Trade Uncertainties and the Hedging Abilities of Bitcoin#

Elie Bouri[1], Konstantinos Gkillas[2,*] and Rangan Gupta[3]
[1]Department of Finance, USEK Business School, Holy Spirit University of Kaslik, Jounieh,
[2]Department of Business Administration, University of Patras, Patras, Greece
[3]Department of Economics, University of Pretoria, Pretoria, South Africa

*Correspondence: Konstantinos Gkillas, Department of Business Administration, University of Patras, University Campus, Rio, P.O. Box 1391, 26500 Patras, Greece. Email: gillask@upatras.gr

Abstract

In this paper, we first estimate monthly realized correlation, based on daily data, between stock returns of the United States (US) and Bitcoin returns. Then we relate the realized correlation over the period of October, 2011 to May, 2019 with a news-based measure of the growth of trade uncertainty of the US. Our results show that the realized correlation is negatively impacted by increase in trade uncertainty, which in turn continues to hold under alternative robustness checks, thus suggesting that Bitcoin can act as a hedge relative to the conventional equity market in the wake of heightened trade policy-related uncertainties, and provide diversification benefits for investors.

Keywords: US Stock Market, Bitcoin, Realized Correlation, Trade Uncertainty
JEL Codes: C22, G10

1. Introduction

In an interview on the 21st of May (2019) in Fortune's "Balancing the Ledger" show, Digital Currency Group founder Mr. Barry Silbert noted how Bitcoin's acceleration coincided with talks breaking down between Beijing and Washington (see Figure A1(a) in the Appendix of the paper). Mr. Silbert went on to say that "If you look at over the past five years—when 'Brexit,' happened, Bitcoin went up. When 'Grexit' happened, Bitcoin went up." In other words, Mr. Silbert meant that Bitcoin is acting as an asset that is insulated from the uncertainties of the traditional financial system, i.e., there seems to be a "flight to safety" property of Bitcoin. And Mr. Silbert is not alone, many market watchers have speculated that Bitcoin, at times referred to as "digital gold", benefited from investors' jitters in the equities and foreign exchange markets, which sent stocks and China's currency downward, as the trade talks between the United States (US) and China did not yield positive results. Having said all this, given the volatility that exists in Bitcoin, there are plenty of cases where the price of Bitcoin went down when other major macro events took place – something also conceded by Mr. Silbert in the interview.[1] In general however, trade uncertainty in the US has been on the rise since Mr. Donald J. Trump became the US president in January, 2016.[2]

We would like to thank two anonymous referees for many helpful comments. However, any remaining errors are solely ours.

[1] The interview can be found at: http://fortune.com/2019/05/20/bitcoin-trump-china-trade-war/.

[2] See, http://review.chicagobooth.edu/economics/2018/article/trump-s-trade-policy-uncertainty-deters-investment, for a detailed formal discussion in this regard by Professor Steven J. Davis, who is William H. Abbott Distinguished Service Professor of International Business and Economics at Chicago Booth and senior fellow of the Hoover Institution at Stanford University. The reader is also referred to Caldara et al., (2020).

Against this backdrop of discussions in the "popular" media about Bitcoin's hedging ability,[3] the objective of this paper is to check for the validity of such claims in a proper statistical manner. For our purpose, we focus at the time-varying correlation between US equity market and Bitcoin returns, and the effect that changes in trade uncertainty has had on this correlation over the short history of the cryptocurrency market. If indeed, Bitcoin is acting as a hedge in the wake of heightened trade uncertainties, the correlation between the returns of US stock market and Bitcoin should be negatively affected.

