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Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index

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Synonyms

Coinbase Index; Inflation expectations; LIBOR; Long-run effects; Short-run effects

Definitions

Coinbase Index (CBI): This index tracks the performance of the digital assets listed by Coinbase, which is weighted by the market capitalization.

One-month London Interbank Offered Rate (LIBOR): The London Interbank Offered Rate is the average interest rate at which the large banks borrow money from other banks in the London market. It is also used as a proxy for the short-term interest rate.

Five-year inflation expectations (FYIE): Measures the expected inflation for the 5-year period that starts from today.

Introduction

A number of international financial institutions, particularly the European Central Bank (2012), have emphasized that investment in cryptocurrencies is sustainable as it does not stimulate financial instability. Some of the common reasons why cryptocurrencies do not stimulate financial instability are as follows (Corbet et al. 2018): (1) lack of connection to the economy, (2) lack of acceptance, and (3) low volume of currency trading. However, recently with a massive growth of investment in the cryptocurrency markets, the global financial working group is only monitoring how the growth of investment in cryptocurrencies can stimulate financial instability. The Coinbase Index is a broad measure that captures the block position as it incorporates the weighted average of the listed digital assets being traded in the USA (Coinbase Incorporation 2019).

Moreover, this index is affected by changes in inflation expectations and LIBOR due to three reasons. First, investors will compare their returns on digital currencies and financial products offered to customers in the financial markets. With the growing investment in blockchain currencies, it is indicative that digital currencies are gaining investor confidence (Corbet et al. 2018). Second, LIBOR influences the interest rate on financial products provided by the banks and non-bank financial institutions. If the interest rate decreases for competing investments, it is likely that investors will invest in cryptocurrencies as

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compared to competing investments (Corbet et al. 2018). Third, if inflation is expected to increase, interest rates will also increase, and this will have an impact on the investment in digital currencies (Corbet et al. 2018).

This paper seeks to investigate the relationship between LIBOR, FYIE, CBI, and CBI returns. Specifically, this paper embarks by determining the volatility relationship in the LIBOR, FYIE, CBI, and CBI returns model. Finally, the Granger causality test is employed to determine bivariate causality between LIBOR, FYIE, CBI, and CBI returns. To date, none of the existing studies have explored the relationship between LIBOR, FYIE, CBI, and CBI returns. There are a handful of studies that have explored the behavior of digital currencies and how investors respond to volatility in digital currencies (Corbet et al. 2018). This paper undertakes a stern effort by exploring the impact of LIBOR and FYIE on the CBI and CBI returns. Figure 1 shows that after the year 2017, there has been a sharp growth in the CBI, with LIBOR increasing and FYIE following a positive and negative cyclical pattern, thus implying that the investor confidence in the digital currencies has greatly increased. Figure 2 shows that FYIE is more volatile than CBI and LIBOR. This paper is divided into five sections. Section "Data and Research Design" outlines the data collection and research design. Sections "Empirical Results and Discussions" and "Discussions" present the empirical results and discussions. Section "Conclusion" presents the conclusion.

Data and Research Design

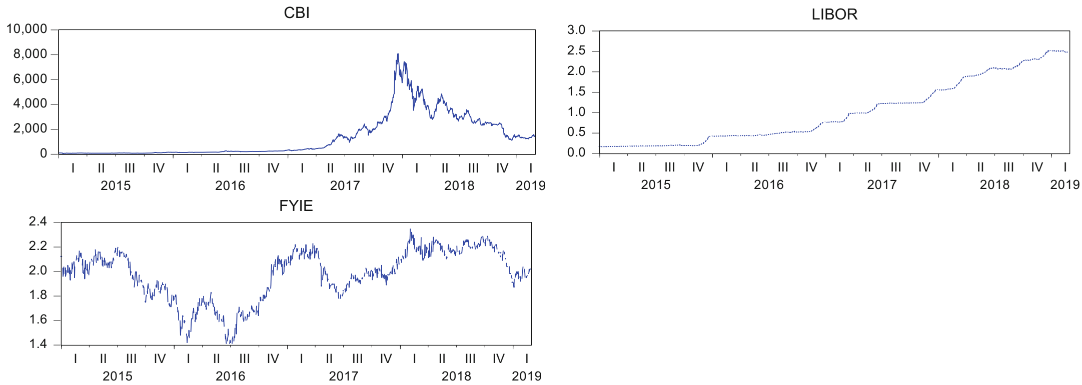
Testing the Relationship Between Inflation Expectations, LIBOR, and Coinbase Index

