

Shall the winning last? A study of recent bubbles and persistence

Akanksha Jalan, Roman Matkovskyy, Valerio Potì

To cite this version:

Akanksha Jalan, Roman Matkovskyy, Valerio Potì. Shall the winning last? A study of recent bubbles and persistence. Finance Research Letters, 2022, 45, pp.102162. $10.1016/j.frl.2021.102162$. hal-03603161

HAL Id: hal-03603161 <https://rennes-sb.hal.science/hal-03603161>

Submitted on 22 Jul 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

[Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License](http://creativecommons.org/licenses/by-nc/4.0/)

Version of Record: <https://www.sciencedirect.com/science/article/pii/S1544612321002415> Manuscript_18f9ec6288ed80e0ec62dab3ed8a90c0

Shall the winning last? A study of recent bubbles and persistence.

Akanksha Jalan, Rennes School of Business, France

akanksha.jalan@rennes-sb.com

Roman Matkovskyy*, Rennes School of Business, France

roman.matkovskyy@rennes-sb.com

Valerio Potì, University College Dublin, M. Smurfit School of Business, Ireland valerio.poti@ucd.ie

* -Corresponding author

Abstract

In this study, we analyze stock market performance of 43 firms that show very large price rises in COVID-19 times for the period $21/11/2019 - 20/1/2021$. These cover 6 industries - work-fromhome companies, stay-at-home companies, Cryptocurrency companies, Bitcoin companies, Coronavirus Vaccine companies and Coronavirus therapeutics companies. Our results demonstrate the presence of bubbles and persistence patterns.

Keywords: COVID19, bubble, persistence.

Shall the winning last? A study of recent bubbles and persistence.

Abstract

In this study, we analyze stock market performance of 43 firms that show very large price rises in COVID-19 times for the period $21/11/2019 - 20/1/2021$. These cover 6 industries - work-fromhome companies, stay-at-home companies, Cryptocurrency companies, Bitcoin companies, Coronavirus Vaccine companies and Coronavirus therapeutics companies. Our results demonstrate the presence of bubbles and persistence patterns.

Keywords: COVID19, bubble, persistence.

Acknowledgements: We are grateful to the editor (Professor Jonathan Batten) and the two anonymous referees for the thoughtful and constructive comments on the paper.

1. Introduction

l

Financial markets experienced significant price rises after the initial fall in response to the COVID pandemic. Gharib, Mefteh-Wali, & Jabeur (2021) document contagion effects of bubbles from oil to gold markets during the 2014/2015 crash and the COVID-19 outbreak¹. It is possible that similar contagion effects have generated price bubbles on multiple stocks in the sectors that were poised to benefit the most from the economic conditions caused by the pandemic, especially tech companies, companies with exposure to cryptocurrencies (particularly Bitcoin), pharmaceutical companies. This prompted us to investigate the possibility that price bubbles formed for stocks in these sectors. To the best of our knowledge, we are the first to investigate the bubble phenomenon in the context of these industries.

Consistent with the above reasoning, we chose to focus on companies with stocks from the six sectors that exhibited the most significant price rises as a consequence of the COVID pandemic i.e., Work-from-home product/service companies, Stay-at-home product/service, cryptocurrency related companies, and Coronavirus Vaccine and therapeutics companies. We hand-select the 43 companies that are most representative of the 6 industries that benefitted the most from the unprecedented COVID-19 crisis owing to the nature of their product/service offered (Table 1).

We also sought guidance from the TipRank.com classification of companies/markets. This service evaluates public stock recommendations made by financial analysts. TipRank also classifies companies that we use in our study in the same way as we did.