Uncertainty is a latent variable, and hence measuring the same associated with trade is not straightforward. However, recent work by Baker et al., (2016) has solved this problem by analyzing the number of newspaper articles dealing with trade related uncertainties, and then quantifying the same into a monthly index for the US. Traditionally, in the literature, researchers would use a Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model (Engle, 2002) to obtain the underlying time-varying correlation between asset returns. However, given our short sample period of October, 2011 to May, 2019, it was not possible to obtain statistically significant correlation, given the overparametrized structure of this approach.[4] Given this, from an econometric modeling perspective, we first recover a measure of underlying monthly realized correlation between US stocks and Bitcoin returns from daily data, and then linearly regress this correlation on the growth in the news-based measure of trade uncertainty. Of course, we could have used a DCC-GARCH-Mixed Data Sampling (DCC-GARCH-MIDAS) model (Colacito et al., 2011), which would have allowed us to estimate the impact of monthly growth in trade uncertainty on the daily correlation of US stock and Bitcoin returns. But recent strong criticisms against the DCC approach involving algebraic non-existence, mathematical irregularity, and non-asymptotic properties (McAleer, 2019), led us to undertake the two-step process of recovering the realized monthly correlation from daily data, and then relating it to growth in trade uncertainty via an ordinary least squares (OLS) regression.

Though Gozgor et al., (2019) has analysed the time-varying relationship between of trade uncertainty on Bitcoin returns using wavelet analysis,[5] to the best of our knowledge, this is the first paper to analyze the impact of trade uncertainty on the correlation between US stock and Bitcoin returns, and determine the hedging ability of the latter for trade policy-generated uncertainties. The remainder of the paper is organized as follows: Section 2 discusses the methodology, while Section 3 presents the data and results and Section 4 concludes.

2. Methodology

We observe the price process (of US stocks and Bitcoin) in month t, consisting of $T + 1$ daily prices or T daily returns, after removing one observation. Assuming that the number of daily observations per month is constant across all months, the returns during such

[3] For a detailed review of this literature, the reader is referred to Fang et al., (2019).

[4] Even though the underlying correlation from the DCC-GARCH model was insignificant, we moved ahead and analysed the impact of the growth in trade policy uncertainty on the DCC, but the effect was insignificant even at the 10% level. Furthermore, we also used daily data on the returns of US equities and Bitcoin to estimate the DCC, but the correlation was still insignificant. When we averaged these daily correlations over a month and studies the impact of the growth in trade policy uncertainty, the effect was insignificant even at the 10% level. Details of all these results are available upon request from the authors.

[5] These authors show that trade policy uncertainty generally tends to positively affect Bitcoin returns, but there are also periods, when the impact is negative.

months' time periods cover $t_0 < t_1 < \cdots < t_{T+1}$. We construct daily returns as the logarithmic difference between two consecutive daily observed prices, within a month, as:

$$R_{t,i} = \log(P_{t,i}) - \log(P_{t,i-1}) \tag{1}$$

where $R_{t,i}$ is a daily return and $P_{i,t}$ accounts for the daily price i and $i = (1, \dots, T)$, where $T + 1$ is the total number of daily prices within month t.
Then, by employing all daily returns we construct the monthly realized variance (RV). For each month t, we retrieve a monthly point for RV_t obtained from daily returns, as follows:

$$RV_t \equiv \sum_{i=1}^{T} R_{t,i}^2 \tag{2}$$

The monthly RV_t is estimated by summing all successive daily squared returns and stands for a benchmark realized volatility estimator. Monthly RV is highly predictable and useful (Barosso and Santa-Clara, 2015). French et al. (1987), and Schwert and Seguin (1990) introduce the construction of realized volatility estimates on the basis of daily returns.

After that, we estimate realized correlation (RC) by realized covariance ($RCov$) - as introduced by Barndorff-Nielsen and Shephard (2004) - divided by the square roots of the RV estimators of assets A and B. Specifically, a monthly point for RC_t obtained from daily returns is given by:

$$RC_t \equiv \frac{RCov_t}{RV_t^A \cdot RV_t^B} \tag{3}$$

where, $RCov_t$ is estimated as the cross-products of two daily returns series throughout each month t:

$$RCov_t \equiv \sum_{i=1}^{T} R_{t,i}^A \cdot R_{t,i}^B \tag{4}$$

Once we recover the RC_t from equation (3), we estimate the following linear regression to relate the growth in trade uncertainty (GTU) to the realized correlation between the logarithmic-returns of US equity index and Bitcoin:

$$RC_t = \alpha + \beta \cdot GTU_t + \varepsilon_t \tag{5}$$

where ε is the regression error. Based on Bitcoins acting as a hedge for conventional equities in the wake of increased trade uncertainty, our hypothesis is that β should be negative and statistically significant.

