11-1-2022

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Research in International Business and Finance 64 (2023) 101803

Contents lists available at ScienceDirect

Research in International Business and Finance

journal homepage: www.elsevier.com/locate/ribaf

Did David win a battle or the war against Goliath? Dynamic return and volatility connectedness between the GameStop stock and the high short interest indices

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ARTICLE INFO

JEL Classifications:
G10
G11
G14
G41

Keywords:
Static and dynamic connectedness
GameStop
Short-interest index
Stock returns
Return volatility
Spillovers
WallStreetBets

ABSTRACT

Can a short-squeeze incident trigger financial contagion over heavily shorted companies? The recent GameStop frenzy provides a unique natural experiment to explore this question. This study examines the static and dynamic return and volatility connectedness among the GameStop stock, the novel market-wide and sectoral short-interest indices, and the U.S. stock market. Contrary to anecdotal evidence, we find that the GameStop stock is not a net transmitter but a net recipient of return and volatility spillovers from other companies shorted in the market. This result agrees with the view that short-interest indices provide price discovery for shorted stocks. Therefore, although David might have won a battle against Goliath, he does not seem to win the war.

1. Introduction

How effective can betting against professional, institutional investors be? How noisy can the activity of uninformed investors to the "smart money" be? Can intentional herding by retail investors be the source of risk shocks for sophisticated investors? The recent story of the GameStop frenzy, featured in social media and financial newspapers worldwide, provides some interesting insights into these

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https://doi.org/10.1016/j.ribaf.2022.101803
Received 21 May 2021; Received in revised form 4 September 2022; Accepted 7 November 2022
Available online 18 November 2022
0275-5319/

questions.[1] GameStop Corp. incurred substantial losses in 2019 and 2020, which led to a significant drawdown in security prices.[2] The financial problems were not unnoticed by major hedge funds, which took out large short positions in the company's securities. In fact, in 2020, between 50% and 100% of the GameStop's total stocks were borrowed to support such short positions.[3] This notwithstanding, the GameStop's stock price recently experienced an unprecedented hike. For instance, during our sample period that runs from November 2nd, 2020, to July 31st, 2021, stock investors in GameStop recorded an astounding cumulative return of 1400%, which a commensurate improvement in fundamentals can hardly justify. Also, there are generally three different peaks in the GameStop price, i.e., the end of January 2021 (USD 469.42), March 2021 (USD 340.10), and June 2021 (337.37 USD).

Anecdotal evidence argues that hedge funds' short-selling strategies were countered and squeezed by a group of retail investors harbored in the Reddit forum "r/WallStreetBets."[4] These traders flocked to purchase the stock in concert, resulting in a short squeeze. Social media was quick at proclaiming a triumph of retail investors (David) in this battle against large institutional investors (Goliath). However, can this event be regarded as a triumph from the perspective of financial theory? In other words, did David win the war against Goliath or just a battle? Specifically, we aim to answer the following questions. Did this short-squeeze incident trigger financial contagion in the indices of heavily shorted stocks? Or, did the short indices provide price discovery for shorted stocks? The short squeeze can erode market depth (Merrick et al., 2005), destabilize stock prices, and manifest itself as a speculative bubble, which can presage a stock market crash (Jarrow, 1992) and give rise to financial contagion. Thus, such a Pyrrhic victory can come at a prohibitively high cost to the economy.

The short squeeze strategy manifesting in the recent surge in GameStop shares raises doubt about classifying noise traders as "dumb money." In fact, this episode conforms to the risky scenario, demonstrated by De Long et al. (1990), which resembles the ongoing GameStop storm:

"An arbitrageur selling an asset short when bullish noise traders have driven its price up must remember that noise traders might become even more bullish tomorrow and so must take a position that accounts for the risk of a further price rise when he has to buy back the stock" (De Long et al., 1990).

In De Long et al. (1991), noise traders not only accrue higher returns than rational investors but also can survive and dominate the market in terms of wealth in the long run. The GameStop saga shows that, at least in the short run, noise traders can thrive, create their own space, and even lead rational investors to lose a substantial portion of their wealth. While the literature is replete with studies about noise traders' role in capital markets (e.g., Black, 1986; Shleifer and Summers, 1990; Shleifer and Vishny, 1997; Peress and Schmidt, 2020), the recent GameStop story is a unique opportunity to witness a direct clash between Wall Street and the WallStreetBets, representing institutional and retail investors, respectively. While it appears that the recent heavy losses of Melvin Capital can be regarded as a temporary win for retail investors, we ask if, and if so, how the return and price volatility of the GameStop stock is transmitted to top short indices, which are typically driven by trades of institutional investors. To answer this question, we map the underlying lead-led forces using a quantile connectedness approach, which enables us to track the connectedness between the GameStop stock and top short indices in response to large positive and negative shocks. Recognized as the torch of "resistance" by retail investors, GameStop drives this choice. The other side of the barricade comprises institutional investors, who pull all their short bets on depressed stocks. These questions are of utmost importance in the light of two recent studies demonstrating that retail investors may have the power to spur instability in equity prices, especially in turbulent times such as the COVID-19 and the 2008 subprime crisis (Aharon et al., 2022; Baig et al., 2022).

Our research can be viewed through the prism of De Long et al. (1990), who were among the first to study the theoretical effects of investor sentiment in stock markets. Specifically, they model two types of investors: i) sentiment-free rational arbitrageurs and ii) irrational (noise) traders—prone to investor sentiment—who compete in the market and set prices. From the behavioral finance perspective, the equity anomalies build on two essential pillars: a) investor bounded rationality that drives the prices away from their fundamental values and results in systematic and predictable errors; and b) limits to arbitrage, which do not allow the anomalies to disappear. Short-selling limitations are the prime reasons mispricing endures (Stambaugh, Yu, and Yuan, 2012). On the other hand, active short selling may improve information efficiency and help correct stock mispricing (Boehmer and Wu, 2013; Cao et al., 2018).

Our contribution to the literature is at least three-fold. First, we are the first to examine the extent to which the rally of amateur individual investors against Wall Street could render short-selling strategies ineffective and, thus, decimate the population of institutional investors. Second, new stock market indices were launched very recently, which quantify the financial performance of short-selling strategies (the so-called short-interest indices). To the best of our knowledge, we are the first to study the relationship of returns and volatilities between a short-traded depressed stock and the short-interest indices, and we are the first to use the novel market-wide and sectoral short-interest indices. Third, we join and contribute to studies of Internet communities and their impact on stock prices (e.g., Tumarkin and Whitelaw, 2001; Das and Chen, 2007; Ackert et al., 2016; Fisher, 2019).

Building on the related body of research, we set out two competing hypotheses. Orchestrated by a large investor or a group of investors acting in concert (Jarrow, 1992), a short squeeze occurs when the price of a security rises, which triggers a decline in the net

[1] See, for example, https://www.ft.com/content/3f6b47f9-70c7-4839-8bb4-6a62f1bd39e0, https://www.nytimes.com/2021/01/27/business/gamestop-wall-street-bets.html, https://www.ft.com/content/ca94c275-43aa-4d12-a0ff-868f2760c8b5 (accessed on 9 February 2021).

[2] GameStop Corp. reported a negative earnings-per-share of USD 6.59 and USD 5.38 in 2019 and 2020, respectively. For further information, see, e.g., https://www.macrotrends.net/stocks/charts/GME/gamestop/eps-earnings-per-share-diluted (accessed on 3 February 2021).

[3] See, e.g., https://www.ft.com/content/3f6b47f9-70c7-4839-8bb4-6a62f1bd39e0 (accessed on 9 February 2021).

[4] See, e.g., https://www.bloomberg.com/news/articles/2021-01-26/short-sellers-crushed-like-never-before-as-retail-army-charges (accessed on 9 February 2021).

Table 1a
Static Return Connectedness.