The literature provides several approaches to detect bubbles, such as the Residual Augmented Least Square Dickey-Fuller test of Taylor & Peel (1998), or the Log-Periodic Power Law method (Sornette, 2003; Jiang et al. 2010). Gürkaynak (2008) shows that econometric detection of asset price bubbles should be taken with some degree of caution. Phillips et al. (2011) propose a SADF test method based on the supremum of a set of forward recursive right-tailed ADF tests. Zhang et al. (2018) document that, in identifying multiple bubbles, the SADF method is less effective than extant

¹ Effects of the COVID-19 outbreak on different markets are discussed, for instance, in Jalan et al. (2021), Yarovaya et al. (2021), Le et al. (2021), Corbet et al. (2021), Aziz et al. (2020), Yarovaya et al. (2020a,b), among others.

alternatives. Phillips, Shi & Yu (2015a,b; 2017) extend the SADF to enhance test performance in identification of multiple bubbles.

The main favorable properties relate to the bootstrap procedure targeted at mitigating the potential impact of heteroskedasticity. The recursive evolving algorithm is more efficient compared to the forward expanding and rolling window algorithms in bubble identification, especially if the selected sample period contains multiple bubbles, as in our case. Phillips and Shi (2017) document consistency of the estimated switch date for crises under various data generating processes. While this method has been tested on different data (Harvey et al.2015; Zhang et al. 2018; Sharma & Escobari 2018; Zhao et al. 2021 etc.), Pavlidis et al. (2018) confirm favorable properties.

We apply this approach for the date stamping of bubbles in our sample and then go on to investigate the persistence of the price spikes using the Yang & Zhao (2020) quantile unit-root test to identify mean-reverting behaviour across quantiles. The unusual conditions that have been experienced in equity markets over our sample period due to the onset of the global pandemic have led to a fattening of the tails of the return distribution for several stocks in our sample. Also, fat tails are typical of cryptocurrencies, to which some of our stocks are exposed. Yang and Zhao (2020) show that their proposed test is more powerful than conventional unit root tests, especially in the presence of heavy tailed distributions, that is mainly the case for the crypto currency market. Furthermore, their test allows testing of the unit root hypothesis against the mean reversion alternative on a quantile-byquantile basis, which is not possible with conventional tests.

Our results indicate the presence of price bubbles in almost all markets analyzed. In terms of persistence, 24 of our 43 companies demonstrate complete absence of mean reversion, implying higher risk in the long run. Several firms in the work-from-home, cryptocurrency and coronavirusvaccine groups show reversion in higher quantiles.

The rest of this paper is organized as follows. Section 2 introduces the data and the methodology while Section 3 presents the empirical results. Section 4 summarizes our paper and provides conclusions.

Table 1. Selected companies by market classification

² While it is hard to trace how its graphical processors are employed by end-uses (i.e., whether they are used in gaming and cryptocurrency mining), an NVIDIA report shows that the demand for GeForce RTX was "incredible" in 2020 (https://nvidianews.nvidia.com/news/nvidia-announces-financial-results-for-fourth-quarter-and-fiscal-2021). The company asserts that the significant increase in the Ethereum network hash rate was driven by their GPUs and ASICs. Also, NVIDIA at the beginning of the sample period launched the crypto-mining processors for professional cryptocurrency mining (Source: https://finance.yahoo.com/news/edited-transcript-nvda-oq-earnings-220000362.html)

³ Visa launched a pilot program for payment with cryptos. On account of the project's scalability and Visa's large market share and dominant position in the payment business, the potential growth from the project can be immense. This provides us a major reason to believe that Visa's stock price is significantly exposed to fluctuations in cryptocurrency prices.

2. Data and methodology

We collect daily close-price observations for the selected 43 companies over the period 21/11/2019 – 20/1/2021 (Thomson-EIKON). The length of our time series is defined by data availability. General statistics are provided in Appendix Tables A1-A2. To detect bubbles, we use the Phillips, Shi & Yu (2015a,b; 2017) approach. The test is designed to make inference on the $\delta_{r_1r_2}$ coefficient of the following recursive regression:

$$
\Delta x_t = \alpha_{r_1 r_2} + \delta_{r_1 r_2} x_{t-1} + \sum_{k=1}^K \beta_{r_1 r_2}^k \Delta x_{t-k} + u_t.
$$
\n(1)

Here, x_t denotes the natural log of the asset price, $\alpha_{r_1r_2}$ is the constant intercept, $\delta_{r_1r_2}$ = $1 - \rho_{r_1 r_2}(\{x_t\})$ is a random walk with drift when $\rho = 1$, and an explosive process when $\rho > 1$ meaning a departure from an efficient market, $u_t \sim NID(0, \sigma_{r_1r_2}^2)$, and *K* is the lag order from minimizing the BIC, and r_1 and r_2 are the start and end points of the regression sample.