3. Data and Results

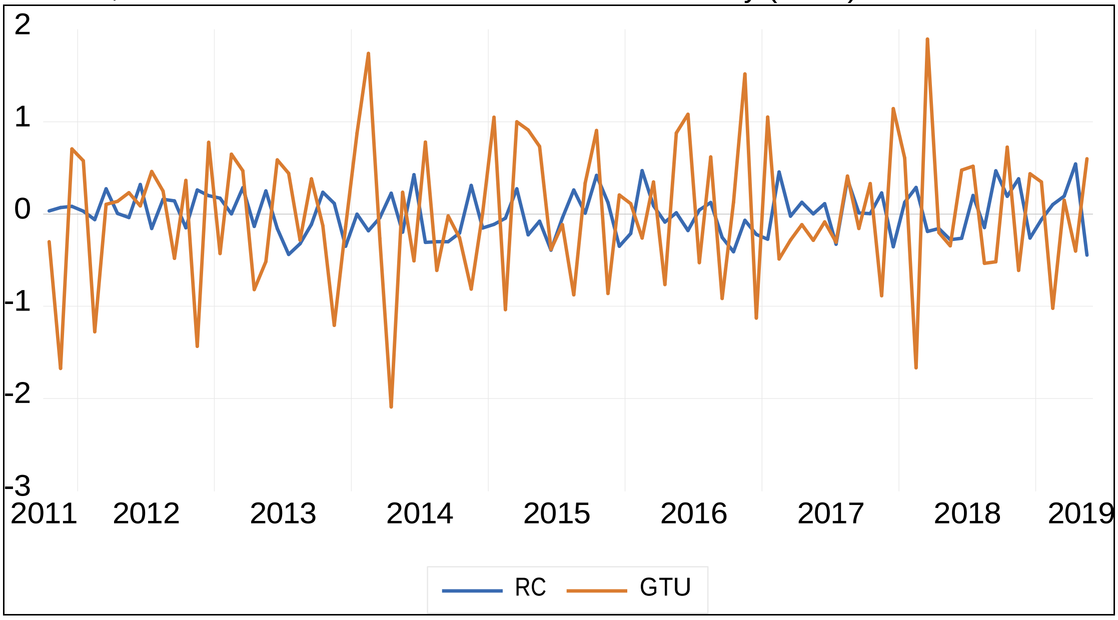
3.1. Data

We first obtain daily US dollar values of the US MSCI stock index and Bitcoin price, and convert them into logarithmic-returns to derive our monthly realized returns correlation (*RC*) using equation (3). The daily data spans 3rd October 2011 to 20th May 2019, resulting in the realized correlation for the monthly period October 2011 to May 2019. The US MSCI stock index is collected from DataStream, while the Bitcoin prices are taken from Bitstamp (https://www.bitstamp.net/), the world's longest standing cryptocurrency exchange. For the monthly trade uncertainty data, Baker et al. (2016) use search results from the Access World News database of over 2,000 US newspapers. The trade-related index requires the article constituting the index to include the three terms: economic, uncertainty, and policy, as well as a set of categorical policy terms, namely import tariffs, import duty, import barrier, government subsidies, government subsidy, WTO, World Trade Organization, trade treaty, trade agreement, trade policy, trade act, Doha round, Uruguay round, GATT or dumping. The data is taken from: http://policyuncertainty.com/categorical_epu.html,[6] and plotted in Figure A1(b) in the Appendix. Given that we are interested in the impact of the changes of trade uncertainty on the realized correlation of US stock and Bitcoin returns, we take the first-differences of the natural logarithms of the trade uncertainty variable, i.e., its growth rate, which we denote as *GTU*.[7]

3.2. Main Results

In Figure 1, we superimpose *RC* and *GTU*. In general, visual inspection does seem to suggest a negative correlation between *RC* and *GTU*. In fact, the correlation is -0.250 with a *t*-statistic of -2.459, i.e. significant at the 5% level.

