p<0.01

Additional regressions were undertaken with a panel of traditional stocks (1) and currencies (2). Both of these regressions included individual fixed effects but no time fixed effects. Traditional stocks showed that 1% increase in interest rate results in -34.6% return and 1 dollar increase in TBF prices results in +0.2% return. As expected, traditional stocks are extremely sensitive to the short-term interest rate shocks from the FOMC announcements but shows almost no sensitivity to the long-term forward guidance of FOMC announcements. Traditional currencies also exhibit some sensitivity to FFF surprises but not as significant as stocks. 1% increase in interest rate results in -10.6% change in exchange rate and 1 dollar increase in TBF price results in a +0.4% change in exchange rate. TBF surprise coefficient for traditional stocks showed no significance but all other coefficients showed strong significance.

Discussion

These results show that Fed fund futures have near zero effect on the return of Currency and Protocol. This implies that these digital assets under the category Currency and Protocol show little to no sensitivity to the short-term interest rate shocks associated with the FOMC announcements. dApp, however, had a substantially large negative coefficient associated with the FFF surprises. Digital assets under dApp experience the short-term effects of monetary policy shock unlike Protocol and Currency, but the exact magnitude is hard to pin down due to its confidence. For the 10-year treasury bond futures, Currency yields a small positive but insignificant coefficient whereas Protocol and dApp yield substantially positive and significant coefficients. This suggests that Protocol and dApp are sensitive to the long-term future guidance associated with FOMC announcements whereas assets under Currency are not. dApp showed a negative effect from FFF surprises and a significant positive effect from TBF surprises. This suggests that dApps are sensitive to both short-term interest rate shocks and the long-term forward guidance associated with FOMC announcements whereas assets under Currency are generally insensitive to both. Assets under Protocol are insensitive to short-term interest rate shocks but are sensitive to the long-term forward guidance of FOMC meeting announcements. This is somewhat in line with the previous literature as these authors pointed out that cryptocurrencies show minimal to no effect from many of the traditional market factors and shocks (Chiu and Koepl 2017; Sovbetov 2018; Catania et al.). The results of this study show that some of these digital assets show minimal to no effect but also a good selection of digital assets show sensitivity to US monetary policy shocks. As many of the previous studies focus solely on Bitcoin or a small panel of digital assets that are similar to Bitcoin, one can see the reason for such inconsistency. These results highlight the fact that short-term interest rate shocks

as well as the long-term forward guidance associated with FOMC announcements have differing effects depending on the level of the application layer. These results seem to point out that the different level of application layer might not be affected the same way from common factors in the financial market.

The recent surge of popularity in blockchain technology has influenced the digital asset market. However, this surge of popularity could have affected various application layers differently. The inherent higher volatility of these digital assets under Currency and Protocol seems to suggest that the prices have a speculative component that is correlated to public awareness and media portrayal which isn't as apparent for dApp as previous studies have demonstrated (Corbet, Larkin, et al. 2017). The effect of public seems to be greater when the blockchain-tokens are utilized at the top application layer because not only is it simply easier to advertise a digital asset with a top application layer due to its popularity over the other two categories as shown by some of the market capitalization statistics but many of the maintenance and production of the digital asset itself involve heavy public involvement at the higher level application layer. Because of this, monetary policy shocks could have a lesser effect on the digital asset return with top blockchain application layer since this asset would have bigger involvement from the public and its users. As shown here, Currency have no significant effect from either FFF or TBF surprises and suggests that it is more reliant on other non-traditional market factors, possibly public awareness and involvement as previous literatures have mentioned (Nakamoto 2008; Balcilar et al. 2017). This becomes more apparent when comparing some of the digital assets' characteristics. Many of the digital assets that fall under the category Currency are minable, and therefore users indirectly control the supply, whereas many digital assets under dApp are not minable, and therefore users have less control over the supply.

Protocol lies somewhere in the middle where some are minable, and some aren't depending on their function. Further research could be conducted to better understand the varying levels of public involvement and its effect on cryptocurrency return.

Another possible explanation can be attributed to the function-specific marketability, or the asset's unique value proposition. When you look at the category Currency, many of these assets are Bitcoin derivatives and are competing for the number two spot after Bitcoin. They do incorporate certain amounts of improvement compared to each other but generally speaking, they are all similar. In this category, Bitcoin holds the lead by a large margin and all other smaller assets are competing based on luck as these assets don't offer something drastically new and exciting. Incremental improvements with transaction speed and fees don't attract heavy amounts of investors as they are still analogous to Bitcoin. This unpredictability of assets under Currency category could potentially overshadow any of the monetary policy shocks on these assets. When you look at Protocol or dApp, many of the popular assets provide a unique function or hold a unique value. Ethereum is the first "smart contract" to be executed on a blockchain platform and holds a strong position in the market. XRP is one of the first decentralized platforms based on blockchain. Newer assets like Stellar, which is a dApp that is a payment platform, can offer new and exciting innovation unlike assets under Currency which are mundane. These assets under Protocol and dApp categories have inherent value and are much less reliant on public movement as each asset provides a unique function that is desirable and therefore, Protocol and dApp could be more sensitive to traditional market factors as they exhibit more characteristics of a traditional asset. Creating more specific categories to better classify these new digital assets by functional characteristics will be of great help for future research.