A rolling version of the ADF statistic is used with a rolling window. As an extension, Phillips, Shi & Yu (2015a,b; 2017) introduced the SADF test (supremum ADF), that uses recursive calculations of the ADF statistics by applying a fixed starting point and an expanding window. The SADF statistic is defined as the supremum value of the $ADFr_2$ sequence for $r_2 \in [r_0, 1]$ in the form of $ADF(r_0) = \frac{\sup\{ADFr_2\}}{r_2 \in [r_0, 1]}$ (r_0 represents the minimum window width).

The generalized SADF (GSADF) statistic is defined as the supremum of the ADF statistics sequence over all feasible ranges of r_1 , r_2 , allowing for changes in end-point fraction r_2 from r_0 to 1 and in the starting point fraction r_1 from 0 to $r_2 - r_0$, ensuring discriminatory power if more than one speculative bubble happens:

$$
GSADF(r_0) = \sup \n\begin{cases}\n r_2 \in [r_0, 1] & \{ADF_{r_1}^{r_2}\} = \sup \n\begin{cases}\n r_2 \in [r_0, 1] & \left\{\frac{\delta_{r_1 r_2}}{\delta e(\delta_{r_1 r_2})}\right\} \\
r_1 \in [0, r_2 - r_0]\n\end{cases}\n\end{cases}\n\tag{2}
$$

Thus, although the SADF and GSADF tests share a common testing variable, they differ in the rolling window setting. The SADF test requires a repeated ADF test on a forward expanding

sample sequence. The GSADF test differs from the SADF test in terms of variability of the starting and end point that can be changed simultaneously.

Following Phillips, Shi & Yu (2015a,b; 2017) approach, we locate specific start and end points of bubbles by calculating and comparing *the backward SADF and BSADF* statistics with the 95% SADF finite sample critical value sequence:

$$
BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \{ADF_{r_1}^{r_2}\}\tag{3}
$$

If $BSADF_{r_2}(r_0)$ is greater than the corresponding critical value of the standard ADF statistic at time Tr_2 , this time point is set as the start date of a bubble. Under the null hypothesis, {x} is a random walk with an asymptotically negligible drift and the limit distributions of SADF and GSADF test statistics are defined as:

$$
\frac{\frac{1}{2}[B(1)^{2}-1]-B(1)\int_{0}^{1}B(s)ds}{\left\{\int_{0}^{1}B(s)^{2}ds-\left[\int_{0}^{1}B(s)ds\right]^{2}\right\}^{2}}
$$
\n(4)

$$
\sup_{r_1 \in [0, r_2 - r_0]} \left\{ \frac{\frac{1}{2} r_w [B(r_2)^2 - B(r_1)^2 - r_w] - \int_{r_1}^{r_2} B(r) dr [B(r_2) - B(r_1)]}{r_w^{1/2} \left\{ r_w \int_{r_1}^{r_2} B(r)^2 dr - \left[\int_{r_1}^{r_2} B(r) dr \right]^2 \right\}^{\frac{1}{2}}} \right\}
$$
(5)

where $r_w = r_2 - r_1$, *B* is a standard Brownian motion. Critical values are derived using Monte Carlo simulations.