Figure 1. Plot of Realized Correlation (*RC*) between MSCI US Stock and Bitcoin Returns, and Growth in News-Based Trade Uncertainty (*GTU*)



Next, as shown in Table 1, we estimate equation (5) with Newey and West (1987) heteroscedasticity and autocorrelation (HAC)-adjusted standard errors, and find that β is equal to -0.079 with a *t*-statistic of -3.324, i.e., significant at the 1% level. Note that, this result continues to hold even if we allow for a lag of *RC* to control for persistence. This indicates strong evidence in favour of the claim that, in the wake of growth in trade uncertainty, Bitcoin does act as a hedge for US equities.[8] We also estimate equation (5)

[6] Note trade uncertainty data is available for the US from January 1985.

[7] This transformation also ensures that *GTU* is a stationary variable based on the Augmented Dickey-Fuller (ADF) test of unit roots (Dickey and Fuller, 1979), along with *RC*, as shown in Table A1 (reporting also the basic summary statistics) in the Appendix of the paper.

[8] We conduct a similar analysis based on the realized correlation between MSCI stock returns of China and Bitcoin returns, and regress it on China's news-based growth in trade uncertainty from October 2011 to May 2015. The trade uncertainty index for China is based on the work of Davis et al. (2019), and is available at: http://policyuncertainty.com/china_monthly.html. Unlike the US, however, we are not able to obtain a significant negative relationship (even at the 10% level, with a *t*-statistic of 1.524) between the realized correlation and growth in trade uncertainty of China.. Interestingly, when we estimate a Markov-switching model, we are able to obtain a significant negative relationship at the 10% level for the regime in which the conditional mean of the realized correlation is relatively higher. So, for China, we find weak evidence for the hedging ability of Bitcoin relative to its stock market in the wake of increased trade uncertainties. Complete details of these results have been reported in Table A2 in the Appendix of the paper.

over the two equal sub-samples of August 2012 to December 2015, and January 2016 to May 2019, to account for the possible heightened trade uncertainty during the current presidential term of Donald J. Trump. In fact, the mean GTU during the second sub-sample was 4.61 percent compared to the -1.39%.[9]

Table 1 shows that the β coefficient is negative and statistically significant at the 5% level across both the sub-samples, but is indeed higher under the second sub-sample, suggesting that Bitcoin has acted as a stronger hedge relative to the US stock market during the current presidential regime following a growth in trade uncertainty. This result can be considered to be hold only from the economic point of view since, based on the equality of the regression coefficients test of Paternoster et al. (1998), the estimate of β across the two sub-samples is found not to be different in the statistical sense. The test statistic is $z=(\beta_1-\beta_2)/[(se_1)^2+(se_2)^2]^{1/2}$, where β_i, i= 1, 2 corresponds to sub-sample 1 (2012:08-2015:12) and 2 (2106:01-2019:05), and se_i are the corresponding standard errors. The value of z=0.0541, which is not significant even at the 10% level. In addition, note that, for the sub-sample 2011:10 to 2015:12, β is equal to -0.061, with a t-statistic of -2.152, i.e. significant at the 5% level. Hence, even though prior to the Donald J. Trump administration, the *GTU* was low on average (-2.96%), Bitcoin continued to serve as a hedge against trade related uncertainties.

Table 1. Estimation Results

Sample Period	α	β	γ
2011:10-2019:05	0.003 (0.022)	-0.079*** (0.024)	
2011:10-2019:05	0.003 (0.024)	-0.078*** (0.023)	-0.064 (0.091)
2012:08-2015:12	-0.018 (0.036)	-0.075** (0.032)	
2016:01-2019:05	0.014 (0.035)	-0.104** (0.043)	
2011:10-2019:05	-0.005 (0.031)	-0.061** (0.028)	

Note: The entries correspond to the estimate of equation (5), i.e., $RC_t=\alpha+\beta\, GTU_t+\varepsilon_t$ based on Newey and West (1987) standard errors in parentheses, with *RC* being the realized correlation between US MSCI stock returns and Bitcoin stock returns, and *GTU* being the growth in news-based trade uncertainty; In the third row we estimate the model with persistence: $RC_t=\alpha+\beta\, GTU_t+\gamma\, RC_{t-1}+\varepsilon_t$ ***, ** denote significance at 1% and 5% levels.

