Macro-Finance Determinants and the COVID-19 Pandemic Shocks in Predicting the Correlation between Cryptocurrencies and Other Thai Financial Assets

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Battle Plan

Outline

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- An extensive literature has documented this effect on financial markets (see inter alia [Baker et al.(2020),Ramelli and Wagner (2020)])
  - Previous research has demonstrated that periods of significant market illiquidity and uncertainty strengthen the negative correlation between stock and bond returns (Connolly et al., 2005, 2007; Baele et al., 2010, 2020).

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- Little know about the correlation between Thai financial assets i.e. Stock, Bond and a new financial asset,. i.e cryptocurrencies
- Also,the influence of EPU on the correlation between crptocurrencies and Thai financlal assets.

Outline

Goal of This Paper

- The purpose of this paper is to understand the effect of economic policy uncertainty (EPU) and the COVID-19 pandemic on the correlation between the cryptocurencies and Thai financial assets.

Main Findings

- The evidence shows that the long-run correlation among asset classes in Thailand during the 2000m1 to the 2022m6 have been varying over time. The long-run correlation between stock and bond tends to turn more negateive during the global financial crisis and covid-19 situation which is supporting the flight-to-quality phenomenon. However, the long-run correlations between crypto currencies and stock or bond are very low. It appealed as an inflationary hedge due to its low (near zero) correlation.

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- Riccardo Colacito, Robert Engle and Eric Ghysels, **A Component Model of Dynamic Correlations**, *Journal of Econometrics* 164, 45-59.

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- A key ingredient is volatility clustering, a feature and its wide-range implications, first explored in the seminal paper on ARCH models by Engle (1982).
- In this model, it can bridge the gap between discrete time models, such as the class of ARCH models, and continuous time models, such as the class of Stochastic Volatility (SV) models with close links to the option pricing literature.

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  - **Step 3**: Link volatility and correlation to macro variables

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  - Allows both for a 2-step (like Schwert but with more precise measures replacing RV) and direct approach of incorporating economic variables.
  - It is often argued that long data spans suffer from so called structural breaks (see e.g. Andreou and Ghysels (2002), Pástor and Stambaugh (2001)). Both the Engle and Rangel Spline-GARCH and the GARCH-MIDAS class of models will be able to deal with this.

A New Class of Component Models for Stock Market Volatility

- Consider:

$$r_{it} - E_{(i-1)t}(r_{it}) = \sqrt{\tau_t g_{it}}\varepsilon_{it}$$

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  where r_{it} is the log return on day i during month t, and where volatility has at least two components, g_{it} and τ_t.
- The component g_{it} is assumed to relate to the day-to-day liquidity concerns (i.e. Order Imbalance)and possibly other short-lived factors (Market Microstructure Factors).
- In contrast, the component τ_t relates to *economic fundamentals*, i.e. to the future expected cash flows and future discount rates, and macro economic variables assumed to tell us something about this source of stock market volatility.

A New Class of Component Models for Stock Market Volatility

- Following Engle and Rangel (2005), we assume the volatility dynamics of the component g_{it} is a (daily) GARCH(1,1) process, namely:

$$g_{it} = (1 - \alpha - \beta) + \alpha \frac{(r_{(i-1)t} - \mu)^2}{\tau_t} + \beta g_{(i-1)t}$$

Period t will refer to either month t, or quarter t or semester t.

We specify the τ_t component by smoothing realized volatility in the spirit of MIDAS regression and MIDAS filtering:

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega) RV_{t-k} \qquad RV_t = \sum_{i=1}^{N_t} r_{it}^2$$

where N_t is the number of days in the month/quarter/half-year t.

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- The model can be differentiated between 'fixed span' τ and 'rolling sample' τ. However, in this draft, I assume a fixed span, i.e. the component τ remains fixed during period t.
- It will matter empirically which frequency to select for RV and one of the advantages of our approach is that t will be a *choice variable*.

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- Here, MIDAS filter applies to *low frequency* data to extract long run component.
- To complete the model we need to specify the weighting scheme. The weighting (or smoothing) function is either a simplified version of the *Beta* lag structure discussed in Ghysels et al. (2006) or the commonly used *Exponentially weighting*.

Extensions to Multivariate Models (DCC-MIDAS Model)

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- Use of the Engle (2002) DCC model.
- Use of the Engle, Ghysels and Sohn (2013) GARCH-MIDAS specification to help identify the dynamics of correlation and its components.