Investment is a complex and dynamic phenomenon that is driven by changes in human behavior. As the global society is moving toward the digital economy, investors have also started investing in digital assets. There are a number of advantages of investing in digital assets (Zhu and Zhou 2016; Crosby et al. 2016; Morabito 2017; Mainelli and Milne 2016). First, a number of studies have confirmed that digital assets provide approximately two digit returns every month. Second, digital assets provide a pessimistic stream of income and allow investors superior control over return on investment. Third, investing in digital assets implies that there will be a lower overhead cost. The costs associated with rent, electricity, and physical facility maintenance are eliminated when we invest in digital assets.

Undoubtedly, the investment in digital assets has grown significantly in the last 5 years. A close synthesis of existing literature confirms that studies on the blockchain market have started emerging in the top tier journals (Dyhrberg 2016a, b; Baur et al. 2018; Giudici and Abu-Hashish 2018; Smales 2018). Dyhrberg (2016a) noted asymmetric GARCH phenomena in the Bitcoin model to manage risk in the blockchain market. Expanding her previous study, Dyhrberg (2016b) confirmed that Bitcoin has the same hedging capabilities as gold. Baur et al. (2018) confirmed that Bitcoin demonstrates different volatility as compared to gold and other financial assets. Giudici and Abu-Hashish (2018) argued that Bitcoin prices are interconnected with other trading exchange prices. Smales (2018) found that Bitcoin prices are more volatile than other exchange commodities. This study contributes to the existing literature in two ways. First, most of the existing studies on blockchain market have compared the volatility of the cryptocurrencies with other financial assets. None of the existing studies have captured the drivers of volatility in the digital assets index. This study expands the literature by exploring how LIBOR and inflation expectations affect volatility in CBI and CBI returns. Second, this study also explains the impact of positive and negative shocks on CBI and CBI returns. None of the existing studies have captured this phenomenon on the digital assets.

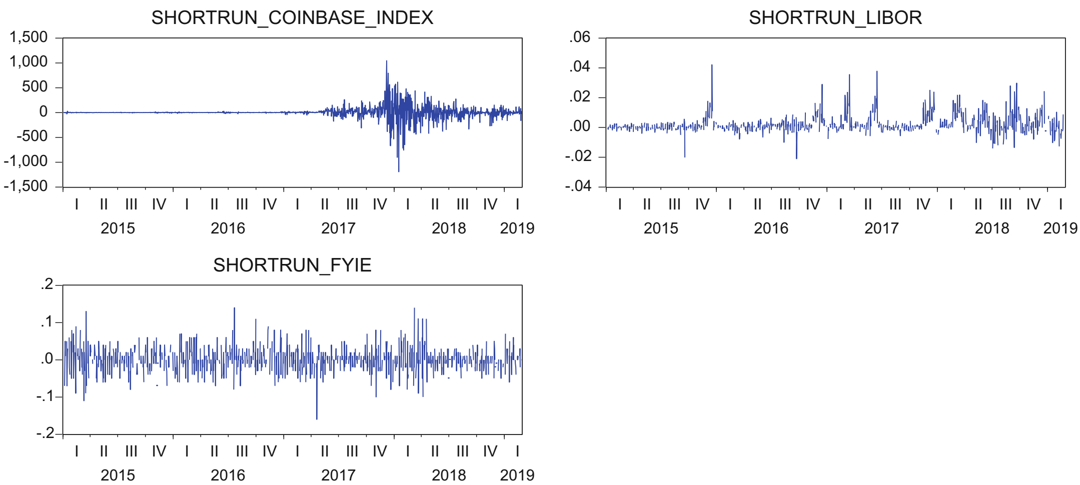
Data

The data for this study was extracted from the FRED economic database (FED). Table 1 provides the details of the variables used in this study. All the variables were converted into the log form before the analysis was conducted.



Source: Developed by the author by using the Eviews 8 software, (2019).

Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index, Fig. 1 Coinbase Index, LIBOR, and FYIE. (Source: Developed by the author by using the EViews 8 software (2019))



Source: Developed by the author by using the Eviews 8 software, (2019).

Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index, Fig. 2 Short-run changes in Coinbase Index, LIBOR, and FYIE. (Source: Developed by the author by using the EViews 8 software (2019))

ARCH Heteroskedasticity Test

The rationale for using this test is to determine the volatility in the time series data as the volatility in the residuals of the long-run model is related to the most recent residuals. The ARCH heteroskedasticity test helps us to determine whether volatility is present in the time series data and the possibility of conducting the GARCH/TGARCH and EGARCH models to capture the volatility in the time series data (Guirguis 2018).

GARCH/TGARCH and EGARCH

The ARCH family models are based on two specifications, and these specifications are as follows: (1) conditional mean equation for conditional variance and (2) conditional mean equation for conditional error distribution. A GARCH (1,1) specification used in this paper is as follows (Katsiampa 2018; Ulusoy and Onbirler 2017):

$$CBI_t = X_t^{\prime\forall} + \varepsilon_t \tag{1}$$

Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index, Table 1 Details on financial variables used in this study

No.	Variable name	Period	Data definitions
1	Coinbase Index (CBI)	01-01-2015 to 02-27-2019	This index tracks the performance of the digital assets listed by Coinbase, which is weighted by the market capitalization. https://fred.stlouisfed.org/series/CBCCIND, February 28, 2019
2	One-month London Interbank Rate (LIBOR)	01-01-2015 to 02-21-2019	The London Interbank Offered Rate is the average interest rate at which the large banks borrow money from other banks in the London market. It is also used as a proxy for the short-term interest rate. https://fred.stlouisfed.org/series/USD1MTD156N, February 28, 2019
3	Five-year inflation expectations (FYIE)	01-01-2015 to 02-27-2019	Measures the expected inflation for the 5-year period that starts from today. https://fred.stlouisfed.org/series/T5YIFR, February 28, 2019

Source: Developed by the authors of this paper (2019)

$$\vartheta_t^2 = \tau + \beta\epsilon_{t-1}^2 + \beta\vartheta_{t-1}^2 \tag{2}$$

Equation 1 captures the mean equation and Eq. 2 captures the variance equation. In Eqs. 1 and 2, τ is the constant term, ϵ_{t-1}^2 captures the news about the volatility in the previous period, and ϑ_{t-1}^2 is the GARCH term.

Short-Run and Long-Run Model

The short-run and long-run models used in this paper for estimation are captured in Eqs. 3 and 4. The long-run model is specified as follows (Naidu 2017):

$$CBI_t = \beta_0 + \beta_1 FYIE_t + \beta_1 LIBOR_t + \in_t \tag{3}$$

The short-run model is specified as follows:

$$CBIR_t = \beta_0 + \beta_1 \Delta FYIE_t + \beta_1 \Delta LIBOR_t + \in_t \tag{4}$$

In Eqs. 3 and 4, CBI_t and $CBIR_t$ represent Coinbase Index and Coinbase Index returns, β_0 is constant, $\Delta FYIE_t$ is change in FIYE, $\Delta LIBOR_t$ is the change in LIBOR, and $\in_t$ is the error term.

Pairwise Granger Causality Test

The bivariate regressions that capture the pairwise Granger causality test are specified as follows (Balboa et al. 2015; Farooq and Hamouda 2016):

$$\mathrm{CBI_t} = \beta_0 + \vartheta_1 CBI_{t-1} + \ldots + \vartheta_1 CBI_{t-l} + \vartheta_1 LIBOR_{t-l} + \ldots + \vartheta_1 LIBOR_{-l} + \in_t \tag{5}$$

$$\mathrm{LIBOR_t} = \beta_0 + \vartheta_1 LIBOR_{t-1} + \ldots + \vartheta_1 LIBOR_{t-l} + \vartheta_1 CBI_{t-l} + \ldots + \vartheta_1 CBI_{-l} + \in_t \tag{6}$$

$$\mathrm{FYIE_t} = \beta_0 + \vartheta_1 FYIE_{t-1} + \ldots + \vartheta_1 FYIE_{t-l} + \vartheta_1 LIBOR_{t-l} + \ldots + \vartheta_1 LIBOR_{-l} + \in_t \tag{7}$$

$$\mathrm{LIBOR_t} = \beta_0 + \vartheta_1 LIBOR_{t-1} + \ldots + \vartheta_1 LIBOR_{t-l} + \vartheta_1 FYIE_{t-l} + \ldots + \vartheta_1 FYIE_{-l} + \in_t \tag{8}$$