To investigate the potential of a market to bounce back to recovery after the initial shock, we apply quantile unit root tests. Following Galvao (2009) and Yang & Zhao (2020), the quantile nonlinear unit root test statistic with covariates is:

$$
t(\tau) = \frac{f(F^{-1}(\tau))}{\sqrt{\tau(1-\tau)}} (Y'_{-1}M_Z Y_{-1})^{\frac{1}{2}} \hat{\delta}(\tau), \tag{6}
$$

where $f(F^{-1}(\tau))$ is a consistent estimator of $f(F^{-1}(\tau))$, with *f* and *F* representing the density and distribution function of u_t , Y_{-1} is the vector of the values taken in the sample period by the lagged dependent variable y_{t-1} , M_z is the projection matrix onto the space orthogonal to $z =$

 $(1, \Delta y_{t-1}, ..., \Delta y_{t-p}, x'_{t-q_1}, x'_{t+q_2})$. The test statistic $t(\tau)$ under the null converges to (Yang & Zhao 2020 and Koenker & Xiao 2004):

$$
\xi(\tau) = \lambda \frac{\int_0^1 W_1 dW_1}{\int_0^1 W_1^2 dr} + \sqrt{1 - \lambda^2} \frac{\int_0^1 W_1 dW_2}{\int_0^1 W_1^2 dr},\tag{7}
$$

where $W_1 = W_1^3 - \int_0^1 W_1^3 dr$; W_1, W_2 are standard Brownian motions, independent of one another, $\lambda = \lambda(\tau) = \frac{\sigma_{u\psi}(\tau)}{\sigma_{u}\sigma_{\psi}(\tau)} = \frac{\sigma_{u\psi}(\tau)}{\sigma_{u}\sqrt{\tau(1-\tau)}}$ $\frac{\partial u \psi(t)}{\partial u \sqrt{\tau(1-\tau)}}$, $\psi_{\tau}(u) = \tau - I(u < 0)$, $e_{t\tau} = \Delta y_t - z_t' \beta(\tau)$,

 $E[\psi_\tau(e_{t\tau})|\mathbb{F}_{t-1}] = 0$. The asymptotic theory for near-integrated processes utilizes the Ornstein-Uhlenbeck process (Chan & Wei, 1987).

We compute these statistics for the distance of the log-price to the stationary mean of each asset, $y_t = x_t - \mu$, where $x_t = \log(p_t)$, and μ is its sample mean. The lag orders are chosen using the BIC. For estimating long-run variance and covariance parameters, we use the Bartlett-Parzen kernel and Quadratic Spectral windows in the kernel estimators following Galvao (2009) and Yang & Zhao (2020). We compare obtained results with pre-calculated critical values at several significance levels.

3. Results

Univariate results suggest that mean return is the highest for the Bitcoin companies' group (0.0094), followed by coronavirus vaccine companies (0.0061). Average median for returns is lower than average mean, indicating that the data is skewed to the right. The highest maximum return for the whole sample is observed for Sorrento (1.58), a coronavirus therapeutic company. The highest standard deviation and variance is noted for Marathon (0.117), a Bitcoin company, while the lowest for Johnson&Johnson (0.076), a coronavirus vaccine company (Tables A1-A2 in appendix).

Bubble estimates show that bitcoin and stay-at-home companies dominate in terms of bubble length (Tables A3-A8), while Coronavirus-Vaccine and Cryptocurrency companies have the lowest average bubble length. March 2020 represents the most common bubble period for most

companies. For Bitcoin companies, bubbles are observed mainly at end-2020-start-2021, while for COVID-vaccine companies, this period is March and July 2020.

Persistence results are presented in Fig.1 and Tables A9-A14 in Appendix. Rejecting the null hypothesis of a unit root implies that shocks are not accumulated over time. Mean reversion also implies that stocks become less risky in the long run, making them more attractive for longterm investors.