A simple class of long run correlation models

Let the vector of returns $\mathbf{r}_t = [r_{1,t}, \ldots, r_{n,t}]'$ follow the process:

$$\mathbf{r}_t = \boldsymbol{\mu} + \boldsymbol{H}_t^{\frac{1}{2}} \boldsymbol{\varepsilon}_t$$

where $\boldsymbol{\varepsilon}_t$ $i.i.d.$ $N(0, \boldsymbol{I}_n)$, $\boldsymbol{\mu}$ is the vector of unconditional means and $\boldsymbol{H}_t$ is the conditional covariance matrix.
Our estimations procedure follows the one proposed by Engle (2002) and includes two steps:

1. estimate conditional volatilities for each return, as if they were distributed as univariate processes; collect them in the sequence of diagonal matrices $\boldsymbol{D}_t$ and construct the vector of standardized residuals; $\boldsymbol{\xi}_t = \boldsymbol{D}_t^{-1}(\mathbf{r}_t - \boldsymbol{\mu})$, $\forall t = 1, \ldots, T$

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2. estimate conditional correlations using the standardized residuals.

We assume that univariate returns follow the GARCH-MIDAS process of Engle, Ghysels and Sohn (2013):

$$r_{i,t} = \mu_i + \sqrt{\tau_{i,t} g_{i,t}} \varepsilon_{i,t}, \quad \forall i = 1, \ldots, n$$

Dynamic correlations are a natural extension of the GARCH-MIDAS model to the DCC model. Using the standardized residuals it is possible to obtain:

$$q_{i,j,t} = \overline{\rho}_{i,j,t} \left(1 - a - b\right) + a \xi_{i,t-1} \xi_{j,t-1} + b q_{i,j,t-1}$$

where:

$$\overline{\rho}_{i,j,t} = \sum_{l=1}^{L_c} \varphi_l \left(\omega\right) c_{i,j,t-l}$$

with $c_{i,j,t} = \dfrac{\sum_{k=1}^{N_c} \xi_{i,k} \xi_{j,k}}{\sqrt{\sum_{k=1}^{N_c} \xi_{i,k}^2} \sqrt{\sum_{k=1}^{N_c} \xi_{j,k}^2}}$

Correlations can then be computed as:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}}\sqrt{q_{j,j,t}}}$$

We regard $\rho_{i,j,t}$ as the short run correlation between assets i and j, whereas $\overline{\rho}_{i,j,t}$ is a slowly moving long run correlation.
We can rewrite this as

$$q_{i,j,t} - \overline{\rho}_{i,j,t} = a\left(\xi_{i,t-1}\xi_{j,t-1} - \overline{\rho}_{i,j,t}\right) + b\left(q_{i,j,t-1} - \overline{\rho}_{i,j,t}\right)$$

conveys the idea of short run fluctuations around a time varying long run relationship.
The above equation has a 'error-correction' flavor, namely that dynamic correlations fluctuate around and revert towards a long run component process characterized by $\overline{\rho}_{i,j,t}$.

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- Macroeconomic variables Quarterly data (2006Q1 and 2017Q3).

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  - The VIX index as the proxies of global financial risk. i.e. US VIX, UK VIX, JP VIX, and HK VIX.

Estimation Issues

- Given the parameter space $\Phi = \{\mu, \alpha, \beta, m, \theta, \omega\}$, we consider the QMLE:

$$LLF = -\frac{1}{2}\sum_{t=1}^{T}[\log g_t(\Phi)\tau_t(\Phi) - \frac{(r_t-\mu)^2}{g_t(\Phi)\tau_t(\Phi)}]$$

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- For lag selection of MIDAS polynomial we profile the log-likelihood. This is model selection without changing parameter space.

Table: 1: GARCH-MIDAS with Macroeconomic variables

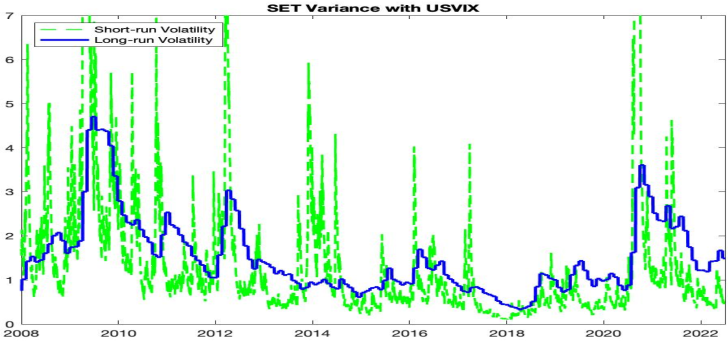
Panel A:GARCH-MIDAS Models: Stock

Variables	lags	μ	α	β	θ	ω	m
EPU	20	0.051	0.131	0.822	0.146	2.871	0.931
		(0.014)	(0.009)	(0.011)	(0.012)	(0.763)	(0.061)
EPU	20	0.034	0.106	0.872	-3.977	4.959	10.276
		(0.15)	(0.007)	(0.008)	(0.605)	(1.913)	(1.505)
VIXUS	20	0.028	0.121	0.855	0.1151	14.78	-0.837
		(0.014)	(0.008)	(0.009)	(0.017)	(3.298)	(0.185)
VIXHK	20	0.027	0.123	0.856	0.135	10.491	-1.370
		(0.014)	(0.007)	(0.008)	(0.022)	(2.525)	(0.301)