	GameStop	High	Tech	REITs	Consumer	Financials	Energy	Healthcare	Industrials	Russell	FROM
Panel A – TVP-VAR											
GameStop	**51.13**	7.43	6.52	4.47	9.56	3.93	3.81	4.11	5.10	3.94	48.87
High	3.67	**18.52**	14.16	6.78	12.85	7.61	5.59	11.7	10.77	8.35	81.48
Tech	3.62	16.12	**21.32**	6.00	10.86	6.78	4.61	10.49	10.35	9.85	78.68
REITs	2.85	9.10	7.18	**27.21**	10.1	11.97	7.75	5.08	11.05	7.70	72.79
Consumer	4.86	14.01	10.46	8.14	**20.48**	8.94	6.5	6.43	11.93	8.26	79.52
Financials	2.16	9.18	7.35	10.79	9.97	**23.58**	8.75	5.6	12.77	9.85	76.42
Energy	2.70	8.31	6.22	8.64	9.03	10.93	**30.75**	5.12	11.38	6.94	69.25
Healthcare	2.71	16.05	12.78	5.07	8.07	6.21	4.70	**27.72**	8.69	8.00	72.28
Industrials	2.49	11.35	9.71	8.68	11.58	11.03	7.98	6.93	**20.42**	9.84	79.58
Russell	2.39	10.17	10.89	7.30	9.43	10.31	5.77	7.21	11.67	**24.87**	75.13
Contribution TO others	27.44	101.73	85.28	65.86	91.45	77.70	55.46	62.65	93.71	72.73	**73.40**
NET connectedness	-21.42	20.25	6.60	-6.92	11.93	1.28	-13.79	-9.63	14.13	-2.41	**TCI**
Panel B – 50th Quantile											
GameStop	**68.07**	4.72	4.06	2.88	6.65	2.55	2.63	2.68	3.37	2.38	31.93
High	1.84	**18.9**	14.46	6.61	13.26	7.84	5.3	12.07	11.03	8.67	81.1
Tech	1.78	16.4	**21.52**	5.68	11.33	7.03	4.34	10.6	10.76	10.55	78.48
REITs	1.52	9.16	7	**29.1**	9.65	11.97	7.16	5.22	11.16	8.07	70.9
Consumer	2.65	14.85	11.16	7.61	**21.35**	8.95	5.95	6.88	12.04	8.59	78.65
Financials	1.23	9.62	7.78	10.2	10.02	**23.81**	8.19	5.74	12.79	10.63	76.19
Energy	1.53	8.55	6.33	8.16	8.97	10.77	**32.44**	4.95	11.6	6.72	67.56
Healthcare	1.4	16.51	12.92	5.12	8.61	6.37	4.19	**26.9**	9.25	8.72	73.1
Industrials	1.37	11.61	10.16	8.37	11.51	10.87	7.56	7.21	**21.51**	9.82	78.49
Russell	1.04	10.63	11.53	7.3	9.63	10.85	5.26	7.74	11.65	**24.38**	75.62
Contribution TO others	14.37	102.06	85.4	61.92	89.62	77.19	50.59	63.08	93.66	74.15	**71.20**
NET connectedness	-17.56	20.95	6.92	-8.98	10.97	1.00	-16.97	-10.01	15.16	-1.48	**TCI**
Panel C – 25th Quantile											
GameStop	**51.75**	6.35	5.64	4.68	8.15	4.56	4.9	4.73	5.29	3.94	48.25
High	2.82	**16.97**	13.59	7.42	12.57	8.53	6.44	11.78	10.88	9.01	83.03
Tech	2.8	15.05	**18.75**	6.65	11.26	7.94	5.59	10.77	10.75	10.44	81.25
REITs	2.57	9.68	7.89	**23.06**	10.11	11.84	8.3	6.65	11.17	8.74	76.94
Consumer	3.68	13.65	11.04	8.31	**18.43**	9.4	7.08	7.8	11.63	8.98	81.57
Financials	2.22	9.93	8.51	10.43	10.27	**19.85**	8.94	7.01	12.25	10.57	80.15
Energy	2.76	9.27	7.5	9.06	9.56	11.05	**25.09**	6.58	11.47	7.66	74.91
Healthcare	2.63	15.00	12.4	6.43	9.28	7.58	5.84	**21.94**	9.77	9.12	78.06
Industrials	2.38	11.22	10.15	8.83	11.18	10.83	8.24	7.95	**19.32**	9.89	80.68
Russell	1.96	10.67	11.32	8.13	10	10.97	6.4	8.47	11.44	**20.64**	79.36
Contribution TO others	23.82	100.83	88.04	69.94	92.38	82.7	61.73	71.74	94.67	78.36	**76.42**
NET connectedness	-24.43	17.80	6.79	-7.00	10.81	2.55	-13.19	-6.32	13.99	-1.00	**TCI**
Panel D – 75th Quantile											
GameStop	**51.11**	6.59	5.73	4.82	8.17	4.41	4.71	4.88	5.47	4.11	48.89
High	2.87	**16.7**	13.5	7.54	12.55	8.62	6.48	11.83	10.89	9.02	83.3
Tech	2.76	14.93	**18.5**	6.78	11.23	8.05	5.7	10.78	10.79	10.48	81.5
REITs	2.59	9.73	7.91	**22.74**	10.12	11.83	8.23	6.83	11.16	8.85	77.26
Consumer	3.63	13.63	10.99	8.42	**18.24**	9.48	7.08	7.9	11.62	9.01	81.76
Financials	2.12	10.04	8.59	10.52	10.31	**19.69**	8.86	7.06	12.2	10.6	80.31
Energy	2.61	9.26	7.5	9.06	9.55	11.06	**25.26**	6.54	11.42	7.73	74.74
Healthcare	2.61	14.99	12.44	6.66	9.37	7.74	5.77	**21.53**	9.77	9.13	78.47
Industrials	2.33	11.3	10.23	9	11.17	10.81	8.2	8.07	**18.97**	9.92	81.03
Russell	1.97	10.65	11.33	8.2	9.96	10.94	6.41	8.54	11.47	**20.53**	79.47
Contribution TO others	23.48	101.13	88.22	70.99	92.44	82.95	61.42	72.44	94.79	78.84	**76.67**
NET connectedness	-25.4	17.83	6.72	-6.27	10.68	2.64	-13.32	-6.03	13.77	-0.62	**TCI**

Notes. The table reports the static pairwise return quantile connectedness of the variables. In Panel A (Panel B, Panel C, Panel D), the TVP-VAR (50th quantile, 25th quantile, 75th quantile) connectedness is displayed. The diagonal values refer to the variation of each variable itself. The rightmost column reflects the total impact of the whole set of variables on the row's variable. The row TO is the spillover of a specific column variable to the whole set of variables. Finally, the last NET row is the difference between the contribution TO and the contribution FROM the set of variables. TCI is the total connectedness index. The log-returns are measured over 10-minute intervals. The sample period runs from November 2nd, 2020, to July 31st, 2021.

Table 1b
Static Volatility Connectedness.

	GameStop	High	Tech	REITs	Consumer	Financials	Energy	Healthcare	Industrials	Russell	FROM
Panel A – TVP-VAR											
GameStop	**41.85**	7.84	6.87	5.29	9.65	5.37	5.02	5.81	5.98	6.32	58.15
High	5.87	**17.87**	13.13	6.81	12.39	7.59	6.24	11.24	10.59	8.26	82.13
Tech	5.94	14.38	**19.38**	6.53	10.87	7.51	6.07	9.61	10.32	9.38	80.62
REITs	5.48	9.09	7.93	**23.32**	9.94	10.79	7.82	6.38	10.43	8.82	76.68
Consumer	7.38	13.02	10.38	7.73	**19.54**	8.52	6.73	7.13	10.98	8.6	80.46
Financials	5.22	9.21	8.36	9.78	9.87	**21.02**	8.20	6.28	11.63	10.43	78.98
Energy	5.3	8.70	7.70	8.37	9.26	9.81	**25.58**	6.58	10.45	8.24	74.42
Healthcare	5.62	14.69	11.51	6.31	9.02	6.89	6.22	**22.18**	9.53	8.02	77.82
Industrials	4.96	11.25	10.11	8.23	11.11	10.17	7.62	7.67	**19.21**	9.67	80.79
Russell	6.06	9.7	10.22	7.59	9.57	10.24	6.56	7.17	10.68	**22.21**	77.79
Contribution TO others	51.84	97.87	86.21	66.63	91.69	76.90	60.48	67.87	90.61	77.74	**76.78**
NET connectedness	-6.31	15.75	5.60	-10.06	11.23	-2.08	-13.94	-9.95	9.82	-0.04	**TCI**
Panel B – 50th Quantile											
GameStop	**59.35**	5	4.63	4.23	6.29	4.01	4.33	3.53	4.8	3.82	40.65
High	2.31	**20.98**	14.5	6.23	12.55	7.27	5.4	11.49	10.73	8.54	79.02
Tech	2.28	15.9	**23.53**	5.63	10.41	7.07	5.26	9.7	10.31	9.89	76.47
REITs	2.63	8.47	7.26	**31.47**	8.91	10.55	7.2	5.41	10.12	7.98	68.53
Consumer	3.12	14.07	10.78	7.14	**24.14**	8.1	6.07	6.65	11.69	8.24	75.86
Financials	2.34	8.86	8.15	9.32	9.06	**26.55**	7.82	5.77	11.81	10.33	73.45
Energy	2.55	7.92	7.12	7.67	8.26	9.38	**33.32**	6.08	10.48	7.21	66.68
Healthcare	2.21	15.14	11.8	5.41	8.14	6.19	5.47	**28.28**	9.04	8.31	71.72
Industrials	2.2	11.31	10.16	7.65	10.87	10.01	7.34	7.22	**23.65**	9.59	76.35
Russell	2.07	10.14	10.81	6.9	8.81	10.26	6.03	7.59	10.98	**26.41**	73.59
Contribution TO others	21.73	96.79	85.22	60.18	83.3	72.85	54.93	63.45	89.97	73.91	**70.23**
NET connectedness	-18.92	17.77	8.75	-8.35	7.43	-0.6	-11.75	-8.27	13.62	0.32	**TCI**
Panel C – 25th Quantile											
GameStop	**40.01**	6.98	6.67	6.65	8.15	6.29	6.47	6.08	6.79	5.92	59.99
High	3.52	**17.44**	13.44	7.39	12.02	8.22	6.74	11.61	10.7	8.92	82.56
Tech	3.54	14.39	**18.8**	7	10.68	8.19	6.61	10.23	10.54	10	81.2
REITs	4.15	9.27	8.24	**22.82**	9.56	11.01	8.55	7.17	10.48	8.75	77.18
Consumer	4.41	13.02	10.84	8.22	**19.02**	9.02	7.32	7.97	11.4	8.77	80.98
Financials	3.66	9.48	8.88	9.99	9.7	**20.28**	8.78	7.29	11.46	10.48	79.72
Energy	4.16	8.98	8.24	8.97	9.12	10.12	**23.66**	7.72	10.73	8.31	76.34
Healthcare	3.6	14.03	11.62	6.95	9.06	7.7	7.05	**21.3**	9.69	9	78.7
Industrials	3.44	11.1	10.28	8.57	10.89	10.25	8.28	8.27	**19.24**	9.67	80.76
Russell	3.42	10.26	10.8	8.06	9.45	10.61	7.32	8.59	10.9	**20.6**	79.4
Contribution TO others	33.91	97.51	89.02	71.81	88.64	81.39	67.1	74.93	92.69	79.82	**77.68**
NET connectedness	-26.08	14.95	7.82	-5.37	7.66	1.68	-9.24	-3.77	11.94	0.42	**TCI**

(*continued on next page*)

Table 1b (*continued*)