HO (unit root) not rejected LOGI ROKU NVDA MSTR PFE REGN LOGI ROKU MRNA REGN TWLO NFLX AMD OSTK MRNA SRNE ZM NFLX BNTX GILD ESTC SQ AMGN ZM HVBTF BNTX TWLO ZM SRNE DOCU IBKR ABBV ESTC DOCU ABBV VNW JNJ UPLD PTON GSK PTON GSK CME AZN PINS LLY MSFT PINS V NVAX LLY GOOGL CHWY CHWY PYPL INO	HO (unit root) rejected	BOX ZM	RIOT MARA CAN	GILD		BOX VNW UPLD MSFT GOOGL	CME v	PFE JNJ AZN NVAX	AMGN	

Fig. 1. Persistence results grouped by quantiles and presence of mean reversion (details in Appendix Tables A9-A14).

For our selected work-from-home companies, mean reversion is observed only for 6 companies, of which 4 provide evidence of reversion only in higher quantiles of the shock. Interestingly, all our stay-at-home companies demonstrate complete absence of mean reversion, making them potentially risky for long-term investment. Of our 7 cryptocurrency companies, only CME and Visa demonstrate mean reversion in higher quantiles. 3 of our 7 Bitcoin companies demonstrate mean reversion in lower quantiles. The coronavirus vaccine and therapeutic group shows evidence of mean reversion largely in lower quantiles only.

4. Conclusion

We document the presence of price bubbles in almost all markets analyzed. In terms of persistence, 24 of our 43 companies demonstrate complete absence of mean reversion, implying higher risk in the long run. Some firms in the work-from-home, cryptocurrency and coronavirus-vaccine groups show reversion in higher quantiles.

The implications of our results are multidimensional. The presence of mean reversion contradicts the Efficient Market Hypothesis and may imply pricing irregularities that are inconsistent with equilibrium asset pricing models (Forbes, 1996).

Another implication of our results is their applicability to trading strategies. Bubbles can be exploited by arbitrageurs to outperform other traders (Westphal & Sornette, 2020). In terms of persistence, several studies (e.g., Balvers et al. 2000; Gropp, 2004) document that excess returns can be generated by exploiting mean reversion of prices. During periods of bubbles, valuation is temporarily mean averting, implying that expected returns from valuation change are positive. Given that bubbles are impacted by both valuation and expected change in profitability (Tarlie et al. 2018), our results can be useful for policy makers in terms of their impact on both valuation and profitability.

Literature on the subject identifies mean-reverting behaviour as a function of numerous factors that can lead to further pricing abnormalities and potential disruption such as market efficiency and company performance (e.g., Jagadeesh and Titman, 1993; Fama and French, 2000), momentums (e.g., Serban, 2010), bullish/bearish market conditions (e.g., Cuñado, Gil-Alana, and de Gracia, 2010 etc.) and herding and market overreaction (e.g., De Bondt and Thaler, 1985, 1987; Zarowin, 1989, 1990). In addition, mean-reversion can be time-varying (e.g., Mukherji, 2011 etc.).

Therefore, given the wide scope and complexity of the phenomenon coupled with the high heterogeneity of markets and companies in our sample, it is beyond the scope of this study to explain the reasons for mean-reversion in some markets/ companies and not in others. However, we acknowledge that more research is needed to investigate the phenomenon in detail to assess relationship among the listed factors. This inquiry can also be extended with implied volatility and risk premiums in the selected markets as explanatory factors for detecting the presence/absence of mean reversion during a crisis, something that we leave for future research.

References

Aziz, S., Jalan, A., Matkovskyy, R., Bouraoui, T. (2020). Does religious philosophy affect investor behaviour in the COVID-19 times: Evidence from herding in (non-)Shariah compliant energy firms. Available at ResearchGate.net.

Balvers, R., Wu, Y., Gilliland, E. (2000). Mean reversion across national stock markets and parametric contrarian investment strategies. J.Finance 55, 745-772.

Chan, N.H., Wei, C.Z. (1987). Asymptotic inference for nearly nonstationary AR(1) processes. A.Statistics 15, 1050-1063.

Corbet, S., Hou, Y., Hu, Y., Lucey, B., Oxley, L. (2021). Aye Corona! The contagion effects of being named Corona during the COVID-19 pandemic, Finance Research Letters 38, 101591.