Notes - The standard deviations are in the parentheses

As seen,the long-run stock volatility mainly increases during the recent Covid-19

Long and short run volatilities
for the Stock with US VIX



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Panel A:GARCH-MIDAS Models: Bond

Variables	lags	μ	α	β	θ	ω	m
RV	24	0.010	0.397	0.517	0.237	26.255	0.274
		(0.003)	(0.015)	(0.011)	(0.014)	(2.681)	(0.018)
EPU	24	0.008	0.352	0.609	-0.262	12.29	0.831
		(0.004)	(0.015)	(0.012)	(0.074)	(10.36)	(0.215)
VIXUS	24	0.008	0.424	0.528	0.012	49.005	0.047
		(0.003)	(0.017)	(0.013)	(0.003)	(153.02)	(0.024)
VIXHK	24	0.027	0.123	0.856	0.135	10.491	-1.370
		(0.014)	(0.007)	(0.008)	(0.022)	(2.525)	(0.301)

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The long-run bond volatility is higher during the recent Covid-19 as well.

Long and short run volatilities
for the Bond with US VIX

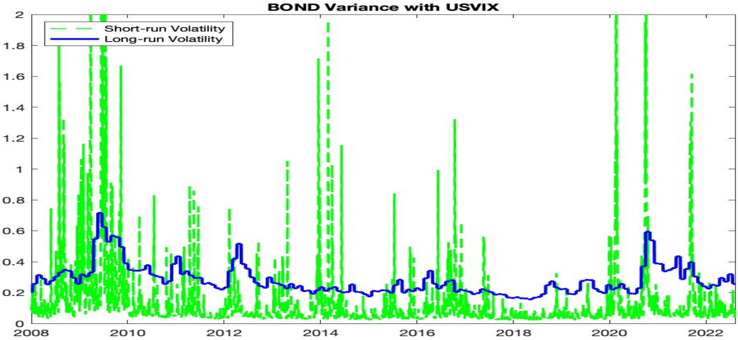

Table: 1: GARCH-MIDAS with Macroeconomic variables

Panel A:GARCH-MIDAS Models: Bitcoin

Variables	lags	μ	α	β	θ	ω	m
RV	24	-0.0018	0.2512	0.726	0.416	1.001	0.334
		(0.079)	(0.007)	(0.007)	(0.047)	(0.012)	(0.039)
EPU	24	0.183	0.069	0.931	0.060	4.995	0.040
		(0.063)	(0.0022)	(0.002)	(0.291)	(27.335)	(0.637)
VIXUS	24	0.73	0.105	0.843	0.939	49.996	8.417
		(0.113)	(0.011)	(0.016)	(0.142)	(82.569)	(2.241)
VIXHK	24	0.027	0.123	0.856	0.135	10.491	-1.370
		(0.014)	(0.007)	(0.008)	(0.022)	(2.525)	(0.301)

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The long-run Bitcoin volatility during the recent Covid-19.

Long and short run volatilities
for the Bitcoin with US VIX

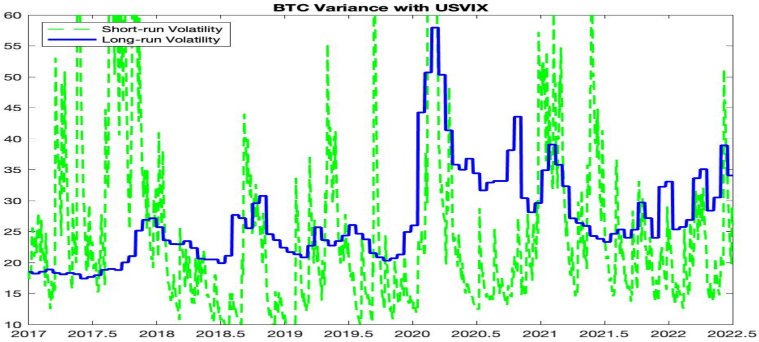

Table: 1(Cont.) DCC-MIDAS models

Panel B: DCC-MIDAS Models				
Asset Classes	MIDAS lags	a	b	ω
SET returns and BOND returns	15	0.033	0.906	1.303
		(0.074)	(0.062)	(0.158)
SET returns and BITCOIN returns	15	0.022	0.638	1.089
		(0.011)	(0.033)	(0.438)
BOND returns and BITCOIN returns	15	0.035	0.206	1.304
		(0.011)	(0.033)	(0.438)