	GameStop	High	Tech	REITs	Consumer	Financials	Energy	Healthcare	Industrials	Russell	FROM
Panel A – TVP-VAR											
Panel D– 75th Quantile											
GameStop	**45.07**	6.54	6.29	5.68	7.69	5.79	6.05	5.7	6.26	4.93	54.93
High	3.21	**18.3**	13.79	7.07	11.94	8.07	6.63	11.6	10.78	8.62	81.7
Tech	3.57	14.4	**19.79**	6.65	10.72	8.05	6.54	10.12	10.61	9.54	80.21
REITs	3.44	9.41	8.49	**24.37**	9.62	10.79	8.22	6.94	10.3	8.41	75.63
Consumer	4.34	12.96	10.97	7.97	**20.37**	8.63	7.18	7.85	11.54	8.18	79.63
Financials	3.26	9.47	8.95	9.79	9.63	**21.72**	8.51	7.04	11.59	10.05	78.28
Energy	3.48	8.84	8.3	8.38	9.2	9.82	**26.04**	7.38	10.75	7.82	73.96
Healthcare	3.21	14.24	11.85	6.65	8.91	7.64	6.87	**22.24**	9.74	8.66	77.76
Industrials	3.22	11.1	10.3	8.12	10.94	10.04	8.01	8.07	**20.92**	9.28	79.08
Russell	2.75	10.26	10.89	7.48	9.18	10.32	6.72	8.23	10.89	**23.28**	76.72
Contribution TO others	30.47	97.21	89.83	67.79	87.82	79.15	64.74	72.92	92.47	75.49	**75.79**
NET connectedness	-24.46	15.51	9.63	-7.83	8.19	0.87	-9.21	-4.85	13.4	-1.23	**TCI**

Notes. The table reports the static pairwise volatility connectedness of the variables. In Panel A (Panel B, Panel C, Panel D), the TVP-VAR (50th quantile, 25th quantile, 75th quantile) connectedness is displayed. The diagonal values refer to the variation of each variable itself. The rightmost column reflects the total impact of the whole set of variables on the row's variable. The row TO is the spillover of a specific column variable to the whole set of variables. Finally, the last NET row is the difference between the contribution TO and the contribution FROM the set of variables. TCI is the total connectedness index. The log-returns are measured over 10-minute intervals. The sample period runs from November 2nd, 2020, to July 31st, 2021.

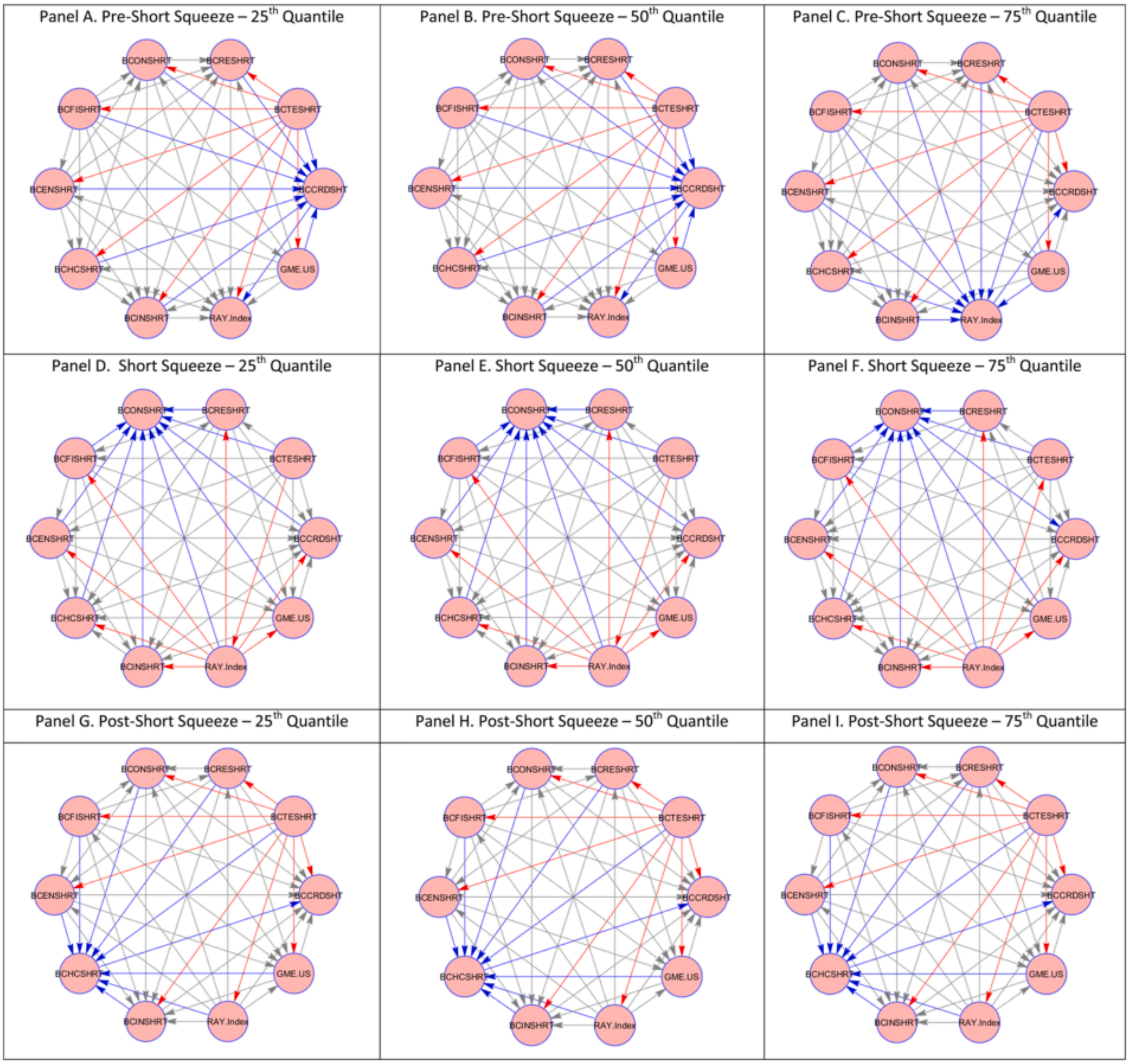

Fig. 1a. *Network Diagrams for Returns. Notes*. This figure illustrates the return networks visualize the pairwise return connectedness among the GameStop stock price (GME.US), the Russell 3000 stock market index (RAY.Index), the market-wide short-interest index (BCCRDSHT), as well as seven sectoral short-interest indices: Consumer (BCONSHRT), Energy (BCENSHRT), Financials (BCFISHRT), Healthcare (BCHCSHRT), Industrials (BCINSHRT), REITs (BCRESHRT), and Technologies (BCTESHRT). In Panels A-C (D-F, G-I), the networks are visualized in the pre (during, post) short squeeze period at the 25th, 50th, and 75th quantiles. The pre-short squeeze period runs from November 2nd, 2020, to December 8th, 2020, when 3rd 'quarter's results for GameStop were announced, and abysmal earnings were reported. The short squeeze period runs from December 8th, 2020, to February 9th, when the end of the short squeeze was announced. The post-short squeeze period spans the remaining period from February 10th, 2021, to July 31st, 2021. Arrows indicate the direction of return transmission. Arrows colored in red determine the highest transmitter. Blue arrows indicate the main recipient in the system. The log-returns are measured over 60-minute intervals. The sample period runs from November 2nd, 2020, to July 31st, 2021.

wealth of the short-selling investor (Lamont, 2012). The short-selling investor may decide to liquidate the position due to i) lower wealth, ii) increased risk aversion, iii) fear of further price rises, or iv) margin calls, which raises the demand for the security and drives its price further up (Lamont, 2012). If the short seller faces liquidity constraints, the former may decide to close the existing short positions in stocks from other industries, especially if such stocks are less liquid (Dechow et al., 2001). Furthermore, if the investors in heavily shorted stocks in other industries become more risk-averse, or anticipate price rises, or expect margin calls, they can decide to cover their positions too. Thus, the short squeeze can propagate across short-selling investors in stocks from different industries.

Hypothesis 1. conjectures that a short squeeze can trigger a rise in financial contagion through return and volatility connectedness in the stock market.