Cuñado, J., Gil-Alana, L., & de Gracia, F. P. (2010). Mean reversion in stock market prices: New evidence based on bull and bear markets. Research in International Business & Finance 24(2), 113–122.

De Bondt, W. F. M., and Thaler, R. H. (1985). Does the Stock Market Overreact? Journal of Finance, XL (July), 793-808.

De Bondt, W. F. M., and Thaler, R. H. (1987). Further Evidence of Investment Overreaction and Stock Market Seasonality. Journal of Finance, XLII (July), 557-581.

Fama, E.F., French, K.R. (2000) Forecasting profitability and earnings. Journal of Business 73, 161-175

Forbes, W.P. (1996). Picking winners? A survey of the mean reversion and overreaction of stock prices literature. J.Econ.Surv., 10(2), 123-158.

Galvao, A.F.Jr. (2009). Unit root quantile autoregression testing using covariates. J.Econometrics 152, 165-178.

Gharib, C., Mefteh-Wali, S. & Jabeur, S.B. (2021). The bubble contagion effect of COVID-19 outbreak: Evidence from crude oil and gold markets. Finance Research Letters 38, 101703.

Gropp, J. (2004). Mean reversion of industry stock returns in the U.S., 1926–1998. J.Empir.Finance 11, 537-551.

Gürkaynak, R.S. (2008). Econometric tests of asset price bubbles: taking stock. J.Econ.Surv. 22(1), 166–186.

Harvey, D.I., Leybourne, S.J., Sollis,R. (2015). Recursive right-tailed unit root tests for an explosive asset price bubble. J.Financ.Econometrics, 13(1), 166-187.

Jagadeesh, N., and Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. Journal of Finance, XLVIII (March), 65-90.

Jalan, A., Matkovskyy, R., Yarovaya, L. (2021). 'Shiny' Crypto Assets: A Systemic Look at Gold-Backed Cryptocurrencies during the COVID-19 Pandemic, Available at SSRN 3796837, http://dx.doi.org/10.2139/ssrn.3796837

Jiang, Z.Q., Zhou, W.X., Sornette, D., Woodard, R., Bastiaensen, K., Cauwels,P. (2010). Bubble diagnosis and prediction of the 2005–2007 and 2008–2009 Chinese stock market bubbles. J.Econ. Behav.Organ. 74(3), 149-162.

Koenker, R., Xiao, Z. (2004). Unit root quantile autoregression inference. J.Am.Stat.Assoc. 99, 775–787.

Le, T. N. L., Yarovaya, L., & Nasir, M. A. (2021). Did COVID-19 change spillover patterns between Fintech and other asset classes? Research in International Business and Finance (in Press)

Pavlidis, E.G., Paya, I., Peel, D.A. (2018). Using market expectations to test for speculative bubbles in the crude oil market. J.Money Credit Bank. 50(5), 833–856.

Phillips, P.C. B., Shi, S. (2017). Detecting financial collapse and ballooning sovereign risk. Cowles Foundation Discussion Paper No.2110. Available at SSRN: https://ssrn.com/ Abstract= 3036545.

Phillips, P.C. B., Shi, S., Yu,J. (2015a). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P500. Inter.Econ.Rev.56(4), 1034–1078.

Phillips, P.C.B., Shi, S., Yu,J. (2015b). Testing for multiple bubbles: Limit Theory for Real-Time Detectors. Inter.Econ.Rev. 56(4), 1079–1134.

Sharma, S., Escobari, D. (2018). Identifying price bubble periods in the energy sector. Energy.Econ. 69, 418-429.

Sornette, D. (2003). Why Stock Markets Crash: Critical Events in Complex Financial Systems. Princeton University Press,Princeton.

Tarlie, M.B., Sakoulis, G., Henrikssonet, R. (2018). Stock market bubbles and anti-bubbles. Int.Rev. Financial Analysis. In Press.