3.3. Robustness Checks

In this subsection, we conduct three robustness checks: First, we include the growth in the overall news-based economic policy uncertainty (*GEPU*) index of the US in equation (5), and reconduct our analysis; Second, we replace the underlying trade policy-related uncertainty index of Baker et al., (2016), by the one proposed by Caldara et al., (2020),[10] which in turn is also a news-based measure of trade uncertainty, but compared to the index of Baker et al., (2016), this measure

[9] The Bai and Perron (2003) tests of multiple structural breaks however, did not detect any regime changes in Equation (5). These results are available upon request from the authors.

[10] The data is available for download from: https://www.matteoiacoviello.com//tpu.htm.

starts in 1960 (though immaterial in our case), and the search terms differ slightly (as Caldara et al., (2020) does not explicitly search for mentions of legislation or institutions such as NAFTA and the WTO). We call it: GTU_{alt}; Finally, instead of using returns on US equities and Bitcoin, we now compute the *RC* based on the growth of daily corresponding trading volumes, with data obtained from the same sources mentioned above for the price of US equities and the cryptocurrency.

As can be seen from Table 2, where we report all the above-mentioned robustness tests:
Including *GEPU*, does not take away the fact that Bitcoin continues to be a hedge in the wake of increases in *GTU*, though *GEPU* does not have a significant negative impact on *RC*, unless considered on its own. This result is not surprising, since the trade-related uncertainty variable not only includes the three terms of economic, uncertainty, and policy, in EPU, but also additional set of categorical policy terms related to trade. But, it must be realized that, since the first three terms are more general in nature, EPU is based on more newpaper article than the trade-related measure of uncertainty. The impact of the growth in the trade policy related uncertainty index of Caladara et al., (2020), i.e., $GTPU_{alt}$, is negative and significant, just like in the case of the *GTPU*. Finally, the impact of *GTU* on the *RC* of volatility (*RC_VOL*) is also found to be negative and significant. All these results confirm the robustness of our main finding that Bitcoin serves as a hedge following increases in uncertainty due to trade policies, even when we include a general measure of policy uncertainty, alternative metric of trade policy uncertainty, and consider volumes instead of returns.

Table 2. Additional Estimation Results

Sample Period	α	β_1	β_2
Panel A: *GTU+GEPU*			
2011:10-2019:05	0.002	-0.063**	-0.135
2011:10-2019:05	0.001		-0.230***
Panel B: GTU_{alt}			
2011:10-2019:05	0.004	-0.047**	
Panel C: *RC_VOL*			
2011:10-2019:05	0.052***	-0.018**	

Note: The entries correspond to the estimate of the following equations in Panels A, B and C respectively: $RC_t=\alpha+\beta_1 GTU_t+\beta_2 GEPU_t+\varepsilon_t$, $RC_t=\alpha+\beta_1 GTU_{alt,t}+\varepsilon_t$, $RC\_VOL_t=\alpha+\beta_1 GTU_t+\varepsilon_t$. See Notes to Table 1.

4. Conclusion

In this paper, we test the claims in the popular media that, in the wake of heightened trade uncertainty, Bitcoin has served as a “flight to safety” relative to the US stock market. Based on monthly realized correlation, derived from daily data, over the period October 2011 to May 2019, which in turn is regressed on growth in a news-based measure of trade uncertainty, we find a negative and statistically significant effect of increased trade uncertainty on the underlying correlation of the US stock and Bitcoin returns, which continues to hold under various robustness checks associated with the inclusion of a general measure of policy uncertainty, alternative metric of trade-related uncertainty and the usage of trading volumes instead of returns. This finding suggests that Bitcoin can serve as a hedge relative to the US stock market following increases in trade policy-related uncertainties, and hence can provide diversification benefits to investors.

References

Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18, 1-22.

Baker, S., Bloom, N., Davis, S. (2016). Measuring economic policy uncertainty. Quarterly Journal of Economics, 131(4), 1593-1636.