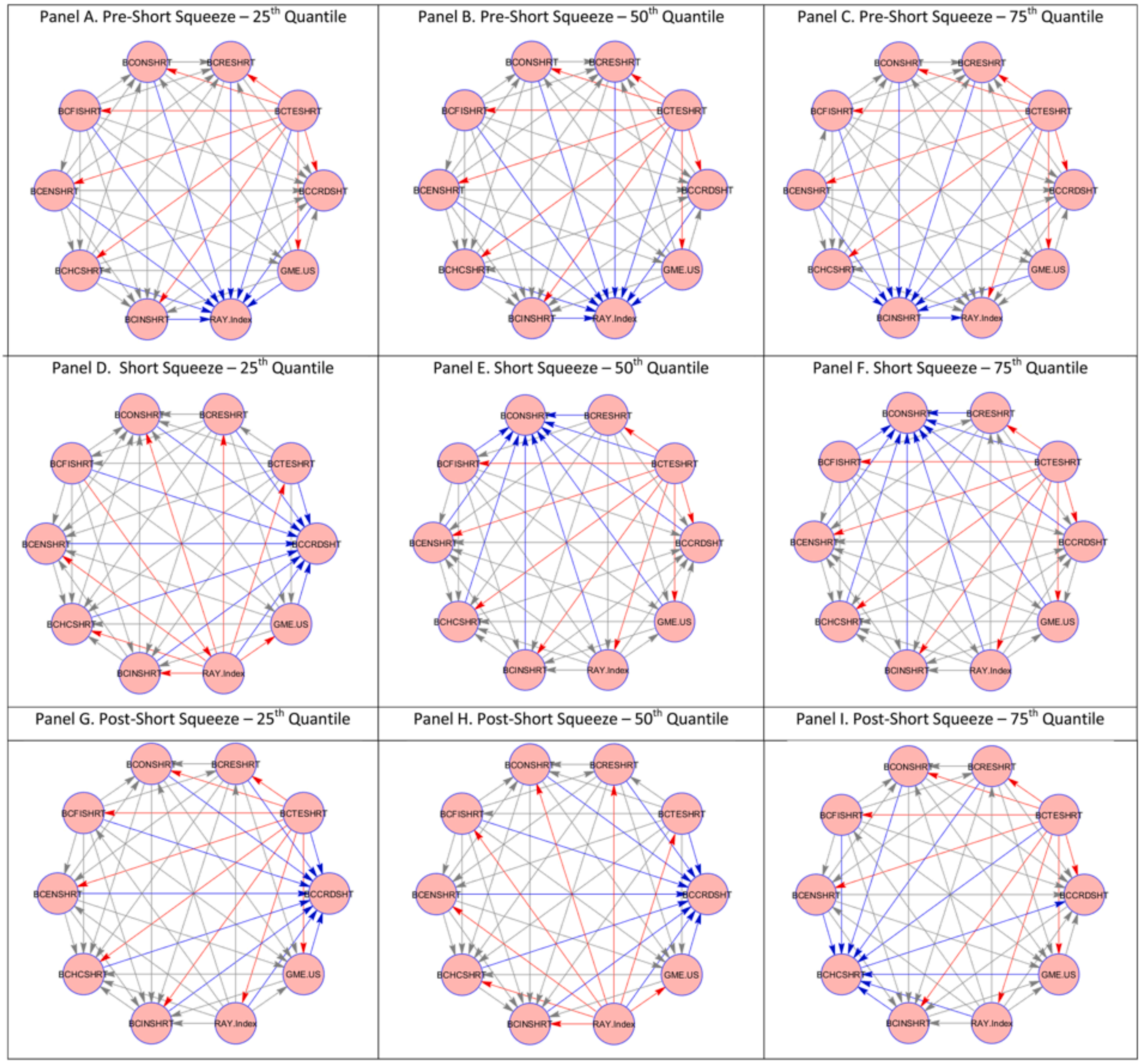

Fig. 1b. *Network Diagrams for Volatilities. Notes*. In this figure, the volatility networks visualize the pairwise volatility connectedness among the GameStop stock price (GME.US), the Russell 3000 stock market index (RAY.Index), the market-wide short-interest index (BCCRDSHT), as well as seven sectoral short-interest indices: Consumer (BCONSHRT), Energy (BCENSHRT), Financials (BCFISHRT), Healthcare (BCHCSHRT), Industrials (BCINSHRT), REITs (BCRESHRT), and Technologies (BCTESHRT). In Panels A-C (D-F, G-I), the networks are visualized in the pre (during, post) short squeeze period at the 25th, 50th, and 75th quantiles. The pre-short squeeze period runs from November 2nd, 2020, to December 8th, 2020, when 3rd quarter's results for GameStop were announced and abysmal earnings were reported. The short squeeze period runs from December 8th, 2020, to February 9th, when the end of the short squeeze was announced. The post-short squeeze period spans the remaining period from February 10th, 2021 to July 31st, 2021. Arrows indicate the direction of return transmission. Arrows colored in red determine the highest transmitter. Blue arrows indicate the main recipient in the system. The log-returns are measured over 60-minute intervals. The sample period runs from November 2nd, 2020, to July 31st, 2021.

Hypothesis 2. argues that an unanticipated return on a short-interest index provides price discovery for a short-traded stock, since information flow associated with short-selling: i) reduces information complexity (Huszár et al., 2017), ii) improves intraday information, iii) accelerates the incorporation of public information into prices, iv) reduces post-earnings-announcement drift in the aftermath of negative earnings surprises, and v) aids price discovery and reduces divergence from fundamentals (Boehmer and Wu, 2013). Informed short sellers' activism generally triggers market quality improvements (Boehmer and Wu, 2013), which can catalyze price discovery of other stocks within and across industries. More recent studies highlight the presence of information diffusion from the short sellers to other market participants (Hu and Chi, 2019), possibly comprising the retail WallStreetBets investors.

Along similar lines, short sellers possess superior information beyond specific stocks, which can benefit both retail investors and

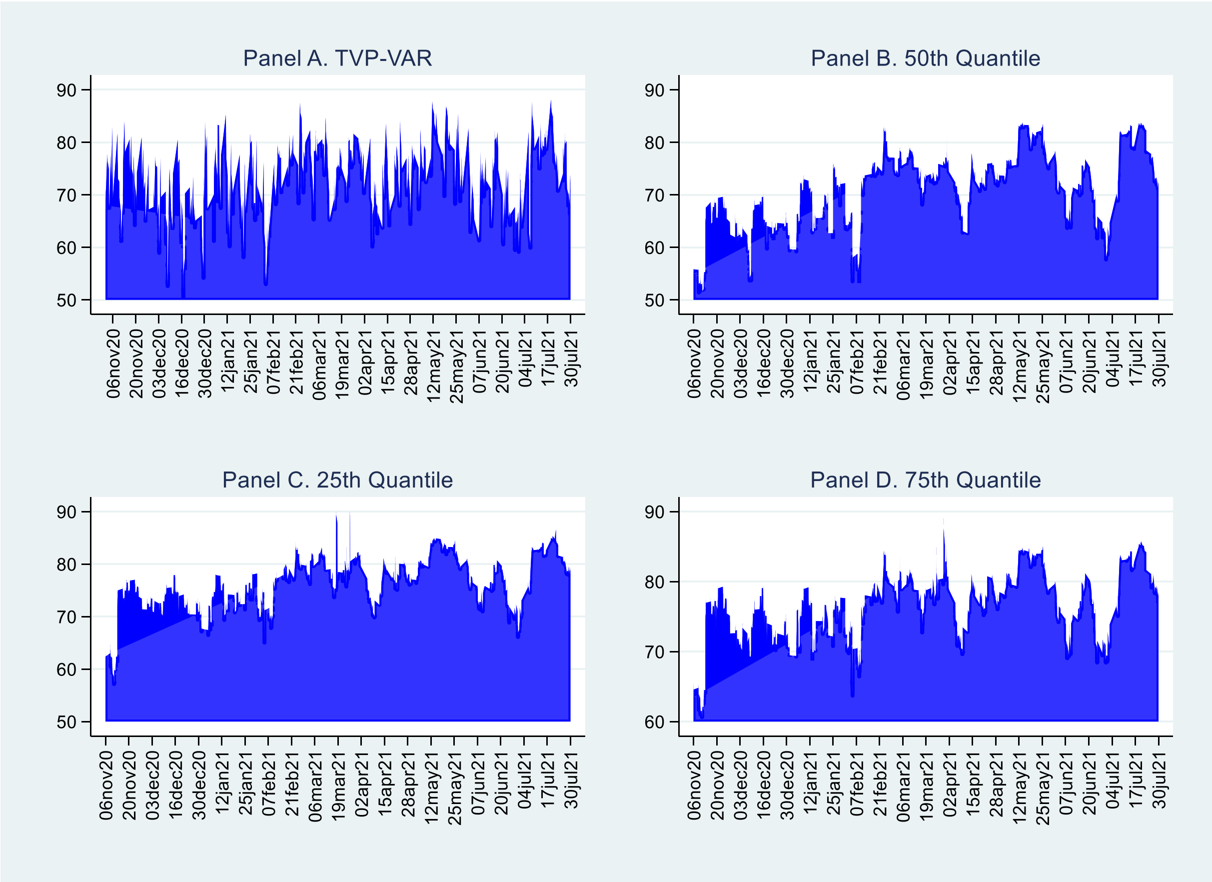

Fig. 2a. *Total Return Connectedness Index. Notes*. The graphs plot the total dynamic return quantile connectedness (spillovers) among the GameStop stock price, the Russell 3000 stock market index, the market-wide short-interest index (High), as well as seven sectoral short-interest indices (Consumer, Energy, Financials, Healthcare, Industrials, REITs, and Technologies). Panel A visualizes the total return spillover implied by the TVP-VAR, Panel B visualizes the total return spillover at the 50th quantile, Panel C depicts the total return spillover at the 25th quantile, Panel D displays the total return spillover at the 75th quantile. The log-returns are measured over 10-minute intervals. The sample period runs from November 2nd, 2020, to July 31st, 2021.

regulators (Huszár et al., 2017). One of the questions that may arise in the context of the possible connection between the GameStop stock and the short-interest indices is whether and, if so, how these indices may contribute to the price discovery if they are unrelated from the perspective of their industry classification. One common feature of such stocks is that they belong to a pool of companies exposed to a high degree of short positions. Thus, the short seller's activism is associated with information production about the shorted stocks, which also transmits to the GameStop stock pricing. According to the literature, liquidity is pivotal in the price discovery process (Chordia, Roll and Subrahmanyam, 2008; Chung and Hrazdil, 2010; Chordia, Subrahmanyam and Tong, 2014). Therefore, the overall increased liquidity derived from the bidirectional liquidity feedback can enhance the price discovery process.

Our methodology uses a quantile-based connectedness measure, which builds on the Diebold-Yilmaz static and dynamic setting, which has become a workhorse in studies of contagion (Yarovaya et al., 2016), price discovery (see, e.g., Antonakakis et al., 2016), short-selling (Umar et al., 2021) across financial assets and markets during the last decade. We use high-frequency (10 min) data recorded from November 2nd, 2020, to July 31st, 2021, to examine the return and volatility connectedness among the stock price of GameStop, the Russell 3000 stock index, as well as eight U.S. short-interest indices.