Taylor, M.P., Peel, D.A. (1998). Periodically collapsing stock price bubbles: a robust test. Econ.Lett. 61, 221-228.

Westphal, R. & Sornette, D. (2020). Market impact and performance of arbitrageurs of financial bubbles in an agent-based model. J.Econ.Behav.Organ. 171, 1-23.

Yang, Y., Zhao, Z. (2020). Quantile nonlinear unit root test with covariates and an application to the PPP hypothesis. Econ.Model. In Press.

Yarovaya, L. Brzeszczynski, J., Goodell, J. W., Lucey, B.M., Lau, C. K. (2020a) Rethinking Financial Contagion: Information Transmission Mechanism During the COVID-19 Pandemic. Available at SSRN: http://dx.doi.org/10.2139/ssrn.3602973

Yarovaya,L., Matkovskyy, R., Jalan, A. (2020b). The COVID-19 Black Swan Crisis: Reaction and Recovery of Various Financial Markets. http://dx.doi.org/10.2139/ssrn.3611587

Yarovaya,L., Matkovskyy, R., Jalan, A. (2021). The effects of a "black swan" event (COVID-19) on herding behavior in cryptocurrency markets. Journal of International Financial Markets, Institutions and Money, 101321.

Zarowin, P. (1989). Does the Stock Market Overreact to Corporate Earnings Information). Journal of Finance, December, 1390-99Serban, A. F. (2010). Combining mean reversion and momentum trading strategies in foreign exchange markets. Journal of Banking & Finance 34(11), 2720–2727.

Zhang, D., Wang, T., Shi,X., Liu,J. (2018). Is hub-based pricing a better choice than oil indexation for natural gas? Evidence from a multiple bubble test. Energy.Econ. 76, 495-503. Zhao Z., Wen, H., Li,K. (2021). Identifying bubbles and the contagion effect between oil and stock markets: New evidence from China. Econ.Model. 94, 780-788.

APPENDIX

Table A1. General statistics for selected companies: Close prices

Table A2. General statistics for selected companies: Log returns

Note: Mean return is the highest for the group of the Bitcoin companies (0.0094), followed by the coronavirus vaccine companies (0.0061). Average median for returns is generally lower than average mean, indicating that the data are skewed to the right. The highest maximum return for the whole sample is observed for Sorrento (1.58), a coronavirus therapeutic company. The highest standard deviation and variance is noted for Marathon (0.1170), a Bitcoin company, while the lowest for Johnson and Johnson (0.076), a coronavirus vaccine company.

Table A3. Bubbles: Work-from-home companies

The table provides the start and end date of price bubbles identified using close price data for the selected companies in the group. Column 3 calculates the 'number of bubble-days' which is simply a measure of the length of the bubble from start to end. This is done to facilitate inter-industry comparison for the presence and intensity of bubbles.

Table A4. Bubbles: Stay-at-home companies

The table provides the start and end date of price bubbles identified using close price data for the selected companies in the group. Column 3 calculates the 'number of bubble-days' which is simply a measure of the length of the bubble from start to end. This is done to facilitate inter-industry comparison for the presence and intensity of bubbles.

Table A5. Bubbles: Cryptocurrency companies

The table provides the start and end date of price bubbles identified using close price data for the selected companies in the group. Column 3 calculates the 'number of bubble-days' which is simply a measure of the length of the bubble from start to end. This is done to facilitate inter-industry comparison for the presence and intensity of bubbles.

Table A6. Bubbles: Bitcoin companies

The table provides the start and end date of price bubbles identified using close price data for the selected companies in the group. Column 3 calculates the 'number of bubble-days' which is simply a measure of the length of the bubble from start to end. This is done to facilitate inter-industry comparison for the presence and intensity of bubbles.