$$\mathrm{CBI_t} = \beta_0 + \vartheta_1 CBI_{t-1} + \ldots + \vartheta_1 CBI_{t-l} + \vartheta_1 FYIE_{t-l} + \ldots + \vartheta_1 FYIE_{-l} + \in_t \tag{9}$$

$$\mathrm{FYIE_t} = \beta_0 + \vartheta_1 FYIE_{t-1} + \ldots + \vartheta_1 FYIE_{t-l} + \vartheta_1 CBI_{t-l} + \ldots + \vartheta_1 CBI_{-l} + \in_t \tag{10}$$

The Granger causality test reports the F-statistics for the possible pairs of (x, y) series which is captured in Eqs. 5, 6, 7, 8, 9, and 10.

Empirical Results and Discussions

Figure 3 shows that from the year 2015 to 2016, a positive and negative cyclical pattern was noted for the volatility in residuals, which moved around an average of 0.5 and −0.5. Two positive peaks were noticed between the year 2015 and 2016. The first positive peak was few decimal places above 0.5, and the second positive peak was noted during January 2016. Negative volatility effects were recorded between the periods 2016 and 2017. The negative volatility effects reached its negative peak of −0.1 between July and October. The model recorded positive volatility effects from November 2016 to January 2018 and negative volatility effects from 2018 to 2019.

Additionally, the results of the autoregressive conditional heteroscedastic (ARCH) test show that the null hypothesis of no ARCH effect is rejected at 1% level of significance. In other words, we can run the GARCH/TGARCH and EGARCH models to estimate the relationship between FYIE, LIBOR, and CBI (Table 2).

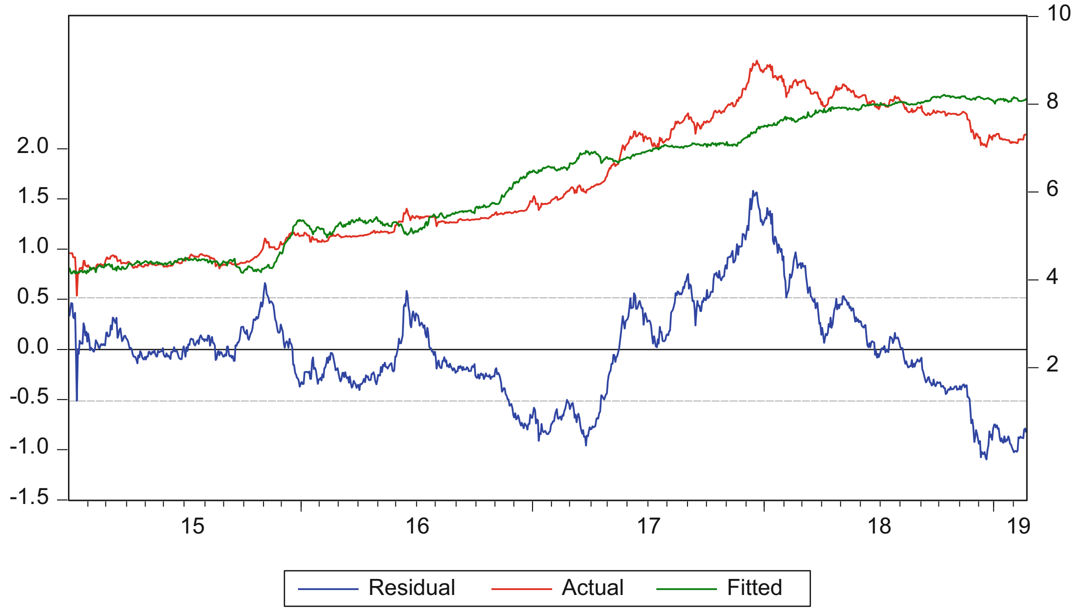
The summary statistics indicate that there is large difference between the maximum and minimum values of the CBI. The difference is around 8044.30142 for CBI, and this difference is insignificant for LIBOR (2.356) and FYIE (1.21). The skewness of LIBOR and CBI is positive as compared to FYIE, which is negative. The kurtosis values indicate that our sample has positive excess kurtosis, as all the kurtosis values are close to or more than 2 (Gujarati and Porter 2010) (Table 3).