Barndorff-Nielsen, O., Shephard, N. (2004). Econometric analysis of realized covariation: High-frequency covariance, regression and correlation in financial economics. Econometrica, 72, 885–925.

Barroso, P., Santa-Clara, P. (2015). Momentum has its Moments. Journal Financial Economics, 116, 111–120.

Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A., and Raffo, A. (2020). The Economic Effects of Trade Policy Uncertainty. Journal of Monetary Economics, 109, 38-59.

Colacito, R., Engle, R. F., Ghysels, E. (2011). A component model for dynamic correlations. Journal of Econometrics, 164(1), 45-59.

Davis, S.J., Liu, D., Sheng, X.S. (2019). Economic Policy Uncertainty in China since 1949: The View from Mainland Newspapers. American University, College of Arts and Sciences, Department of Economics, Mimeo.

Dickey, D.A. and Fuller, W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74, 427-31.

Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. Journal of Business & Economic Statistics, 20(3), 339-50.

Fang, L., Bouri, E., Gupta, R., Roubaud, D. (2018). Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin? International Review of Financial Analysis, 61, 39-36.

French, K.R., Schwert, G.W., Stambaugh, R.F. (1987). Expected stock returns and volatility. Journal of Financial Economics, 19, 3–29.

Gozgor, G., Tiwari, A.K., Demir, E., and Akron, S. (2019). The relationship between Bitcoin returns and trade policy uncertainty. Finance Research Letters, 29, 75-82.

McAleer, M. (2019). What They Did Not Tell You About Algebraic (Non-)Existence, Mathematical (IR-)Regularity and (Non-)Asymptotic Properties of the Dynamic Conditional Correlation (DCC) Model. Journal of Risk and Financial Management, 12(2), 1-9.

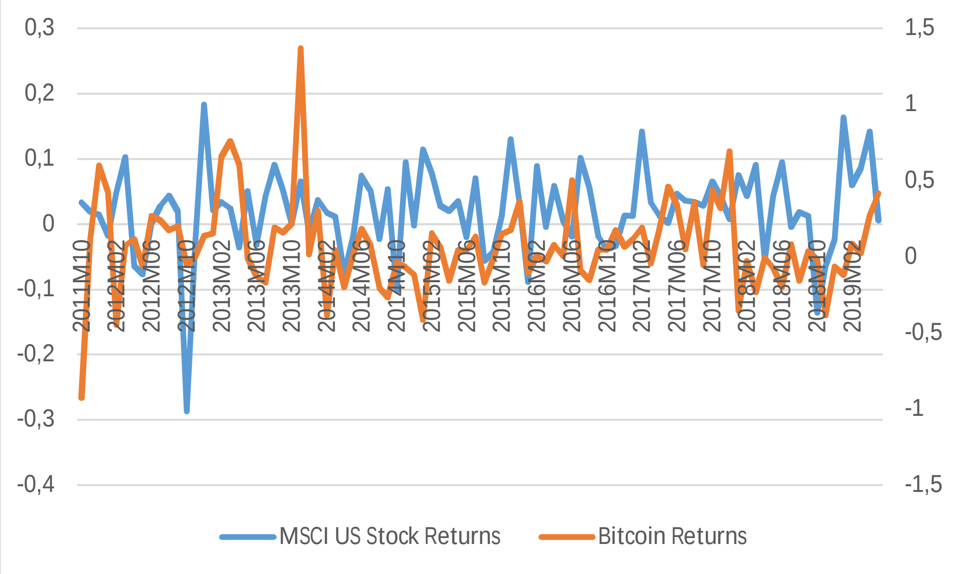
Newey, W., West, K. (1987). A simple positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. Econometrica, 55, 703–08.

Paternoster, R., Brame, R., Mazerolle, P., Piquero, A.R. (1998). Using the Correct Statistical Test for Equality of Regression Coefficients. Criminology, 36(4), 859-866.

Schwert, G.W., Seguin, P.J. (1990). Heteroskedasticity in Stock Returns. Journal of Finance, 45, 1129–1155.