Table A7. Bubbles: Coronavirus Vaccine companies

The table provides the start and end date of price bubbles identified using close price data for the selected companies in the group. Column 3 calculates the 'number of bubble-days' which is simply a measure of the length of the bubble from start to end. This is done to facilitate inter-industry comparison for the presence and intensity of bubbles. \mathbf{v}

Table A8. Bubbles: Coronavirus therapeutics companies

The table provides the start and end date of price bubbles identified using close price data for the selected companies in the group. Column 3 calculates the 'number of bubble-days' which is simply a measure of the length of the bubble from start to end. This is done to facilitate inter-industry comparison for the presence and intensity of bubbles. λ because λ

Table A9. Tests for quantile unit root, Work-from-home companies

Table contains the results of the quantile nonlinear unit root tests with covariates, *YZtkss*, estimated as in Yang and Zhao (2020). The asymptotic critical values are calculated with significance at the 1%, 5% and 10% levels. The null hypothesis of the presence of a unit root is rejected if the calculated test statistic is lower in value than calculated asymptotic critical values at the 1% (***), 5% (**) and 10% (*) levels of significance. Statistically significant values of *YZtks* are highlighted in bold, while the respective asymptotic critical values that indicate a significance level are underlined.

Table A10. Tests for quantile unit root - Stay-at-home companies

Table shows the results of the quantile nonlinear unit root tests with covariates, *YZtkss*, estimated as in Yang and Zhao (2020). The asymptotic critical values are calculated with significance at the 1%, 5% and 10% levels. The null hypothesis of the presence of a unit root is rejected if the calculated test statistic is lower in value than calculated asymptotic critical values at the 1% (***), 5% (**) and 10% (*) levels of significance. Statistically significant values of *YZtks* are highlighted in bold, while the respective asymptotic critical values that indicate a significance level are underlined.

Table A11. Tests for quantile unit root - Cryptocurrency companies

Table shows the results of the quantile nonlinear unit root tests with covariates, *YZtkss*, estimated as in Yang and Zhao (2020). The asymptotic critical values are calculated with significance at the 1%, 5% and 10% levels. The null hypothesis of the presence of a unit root is rejected if the calculated test statistic is lower in value than calculated asymptotic critical values at the 1% (***), 5% (**) and 10% (*) levels of significance. Statistically significant values of *YZtks* are highlighted in bold, while the respective asymptotic critical values that indicate a significance level are underlined.

Table A12. Tests for quantile unit root - Bitcoin companies

Table shows the results of the quantile nonlinear unit root tests with covariates, *YZtkss*, estimated as in Yang and Zhao (2020). The asymptotic critical values are calculated with significance at the 1%, 5% and 10% levels. The null hypothesis of the presence of a unit root is rejected if the calculated test statistic is lower in value than calculated asymptotic critical values at the 1% (***), 5% (**) and 10% (*) levels of significance. Statistically significant values of *YZtks* are highlighted in bold, while the respective asymptotic critical values that indicate a significance level are underlined.

Table A13. Tests for quantile unit root - Coronavirus Vaccine companies

Table shows the results of the quantile nonlinear unit root tests with covariates, *YZtkss*, estimated as in Yang and Zhao (2020). The asymptotic critical values are calculated with significance at the 1%, 5% and 10% levels. The null hypothesis of the presence of a unit root is rejected if the calculated test statistic is lower in value than calculated asymptotic critical values at the 1% (***), 5% (**) and 10% (*) levels of significance. Statistically significant values of *YZtks* are highlighted in bold, while the respective asymptotic critical values that indicate a significance level are underlined.

Table A14. Tests for quantile unit root - Coronavirus therapeutics companies Table shows the results of the quantile nonlinear unit root tests with covariates, *YZtkss*, estimated as in Yang and Zhao (2020). The asymptotic critical values are calculated with significance at the 1%, 5% and 10% levels. The null hypothesis of the presence of a unit root is rejected if the calculated test statistic is lower in value than calculated asymptotic critical values at the 1% (***), 5%(**) and 10% (*) levels of significance. Statistically significant values of *YZtks* are highlighted in bold, while the respective asymptotic critical values that indicate a significance level are underlined.