To further this analysis, the results from the digital asset regressions and traditional asset/currency regressions were compared. The effect of FFF surprises on traditional stocks is a large negative coefficient that is also significant. This effect is greater than both Currency and Protocol by a large margin. Traditional currencies also displayed a significant negative coefficient but smaller in magnitude. dApp, however, still showed the greatest effect from FFF surprises. Looking at these results, we see that dApp behaves closest to traditional stocks under short-term interest rate shock. Unlike the effect of FFF surprises, the effect of TBF surprises on both traditional stocks and currencies are very minimal while only the effect on currencies is significant. This suggests that digital assets in general are much more sensitive to the long-term forward guidance associated with FOMC announcements than traditional stocks and currencies. The lack of regulation and governance could potentially attribute to this sensitivity as newer regulatory measures and the long-term expectations of digital assets to the Fed can have large influence on the digital asset market.

The central limitation of this study is the strict-exogeneity assumption. This assumption is violated when feedback from dependent variable affects future values of the explanatory variables. Unfortunately, many of the dependent variables of interest in financial settings are almost surely related to subsequent explanatory variables (Grieser and Hadlock 2015). This can create problems with the consistency of estimators, but it is difficult to make a strong statement regarding the magnitude of the inconsistency. This problem of inconsistency has the order of $1/T$ which suggests that as T , or time period, grows larger, the problem of inconsistency grows smaller, but this result depends on the presence of stable fixed-effects. Under this strict exogeneity assumption, mean differenced errors are uncorrelated with any regressors from any

time period. To explore the intuition behind the violation of this assumption, I will use a simpler model to discuss the assumption. Imagine a model as follows:

$$r_{i,t} = a_0 + a_1 FFF_t + \mu_i + \gamma_t + u_t$$

where u_t is the error term at time t . For the strict exogeneity assumption to hold, this model must satisfy following equation $E(u_t|X_s) = 0$ where s equals any time value t and X equals any explanatory variable. A monetary policy shock at time t will likely have an impact on the future values of digital asset returns as these shocks might persist through the next couple days. This line of thinking suggests that the error term has components of FFF_{t-n} where $n > 0$. Because of this, we can conclude that there will be some level of correlation between the error at time t and FFF_{t-n} . This correlation violates $E(u_t|FFF_s) = 0$ and introduces a positive bias because the a_1 coefficient will begin to capture the additional effects of FFF_{t-n} that is residing in the error term. According to Grieser and Hadlock (2015), less conventional approaches like GMM estimators can provide better results. A further study with a different method of estimation like GMM can prove beneficial.

Conclusion

As the results show, US monetary policy shocks have uneven and varying effects on digital assets depending on their functional categories. Digital assets under the category Currency show no sensitivity to either of the surprises. Assets under Protocol show no sensitivity to short-term surprise but show sensitivity to the long-term guidance of FOMC announcements. Assets under dApp show sensitivity to both of the surprises. It is clear that some classifications of digital assets behave in a unique and an unpredictable manner with large speculative

components like previous literatures have claimed but some digital assets, depending on its functional characteristics, behave more closely to traditional stocks and currencies.

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Appendix I: Python Code for Data Set

```

import requests
import pandas as pd
import matplotlib.pyplot as plt

def get_data_spec(coin, date, time_period):
    url = "https://min-api.cryptocompare.com/data/{0}?fsym={1}&tsym=USD&limit=2000&tc"
    r = requests.get(url)
    ipdata = r.json()
    return ipdata

def get_df_spec(time_period, coin, from_date, to_date):
    date = to_date
    holder = []
    while date > from_date:
        data = get_data_spec(coin, date, time_period)
        holder.append(pd.DataFrame(data['Data']))
        date = data['TimeFrom']
    df = pd.concat(holder, axis = 0)
    df = df[df['time'] > from_date]
    df['time'] = pd.to_datetime(df['time'], unit='s')
    df.set_index('time', inplace=True)
    df.sort_index(ascending=False, inplace=True)
    df.rename(columns={'close': coin}, inplace=True)
    return df[coin]

coins = ['BTC', 'ETH', 'XRP', 'LTC', 'ETC', 'XEM', 'DASH', 'IOT', 'BTS', 'XMR', 'SI
holder = []
from_date = 1231459200 # Creation of BitCoin
to_date = 1547736702 # 01/17/2019 2:51UTC
time_period = 'histoday'
for coin in coins:
    holder.append(get_df_spec(time_period, coin, from_date, to_date))
df = pd.concat(holder, axis = 1)
df.to_excel('cryptoprice.xlsx', sheet_name='sheet1', index=False)

```