APPENDIX

Figure A1(a): Monthly US Stock and Bitcoin Returns:



Note: Left vertical axis corresponds to MSCI stock returns, while the right is Bitcoin returns.

Figure A1(b): US Trade Uncertainty

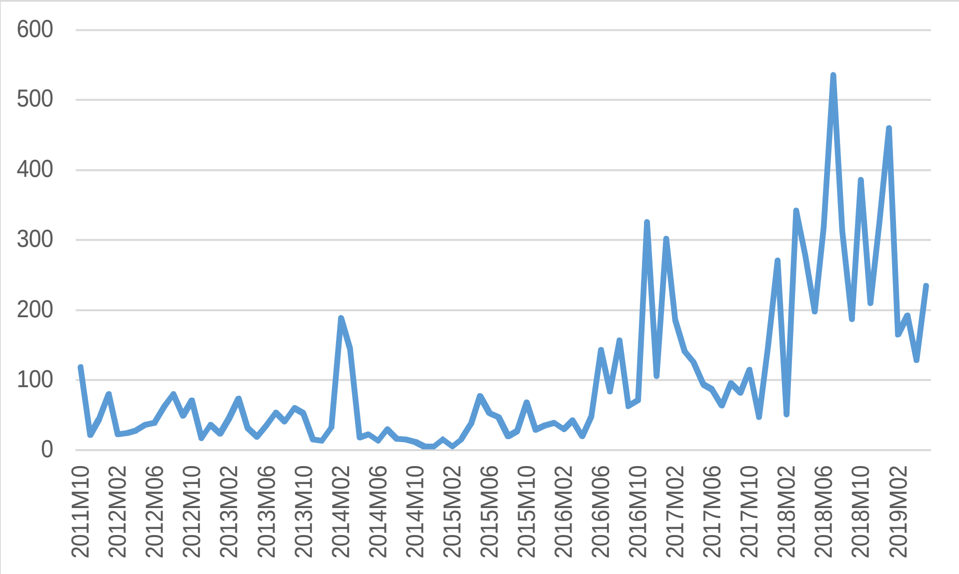


Table A1: Basic Statistics:

	Variable	
Statistic	*RC*	*GTU*
Mean	0.0024	0.0042
Median	0.0014	0.0486
Maximum	0.5432	1.8986
Minimum	-0.4454	-2.0922
Std. Dev.	0.2408	0.7619
Skewness	0.1664	-0.1669
Kurtosis	2.2132	3.0235
Jarque-Bera	2.7978	0.4293
p-value	0.2469	0.8068
N	92	
ADF-Test	9.9500	-10.2984
p-value	0.0000	0.0000

Table A2. Markov-Switching Model Estimates for China

Coefficient	Estimate	Std. Error	*z*-Statistic	Prob.
		Regime 1		
α_{01}	-0.4872	0.2686	-1.8134	0.0698
α_{31}	1.2527	0.6310	1.9852	0.0471
α_{11}	0.2305	0.0527	4.3758	0.0000
α_{21}	-0.1969	0.0502	-3.9267	0.0001
$\log(\sigma_1)$	1.4680	0.0456	32.1727	0.0000
		Regime 2		
α_{02}	-1.3736	3.0619	-0.4486	0.6537
α_{32}	5.4103	4.2160	1.2833	0.1994
α_{12}	0.4356	0.1262	3.4508	0.0006
α_{22}	-0.2981	0.1339	-2.2257	0.0260
$\log(\sigma_2)$	2.7522	0.0994	27.6852	0.0000
		Transition Matrix Parameters		
$p_{0,11}$	3.7404	0.4925	7.5944	0.0000
$p_{0,21}$	-1.9560	0.5215	-3.7506	0.0002

Mean *rgr*	0.081765	S.D. *rgr*	8.178857
S.E. of regression	7.527664	SSR	23176.28
Durbin-Watson stat	1.948417	Log likelihood	-1330.120
AIC	6.406302	SIC	6.521945

Note: Estimates correspond to: $RC_t = \alpha_{0,St} + \beta_{S_t} GTU_t + \varepsilon_t$. See Notes to Table 1.