Our results show that GameStop Corp. is a net recipient of return and volatility spillovers from the short-interest indices. This result holds for the 50th quantile (median) of both the return and volatility distributions. TVP-VAR methodology (a mean-based setting) confirms this result. Considering the lower and upper parts of the return and volatility distribution, represented by the 25th and 75th quantiles, respectively, results remain qualitatively similar. To further validate our baseline results, we use data measured with different frequencies, such as 30 and 60 min. The results remain intact for the 30-minute frequency, albeit vary at the 60-minute frequency. Thus, while several hedge funds incurred losses from betting against the GameStop stock, this outcome cannot be generalized to the whole population of institutional investors. Despite the overwhelming interest that the GameStop frenzy received in social media platforms in the United States and across the globe, our findings do not provide supportive evidence of financial contagion in the

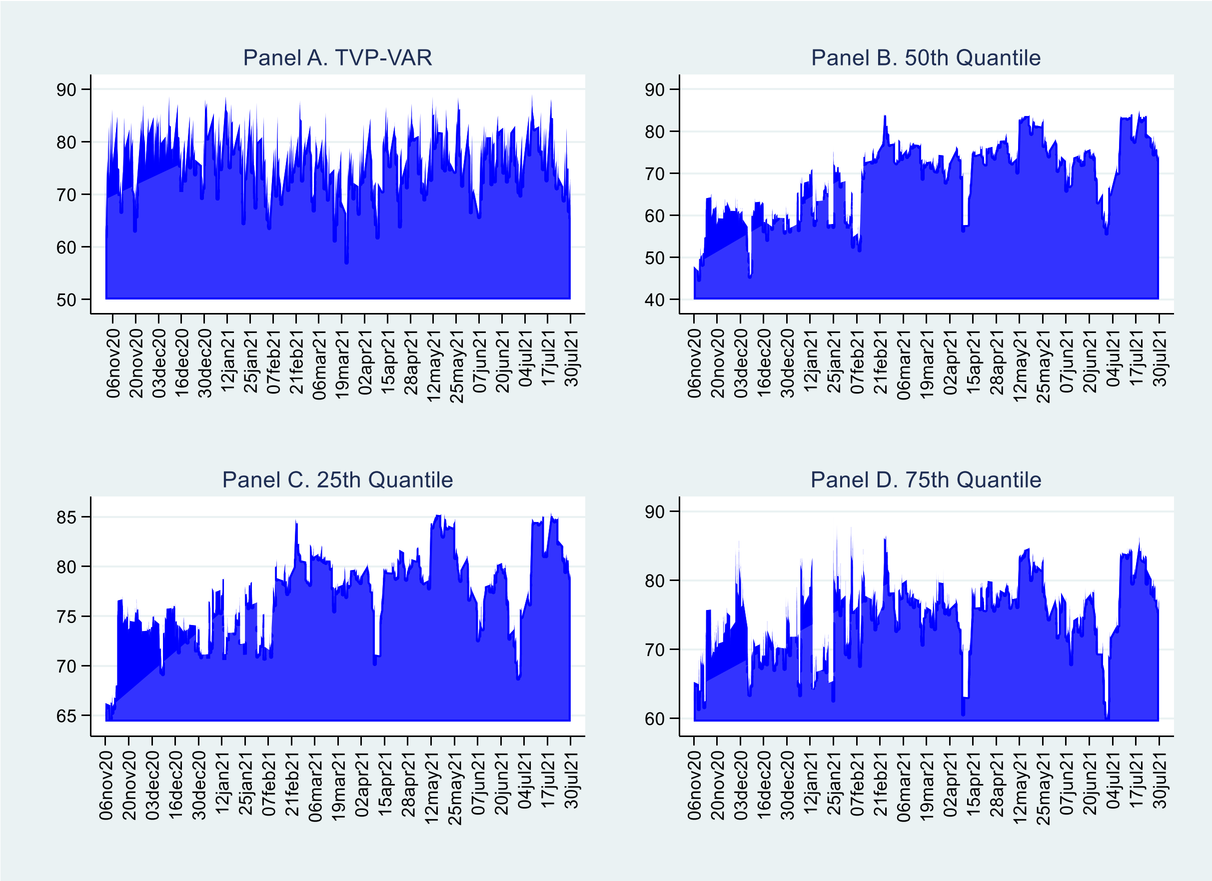

Fig. 2b. *Total Volatility Connectedness Index. Notes*. The graphs plot the total dynamic volatility quantile connectedness (spillovers) among the GameStop stock price, the Russell 3000 stock market index, the market-wide short-interest index (High), as well as seven sectoral short-interest indices (Consumer, Energy, Financials, Healthcare, Industrials, REITs, and Technologies). Panel A visualizes the total volatility spillover implied by the TVP-VAR, Panel B depicts the total volatility spillover at the 50th quantile, Panel C visualizes the total volatility spillover at the 25th quantile, Panel D displays the total volatility spillover at the 75th quantile, The log-returns are measured over 10-minute intervals. The sample period runs from November 2nd, 2020, to July 31st, 2021.

U.S. stock market (Hypothesis 1). We further construct the network diagrams for pairwise return and volatility connectedness, which do not uphold Hypothesis 1. In this respect, Pasquariello (2007) asserts that greater participation of institutional investors can reduce the market's vulnerability to financial contagion. By contrast, our results substantiate Hypothesis 2.

The remainder of the paper is as follows. Section 2 describes data, Section 3 lays out the methodology, Section 4 reports our research findings, and Section 5 concludes the paper.

2. Data

We source both firm-level and index-level data from Bloomberg. The sample includes the GameStop prices and High Short Interest indices calculated by Barclays Capital. The High Short Interest indices were initially designed as indicative investment strategies for Barclays customers and represent equal-weighted portfolios of U.S. stocks with the top short interest, proxied by the number of shares shorted as a percentage of the total free float. The companies for the portfolios are selected from the Russell 3000 index, which mirrors the behavior of the broad U.S. equity market. We use both an aggregate High Short Interest index and sub-indices representing the most shorted stocks from different industries.

The composite High Short Interest index represents the heavily shorted stocks in the U.S. stock market. It comprises 100 companies with the highest short interest (defined above) out of all firms covered by Russell 3000. The sub-indices represent the most shorted companies in seven industries: consumer, energy, financials, healthcare, industrials, real estate investment trusts (REITs), and

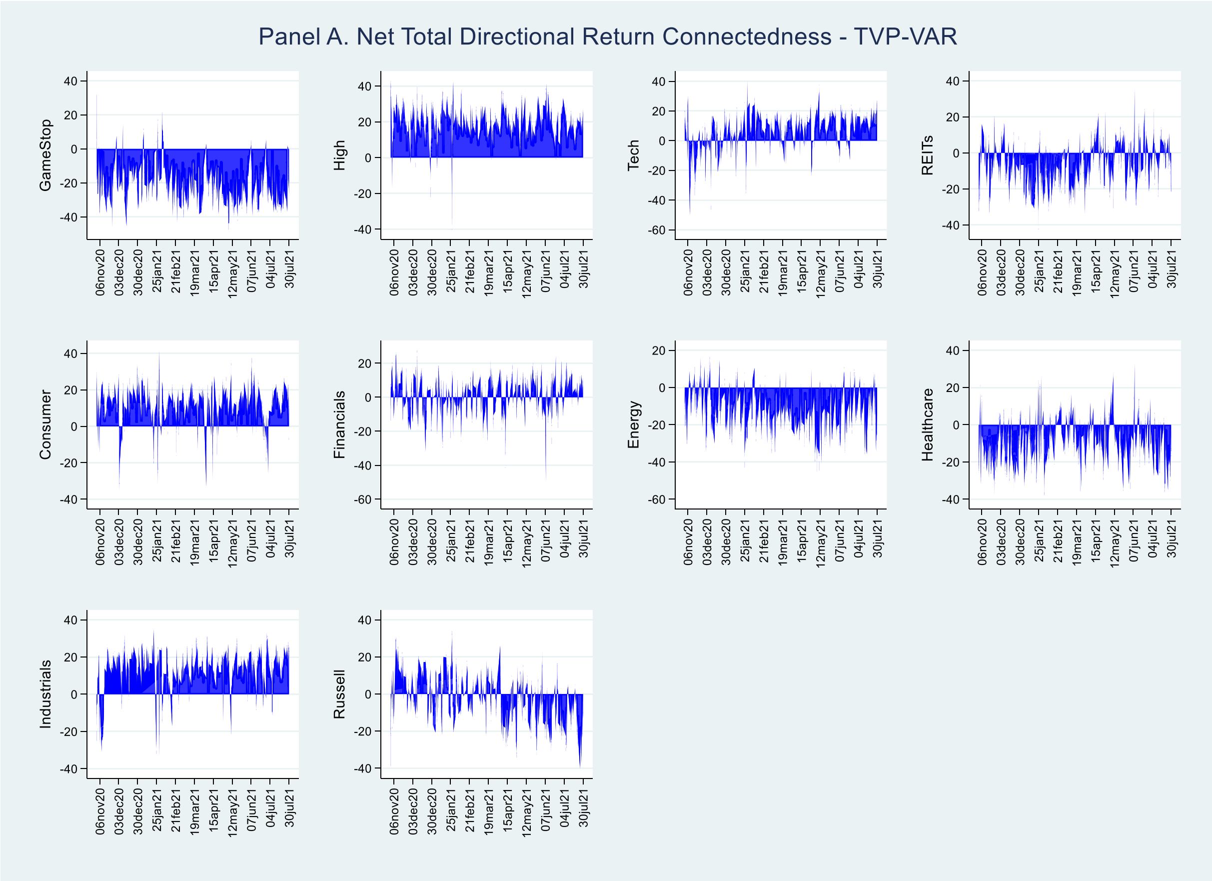

Fig. 3a. *Net Total Directional Return Connectedness. Notes*. This figure illustrates the net total directional return quantile connectedness among the GameStop stock price, the Russell 3000 stock market index, the market-wide short-interest index (High), as well as seven sectoral short-interest indices (Consumer, Energy, Financials, Healthcare, Industrials, REITs, and Technologies). In Panel A (Panel B, Panel C, Panel D), the TVP-VAR (50th quantile, 25th quantile, 75th quantile) connectedness is displayed. The log-returns are measured over 10-minute intervals. The sample period runs from November 2nd, 2020, to July 31st, 2021.

technology.[5] Each contains 10% of the firms from the respective sectors included in Russell 3000. All indices are reconstructed and rebalanced monthly. For further information available in Bloomberg, Table A1 in the Online Appendix provides the precise tickers of all the securities covered in the study. To our knowledge, these novel equity indices have not been explored before.