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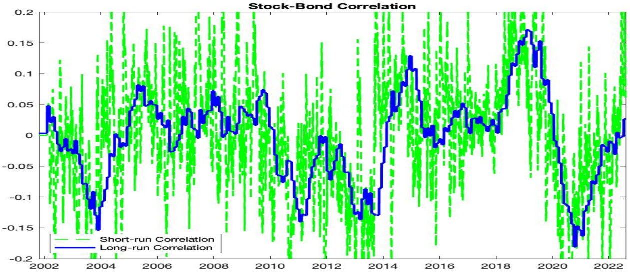
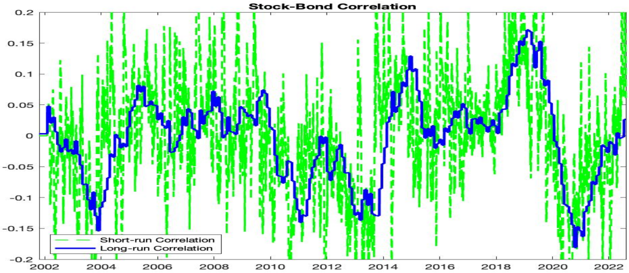
Long-run stock-bond correlation changes sign over the sample period...

Long and short run correlations between SET return and government bond return from 2002m1 and 2022m6.

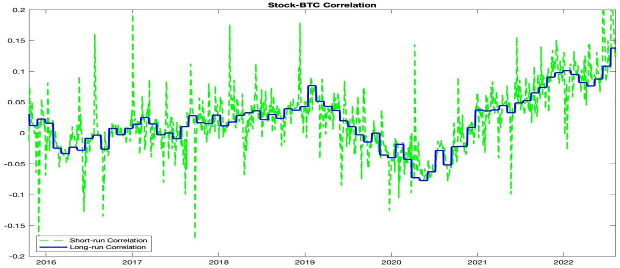


The negative stock-bond correlations observed in this study indicate that the market uncertainty is high during the pandemic, and investors prefer safe government bonds to risky stocks (flight-to-safety) i.e. the work of Baele et al. (2020)



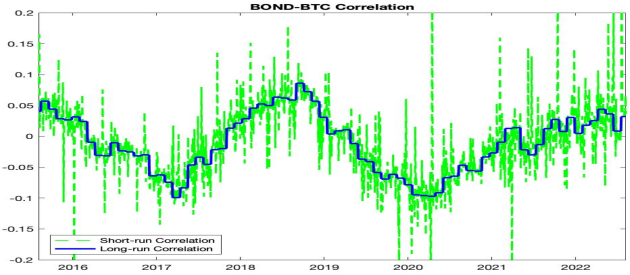
Long-run stock-BITCOIN correlation changes sign over the sample period, it appealed to many as an inflationary hedge due to its low (near zero) correlation with traditional assets such as stocks

Long and short run correlations between SET return and BITCOIN return from 2015m09 and 2022m6.



Long-run Bond-BITCOIN correlation over the time period of study is very low as well.

Long and short run correlations between Bond return and BITCOIN return from 2015m09 and 2022m6.



Outline

Conclusion

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Further Research: Incorporating Macroeconomic Information Directly

- The (*two-sided*) specification we consider (for quarterly macro data and a fixed span) is:

$$\sqrt{\tau_t} = m + f_t^{(real)} + f_t^{(nominal)}$$

$$f_t^{(real)} = \sum_{k=-K_b^{(r)}}^{K_f^{(r)}} \varphi_k(\omega_1, \omega_2)\left[\theta_1^{(k)} X_{t+qk}^{spread} + \theta_2^{(k)} X_{t+qk}^{IP}\right]$$

$$f_t^{(nominal)} = \sum_{k=-K_b^{(n)}}^{K_f^{(n)}} \varphi_k(\omega_3, \omega_4)\left[\theta_3^{(k)} X_{t+qk}^{PPI} + \theta_4^{(k)} X_{t+qk}^{MB}\right]$$

where X_{t-qk}^{j} is lag k (quarters) of macroeconomic variable j.
Moreover, $\theta_j^{(k)} = \theta_{jf}$ when $k \geq 0$ and θ_{jb} when $k < 0$.