Table 4 captures the results of the GARCH/TGARCH and EGARCH models. Specifically, coefficient 3 in the EGARCH shows that there is a negative and statically significant level of last period or short period volatility in the model. In the long run, volatility in the LIBOR and FYIE has a positive and statistically significant impact on CBI and CBI returns. The magnitude of the coefficients indicates that CBI returns are greatly affected by volatility in the LIBOR and FYIE as compared to CBI. Coefficient 5 indicates that negative shocks in the model have a greater impact on volatility in CBI and CBI returns as compared to positive shocks of the same intensity. This clearly indicates that negative news that drives inflation expectations and LIBOR will have greater impact on volatility of CBI and CBI returns. Therefore, it can be concluded from our model that we have an asymmetric volatility spillover effect. The GARCH coefficients are negative for both CBI and CBI returns. The impact of FYIE volatility is highest on CBI returns as compared to CBI. In comparison with the EGARCH model, the GARCH/TGARCH model recorded a positive and highest constant in the volatility equation. This indicates that CBI exhibits very different volatility processes in comparison with CBI returns. Similar to the EGARCH model, the asymmetric GARCH term is negative and statistically significant which indicates that negative shocks have greater impact on volatility of CBI and CBI returns as compared to positive shocks of the same intensity.

Table 5 shows that there are four breakpoints noted in our series, and these breakpoints are noted in the following days: (1) 5/23/2017, (2) 1/16/2018, (3) 5/31/2016, and (4) 10/14/2015. A dummy variable was created for these days before running the long-run and short-run model.

Table 6 shows the long-run impact of LIBOR and FYIE on CBI and CBI returns. The constant is positive and statistically significant for CBI and CBI returns. In the long run, 1% increase in LIBOR will increase CBI by 1.46%, at 1% level of significance. Similarly, 1% increase in LIBOR will increase CBI returns by 1.85%, at 1% level of significance. A 1% increase in FYIE will increase CBI by 1.68%, and a 1% increase in FYIE will increase CBI returns by 2.24%, at 1% level of significance. The R^2 and adjusted R^2 in both the models are more than 50%, thus indicating that our model is statistically robust.

Table 7 shows that the short-run impact of LIBOR and FYIE on CBI returns is positive and statistically significant at 1% level of significance. In the short run, a 1% change in LIBOR will change CBI returns by 1.76%. Furthermore, a 1% change in FYIE will change CBI returns by 2.089%. Our short-run model is robust as both the R^2 and adjusted R^2 values are more than 50%. The Breusch-Pagan-Godfrey heteroskedasticity test indicates that our short-run model is homoscedastic.



Source: Created by authors by using Eviews8 software (2019).

Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index, Fig. 3 Volatility of inflation expectations, LIBOR, and Coinbase Index. (Source: Created by authors by using EViews 8 software (2019))

Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index, Table 2 Heteroskedasticity test: ARCH

F-statistic	30150.57	Prob. F(1,785)	0.0000
Obs*R-squared	767.0296	Prob. chi-square(1)	0.0000

Source: EViews Output (2019)

Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index, Table 3 Summary statistics for CBI, LIBOR, and FYIE

Summary statistics	Coinbase_Index	LIBOR	FYIE
Mean	1344.085	1.010143	1.971819
Median	338.7149	0.772500	2.000000
Maximum	8082.269	2.522380	2.350000
Minimum	37.96758	0.166250	1.410000
Std. dev.	1673.920	0.760321	0.207854
Skewness	1.519523	0.572448	−0.693310
Kurtosis	4.870802	1.947168	2.687888
Sum	2,041,665	1054.589	2048.720
Sum sq. dev.	4.25E+09	602.9455	44.84506
Observations	1519	1044	1039

Source: EViews Output (2019)

Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index, Table 4 GARCH/TGARCH and EGARCH