For completeness, we also include the Russell 3000 index in our study. All the market data is expressed in U.S. dollars. To dynamically track the relationship between the behavior of different securities, we use high-frequency data. Specifically, we calculate log-returns estimated over 10-minute intervals. Our study period runs from 02/11/2020–07/31/2021 and overlaps with the recent GameStop frenzy. The starting point is dictated by data availability in Bloomberg; we use all intraday data available at the time of conducting this research. In total, our sample encompasses 74,400 security-return observations. Table A1 and Fig. A1 in the Online Appendix report the statistical properties and the time variation of the securities in our sample.

3. Methods

We employ the quantile vector autoregression (QVAR) model, proposed by Ando et al. (2022), to study dynamic return and volatility connectedness between the GameStop stock and the short-interest indices.[6] This approach allows asymmetric responses of variable Z_t to large and small shocks in variable X_t.More generally, quantile regression can be employed to test the dependency of Z_t on X_t over the whole range of the conditional distribution of $Z_t|X_t$ (Koenker and Bassett, 1978). In a multiple-equation framework, the

[5] Notably, GameStop Corp. is an American video game, electronics, and gaming merchandise retailer. In consequence, it is classified as a company from consumer (discretionary) sector, and it is included in respective stock indices.

[6] The connectedness index we employ in this study is informed by Diebold and Yilmaz (2009, 2012, 2014).

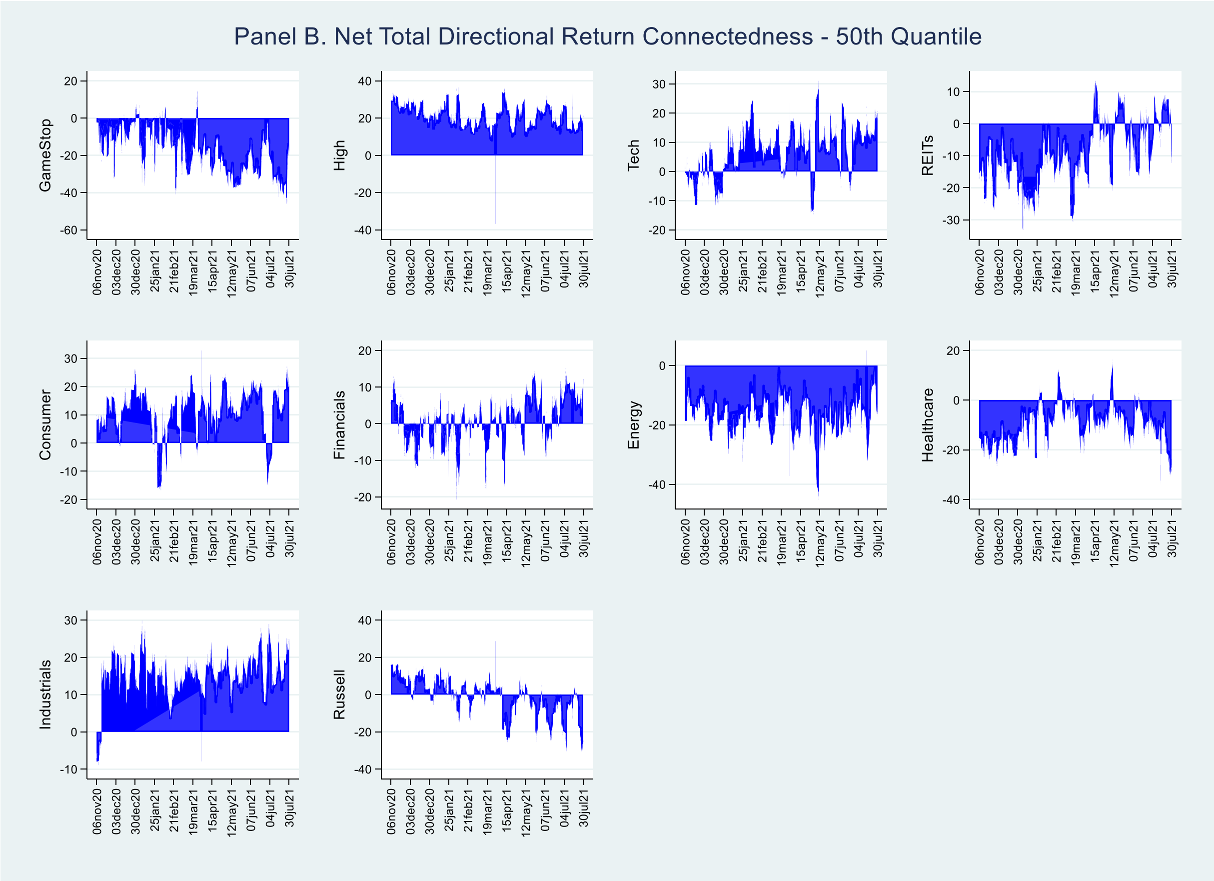

Fig. 3a. (*continued*).

quantile connectedness approach can be used to examine the presence of contagion. The VAR model is laid out in Eq. (1).[7]

$$Z_t = \Lambda Y_{t-1} + \varepsilon_t,\ \text{where}\ \varepsilon_t \sim N[0, S], \tag{1}$$

such that:

$$Y_{t-1} = \begin{pmatrix} Z_{t-1} \\ Z_{t-2} \\ \vdots \\ Z_{t-p} \end{pmatrix}, \qquad \Lambda = \begin{pmatrix} \Lambda_1 \\ \Lambda_2 \\ \vdots \\ \Lambda_p \end{pmatrix}.$$

Y_{t-1} are $N \times 1$ and $Np \times 1$ vectors, respectively. Λ and Λ_i denote $N \times Np$ and $N \times N$ matrices, respectively, ε_t is an $N \times 1$ vector, and p is the lag length. S is the variance-covariance matrix with the dimension $N \times N$. If Z_t is covariance stationary, then Eq. (1) can be transformed into a vector moving average representation of the Wold representation theorem:

$$Z_t = \Pi(L)\varepsilon_t, \tag{2}$$

where $\Pi(L)$ is an $N \times N$ infinite lag polynomial matrix of coefficients, which feed into the calculation of the generalized forecast error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran and Shin, 1998). Building on Eq. (2), the quantile function for Z_t at the τ-th conditional quantile can be written for the Wold representation as:

$$Q_\tau(Z_t|\Omega_{t-1}) = \Pi_\tau(L)\varepsilon_{t,\tau}, \tag{3}$$

where Ω_{t-1} denotes all information available by t–1. The GFEVD is given by $\widetilde{\psi}^{g}_{ij,\tau}(H)$, which determines the *pairwise directional connectedness* from variable j to i at the τ-th conditional quantile, or the variance share that variable j contributes to i.

[7] In this paper, we present an abridged version of this approach. Complete details are available in Ando et al. (2022).

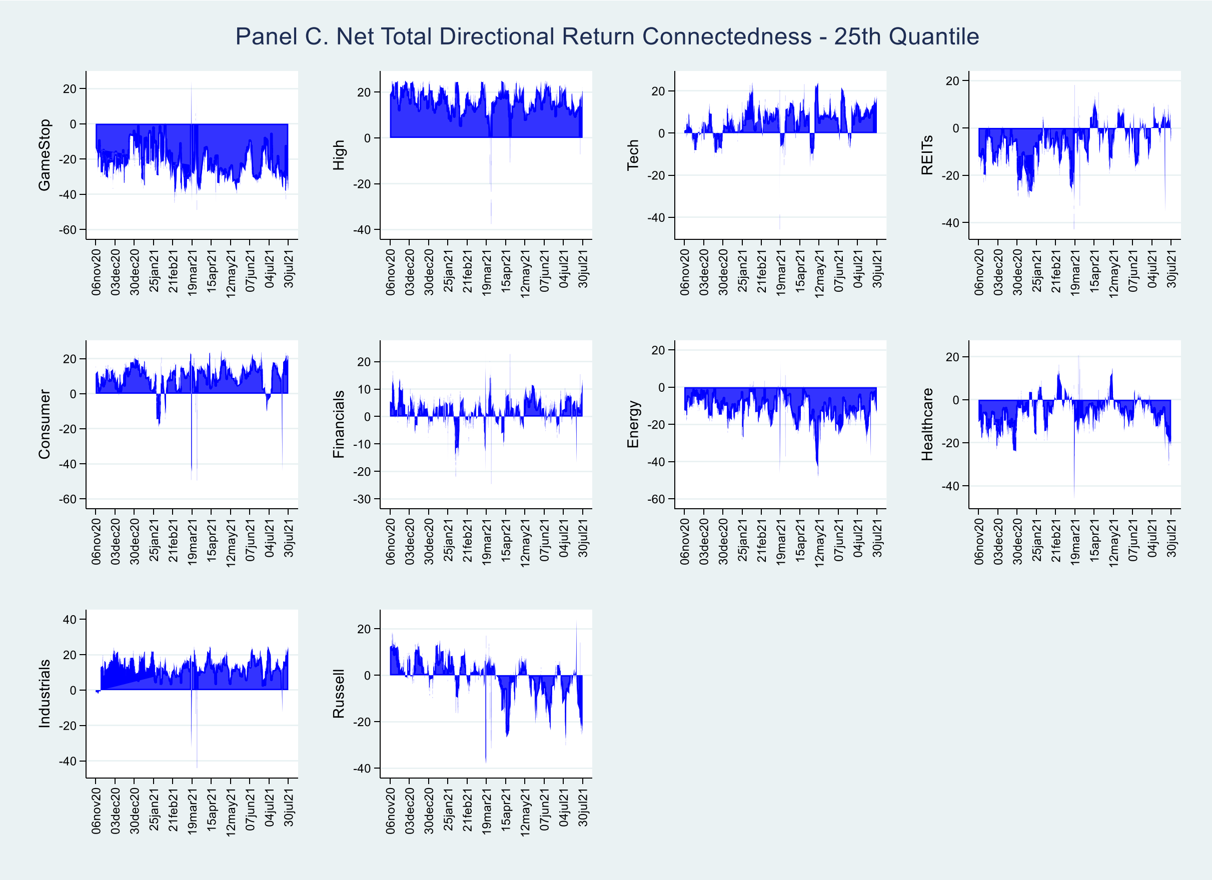

Fig. 3a. (*continued*).

$$\widetilde{\psi}^{g}_{ij,\tau}(H) = \frac{\psi^{g}_{ij,\tau}(\mathrm{H})}{\sum_{j=1}^{N}\psi^{g}_{ij,\tau}(\mathrm{H})}, \tag{4}$$

with $\psi^{g}_{ij,\tau}(\mathrm{H}) = \frac{S_{ii,\tau}^{-1}\sum_{h=0}^{H-1}(e_i'\Pi_{h,\tau}S_\tau e_j)^2}{\sum_{h=0}^{H-1}(e_i'\Pi_{h,\tau}S_\tau\Pi_{h,\tau}' e_i)}$, $\sum_{j=1}^{N}\widetilde{\psi}^{g}_{ij,\tau}(\mathrm{H}) = 1$, $\sum_{i,j=1}^{N}\widetilde{\psi}^{g}_{ij,\tau}(\mathrm{H}) = \mathrm{N}$, where H is the forecast horizon, and e_i is the selection vector, which takes value one in the *i*-th position. We assume H $= 20$. The *total connectedness index* at the τ-th conditional quantile, $C^{g}_{\tau}(\mathrm{H})$, quantifies the average share of one variable's forecast error variance explained by all other variables:

$$C^{g}_{\tau}(\mathrm{H}) = \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\psi}^{g}_{ij,\tau}(\mathrm{H})}{\sum_{i,j=1}^{N}\widetilde{\psi}^{g}_{ij,\tau}(\mathrm{H})}. \tag{5}$$

The *total directional connectedness TO* at the τ-th conditional quantile, $C^{g}_{i\rightarrow j,\tau}(\mathrm{H})$, measures the percentage contribution of a shock in variable *i* to the forecast error variance of all other variables *j*:

$$C^{g}_{i\rightarrow j,\tau}(\mathrm{H}) = \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\psi}^{g}_{ji,\tau}(\mathrm{H})}{\sum_{j=1}^{N}\widetilde{\psi}^{g}_{ji,\tau}(\mathrm{H})}. \tag{6}$$

Next, the *total directional connectedness FROM* at the τ-th conditional quantile, $C^{g}_{i\leftarrow j,\tau}(\mathrm{H})$, determines the percentage contribution to the forecast error variance of variable *i* of shocks in all other variables *j*:

$$C^{g}_{i\leftarrow j,\tau}(\mathrm{H}) = \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\psi}^{g}_{ij,\tau}(\mathrm{H})}{\sum_{i=1}^{N}\widetilde{\psi}^{g}_{ij,\tau}(\mathrm{H})}. \tag{7}$$

Further, the *net total directional connectedness* at the τ-th conditional quantile, $C^{g}_{i,\tau}(\mathrm{H})$, is the difference between the total directional connectedness TO others and the total directional connectedness FROM others:

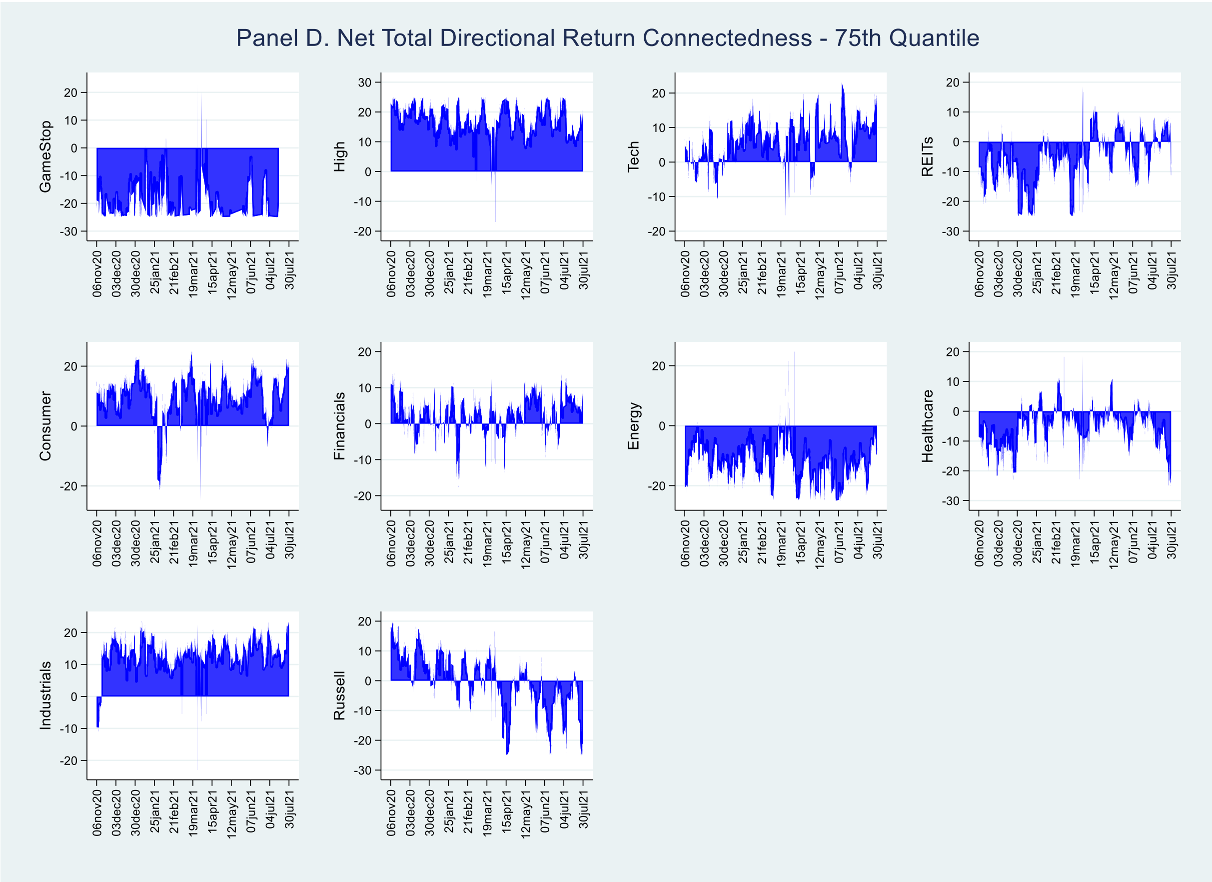

Fig. 3a. (*continued*).

$$C^g_{i,\tau}(\mathrm{H}) = C^g_{i\rightarrow j,\tau}(\mathrm{H}) - C^g_{i\leftarrow j,\tau}(\mathrm{H}). \tag{8}$$

A *positive (negative)* value will indicate that variable *i* is a *transmitter (receiver)* at the τ-th conditional quantile. Finally, the *net pairwise directional connectedness* at the τ-th conditional quantile, $C^g_{ij,\tau}(\mathrm{H})$, measures the balance of the bilateral dynamic connectedness between variable *i* and variable *j*:

$$C^g_{ij,\tau}(\mathrm{H}) = \widetilde{\psi}^g_{ji,\tau}(\mathrm{H}) - \widetilde{\psi}^g_{ij,\tau}(\mathrm{H}). \tag{16}$$

As a robustness check, we also employ the time-varying parameter vector autoregression (TVP-VAR) model, proposed in Antonakakis et al. (2018, 2020). Details are provided in the Online Appendix, Section A1.[8]

We examine both return and volatility connectedness. Consistently with other connectedness studies (see, e.g., Forsberg and Ghysels, 2007; Antonakakis and Kizys, 2015; Wang et al., 2016), we measure volatility with absolute returns.

4. Results

Table 1a summarizes the total *static* connectedness index (TCI) for the return series. Panel A displays the result obtained with the TVP-VAR (Antonakakis et al., 2018, 2020). Panels B-D display the corresponding findings for the middle (50th quantile), lower (25th quantile), and upper quantiles (75th quantile) of the return distribution, implied by the QVAR. Table 1b summarizes the total static TCI for the volatility series.

As can be seen from Table 1a, the static TCI is estimated at 73.40% and 71.20% using the TVP-VAR and the QVAR (at the 50th quantile of the return distribution), respectively. However, it grows larger if an unexpected return occurs in the lower or upper tails of the return distribution (76.42% and 76.67%, respectively). The inspection of negative and positive shocks in the volatility series also shows a great degree of connectedness between GameStop and high short indices (77.68% at the 25th quantile and 75.79% at the 75th

[8] Variants of the TVP-VAR are employed to examine dynamic connectedness in the economy and financial markets in Mensi et al. (2018), Jiang et al. (2019), André et al. (2021), Bouri et al. (2021), and Chatziantoniou and Gabauer (2021) inter alia.