	GARCH/TGARCH			EGARCH	
	Lg (CBI)	Lg(CBI returns)		Lg(CBI)	Lg(CBI returns)
Mean equation			**Mean equation**		
Constant	−19.68[−0.006]	1.356[5.135][a]	Constant	−107.82 [−0.049]	0.79[1.944]
AR(1)	1.000183 [40.05][a]	0.926[114.83][a]	AR(1)	1.000[2338.51][a]	0.94[107.85][a]
Variance equation			**Variance equation**		
Constant	0.9316[131.01][a]	−0.0122 [−0.127]	**C(3)**	−0.603 [−11.206][a]	−1.31 [−8.57][a]
Lg($LIBOR_t$)	0.079 [11.14][a]	−0.619 [−9.47][a]	**C(4)**	0.269[19.653][a]	0.69[12.90][a]
Lg($FYIE_t$)	−0.997 [−132.83][a]	0.819[5.84][a]	**C(5)**	−0.04[−4.232][a]	−0.10 [−2.65][a]
GARCH(−1)	−0.719 [−24.75][a]	−0.015 [−2.436][b]	**C(6)**	0.95[195.348][a]	0.25[5.16][a]
Resid$(-1)^2$	0.4163[0.751]	0.770 [12.87][a]	**C(7)**	0.13[3.988][a]	1.14[5.57][a]
AIC	−0.273194	2.83	**C(8)**	−0.001[−0.353]	−0.20 [−6.78][a]
SIC	−0.248638	2.85	**AIC**	**−3.80**	2.84
			SIC	**−3.78**	2.87

Source: EViews output (2019)
[a]Represents significance at 1%
[b]Represents significance at 5%

Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index, Table 5 Bai-Perron tests of L + 1 vs. L sequentially determined breaks

Sequential F-statistic determined breaks			4
		Scaled	Critical
Break test	F-statistic	F-statistic	Value[a]
0 versus 1[a]	889.7891	2669.367	13.98
1 versus 2[a]	420.5951	1261.785	15.72
2 versus 3[a]	97.59589	292.7877	16.83
3 versus 4[a]	34.02447	102.0734	17.61
4 versus 5	0.000000	0.000000	18.14
Break dates			
	Sequential	Repartition	
1	5/23/2017	10/14/2015	
2	1/16/2018	5/31/2016	
3	5/31/2016	5/02/2017	
4	10/14/2015	1/16/2018	

Source: EViews Output (2019)
[a]Bai-Perron (Econometric Journal, 2003) critical values
[b]Significant at the 0.05 level

Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index, Table 6 Long-run impact of LIBOR and FYIE on CBI and CBI returns

	$LgCBI_t$	$LgCBI_t$ returns
Variables		
$LgLIBOR_t$	1.458825[76.27841][a]	1.854469[23.10593][a]
$LgFYIE_t$	1.687443[10.84558][a]	2.235136[3.561591][a]
Dum_t	0.362532[1.407092]	0.635251[0.709270]
Constant	5.611967[51.73833][a]	1.071676[2.457747][b]
R^2	0.881261	0.553246
ΔR^2	0.880908	0.550844

Source: EViews output (2019)
[a]Represents significance at 1%
[b]Represents significance at 5%

Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index, Table 7 Short-run impact of LIBOR and FYIE on CBI returns

	$LgCBI_t$ returns
Variables	
$\Delta LgLIBOR_t$	1.764315[33.77284][a]
$\Delta LgFYIE_t$	2.088872[4.948851][a]
ECT	1.500800[17.38526][a]
Dum_t	0.668714[0.765452]
Constant	4.997807[36.24945][a]
R^2	0.697219
ΔR^2	0.695670
Heteroskedasticity test: Breusch-Pagan-Godfrey	F-statistic 2.110886 Prob. F(4,782) 0.0777

Source: EViews Output (2019)
[a]Represents significance at 1%

The pairwise Granger causality test indicates that there is no causality between LIBOR, CBI, and FYIE (see Table 8).

Discussions

This study has empirically proved that negative shocks have greater impact on the volatility of CBI and CBI returns as compared to positive shocks of the same intensity. Negative news driving inflation expectations and LIBOR will shift investor confidence from physical assets to the blockchain market. The positive and statistically significant impact of FYIE on CBI returns indicates that investors are more likely to invest in the blockchain market if they believe that inflation will increase in the future (Zhu and Zhou 2016; Crosby et al. 2016; Morabito 2017; Mainelli and Milne 2016). There are a couple of reasons for this. First, to counter the negative repercussions of future inflation, current investments in the blockchain market will increase future cash flows that can be used to counter the negative impact of inflation on consumption. Second, an increase in forward inflation expectations will encourage investors to invest in the blockchain market now as this will help them to smooth future consumption. The findings from the short-run and long-run impact of LIBOR and FYIE on CBI and CBI returns indicate that as LIBOR and FYIE increase, it is most likely that CBI and CBI returns will increase as investors choose to invest in assets that will maximize their financial returns.

Exploring the Nexus Between Inflation Expectations, LIBOR, and Coinbase Index, Table 8 Pairwise Granger causality test

Null hypothesis	F-statistic	Prob.
LGLIBOR does not Granger cause LGCBI	0.35382	0.7021
LGCBI does not Granger cause LGLIBOR	0.29003	0.7483
LGFYIE does not Granger cause LGCBI	2.01354	0.1344
LGCBI does not Granger cause LGFYIE	0.16435	0.8485
LGFYIE does not Granger cause LGLIBOR	0.15894	0.8531
LGLIBOR does not Granger cause LGFYIE	0.39271	0.6754

Source: EViews Output (2019)

Conclusion

In summary, this study examined the relationship between inflation expectations, London Interbank Offered Rate (LIBOR), and Coinbase Index (CBI). The findings from this study confirm that there is a positive and statistically significant relationship between these three variables, both in the short run and long run. Due to the increase in investment in the blockchain market, some studies have argued that there is a need for more empirical work that captures the effect of volatile factors driving CBI (Corbet et al. 2018). This study takes a stern step by examining the common factors that might have an impact on the blockchain market. One of the main limitations of this study is that it is based on only two factors that may affect CBI. We need further studies that can capture the effect of similar volatile variables driving changes in the blockchain market.

Cross-References

▶ Coinbase Index (CBI)
▶ Five-Year Inflation Expectations (FYIE)
▶ One-Month London Interbank Rate (LIBOR)

References

Balboa M, López-Espinosa G, Rubia A (2015) Granger causality and systemic risk. Financ Res Lett 15:49–58

Baur DG, Dimpfl T, Kuck K (2018) Bitcoin, gold and the US dollar–a replication and extension. Financ Res Lett 25:103–110

Coinbase Incorporation Index (2019) Coinbase index: construction and methodology. Retrieved from https://am.coinbase.com/documents/cbi-methodology.pdf

Corbet S, Lucey B, Yarovaya L (2018) Datestamping the Bitcoin and Ethereum bubbles. Financ Res Lett 26:81–88

Crosby M, Pattanayak P, Verma S, Kalyanaraman V (2016) Blockchain technology: beyond bitcoin. Appl Innov 2(6–10):71

Dyhrberg AH (2016a) Bitcoin, gold and the dollar–a GARCH volatility analysis. Financ Res Lett 16:85–92

Dyhrberg AH (2016b) Hedging capabilities of bitcoin. Is it the virtual gold? Financ Res Lett 16:139–144

European Central Bank (2012) Virtual currency schemes. October, 1–55

Farooq O, Hamouda M (2016) Stock price synchronicity and information disclosure: evidence from an emerging market. Financ Res Lett 18:250–254

Giudici P, Abu-Hashish I (2018) What determines bitcoin exchange prices? A network VAR approach. Financ Res Lett 28:309

Guirguis M (2018) Noise created through the interactions of arbitrageurs and noise traders in the FOREX market. An analysis based on ARCH, GARCH, TGARCH and EGARCH models (September 23, 2018)

Gujarati DN, Porter DC (2010) Essentials of econometrics. McGraw Hill, Singapore

Katsiampa P (2018) Volatility co-movement between Bitcoin and Ether. Financ Res Lett 30:221

Mainelli M, Milne A (2016) The impact and potential of blockchain on the securities transaction lifecycle. Swiftinstitute Working Paper NO. 2015-007, https://www.swiftinstitute.org/wp-content/uploads/2016/05/The-Impact-and-Potential-of-Blockchain-on-the-Securities-Transaction-Lifecycle_Mainelli-and-Milne-FINAL-1.pdf

Morabito V (2017) Business innovation through blockchain. Springer International Publishing, Cham

Naidu S (2017) Exploring the dynamic effects of urbanization and real effective exchange rate on tourism output of Singapore. Tour Anal 22(2):185–200

Smales LA (2018) Bitcoin as a safe haven: is it even worth considering? Financ Res Lett 30:385

Ulusoy V, Onbirler ÖÜ (2017) Marginal speculation and hedging in commodity markets. Financ Res Lett 23:269–282

Zhu H, Zhou ZZ (2016) Analysis and outlook of applications of blockchain technology to equity crowdfunding in China. Financ Innov 2(1):29