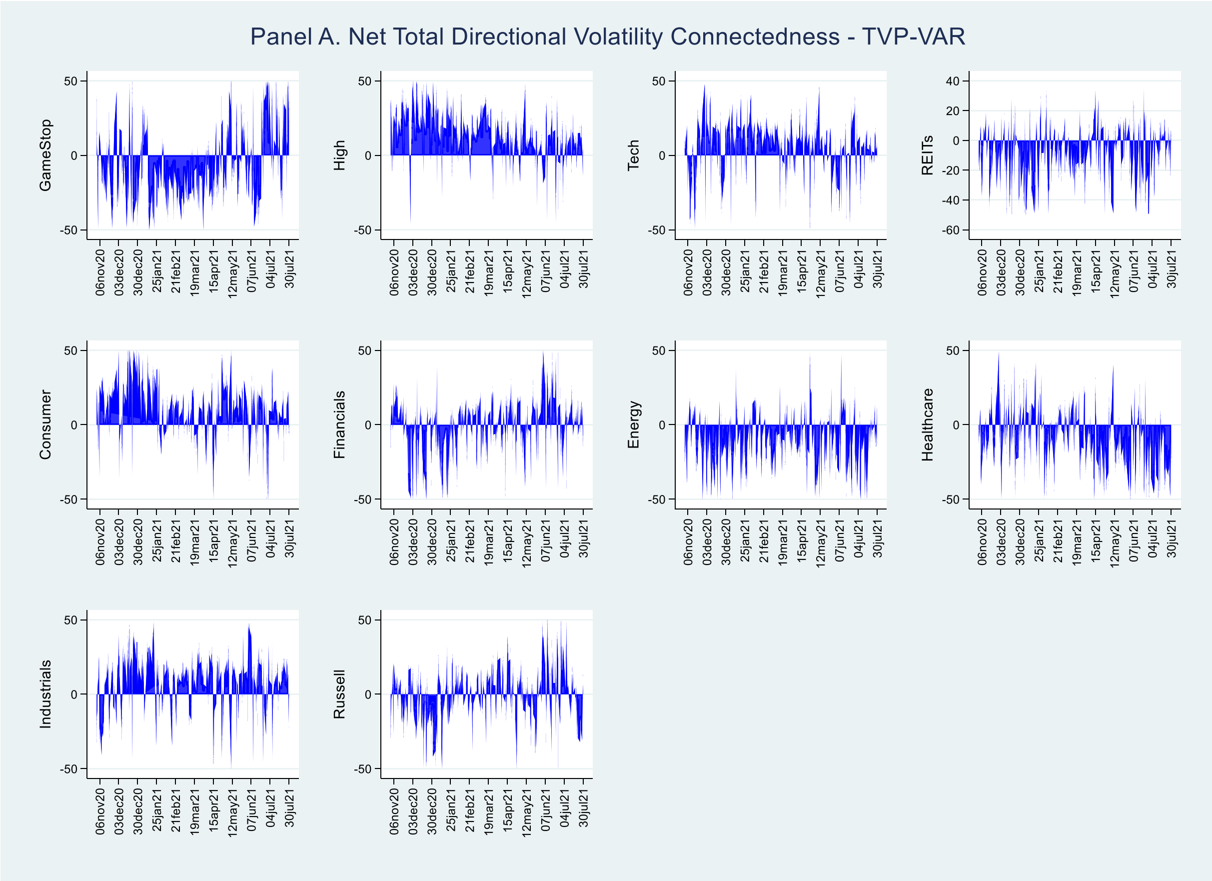

Fig. 3b. *Net Total Directional Volatility Connectedness. Notes.* This figure illustrates the net total directional volatility quantile connectedness among the GameStop stock price, the Russell 3000 stock market index, the market-wide short-interest index (High), as well as seven sectoral short-interest indices (Consumer, Energy, Financials, Healthcare, Industrials, REITs, and Technologies). In Panel A (Panel B, Panel C, Panel D), the TVP-VAR (50th quantile, 25th quantile, 75th quantile) connectedness is displayed. The log-returns are measured over 10-minute intervals. The sample period runs from November 2nd, 2020, to July 31st, 2021.

quantile). In addition, both the return and volatility networks point to a relatively high total connectedness in the middle 50th quantile. Even though the values are slightly lower, they still hint on a high level of connectivity (71.20% and 70.23% for return and volatility series, respectively). Finally, Panel A in each table shows that the TVP-VAR approach does not alter the results and exhibits a similar relationship (73.4% and 76.78% for return and volatility series, respectively).

While most of the GameStop return and volatility variation is self-determined (diagonal), an economically significant share of its variation is driven by the short-interest indices. In fact, GameStop's net directional return and volatility spillovers are generally negative, implying that the stock mainly absorbs shocks from the short-interest and diversified portfolios. This result holds for both the left and right tail return connectedness in both the return and volatility series. For instance, the NET static return connectedness of GameStop is –24.43 and –25.4 at the 25th and 75th quantiles, respectively. Similarly, the corresponding NET spillovers for the GameStop volatility are –26.08 and –24.46. Comparing the estimated NET spillovers in the left and right tails versus the middle quantile for both the return and volatility variables shows that GameStop seems to absorb more risk spillovers under extreme conditions than in a relatively ordinary period.

To delve deeper into the static connectedness analysis, we construct network diagrams (Figs. 1a and 1b, respectively) to visualize the pairwise return and volatility connectedness before, during and after the short squeeze. The pre-short squeeze period runs from November 2nd, 2020, to December 8th, 2020, when the 3rd quarter results for GameStop were announced, and abysmal earnings were reported. The short squeeze period runs from December 8th, 2020, to February 9th, 2021, when the end of the short squeeze was announced.[9] The post-short squeeze period spans the remaining period from February 10th, 2021, to July 31st, 2021. In Panels A-C (D-

[9] For details, please see https://www.cnbc.com/2021/02/09/gamestop-breaks-below-50-a-share-as-short-squeeze-comes-to-an-end.html. Accessed on September 1st, 2022.

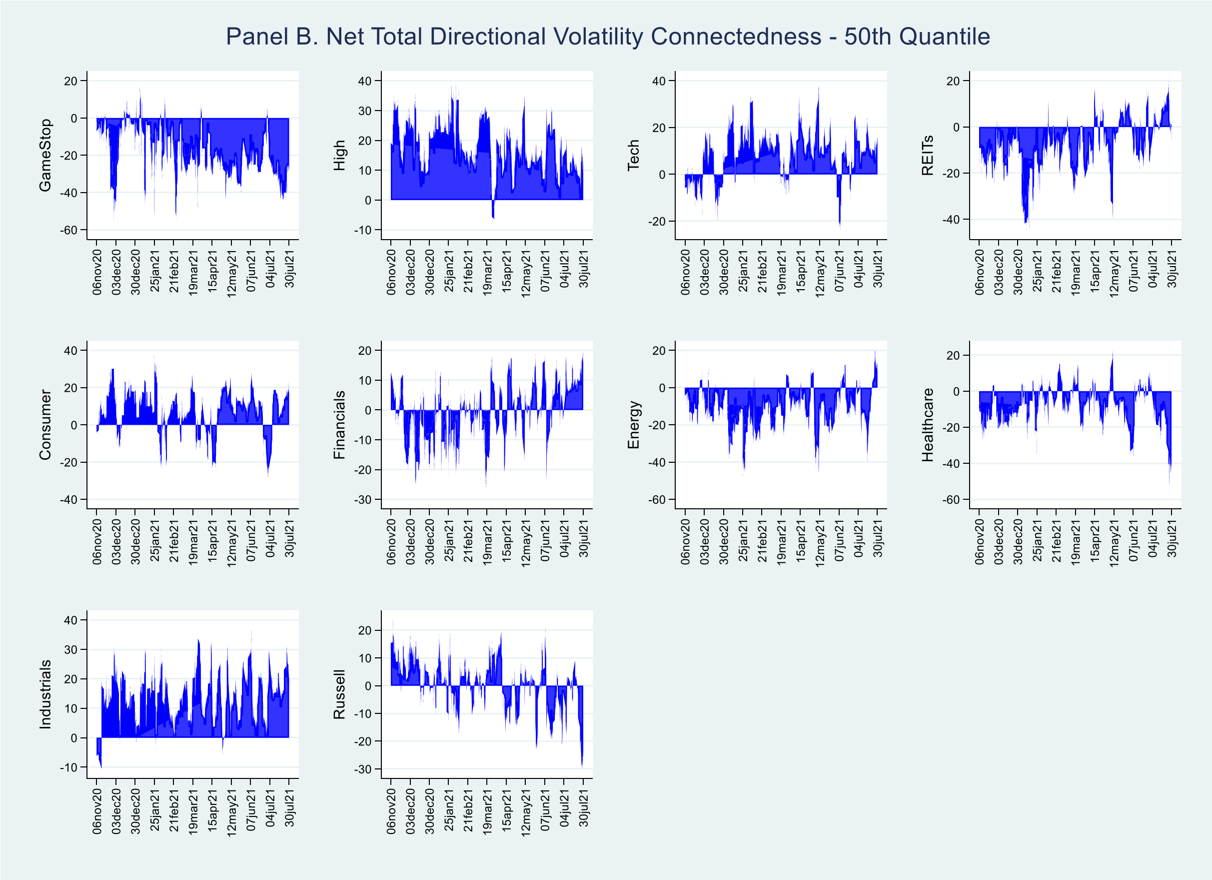

Fig. 3b. (*continued*).

F, G-I), the networks are visualized in the pre (during, post) short squeeze period at the 25th, 50th, and 75th quantiles. Arrows indicate the direction of return transmission. Arrows colored in red determine the highest transmitter. Blue arrows indicate the main recipient. Fig. 1a shows that during the short squeeze period, the GameStop stock does not become the main transmitter of returns within the system. This result holds at the 25th, 50th, and 75th quantiles.

On the contrary, moving from the pre-short squeeze through the short squeeze to the post-short squeeze period, the GameStop stock tends to become a receiver of return transmission from the other assets within the system. Along similar lines, Fig. 1b indicates that the GameStop stock, in general, did not transmit volatility spillovers to the market and sector indices. All in all, the network diagrams – which show limited evidence of contagion throughout the sample period – do not support Hypothesis 1.

To summarize, the results so far imply that even though the large swings in the GameStop stock price received overwhelming attention from social media, it did not become a source of return and volatility spillovers to the short-interest indices. This suggests that David might have won a battle but failed to win the war.

Next, since a static analysis may suffer from the shortcoming of being time-invariant, we turn to examine the *dynamic* return and volatility connectedness among the GameStop stock and the short-interest indices. The dynamic total spillovers are illustrated in Fig. 2.

Fig. 2 displays the *total return (2a) and volatility (2b) connectedness*. It shows that the total connectedness underwent significant changes in magnitude over time. The dynamic relationship between the variables witnessed several peaks and troughs. This effect is visible for both the return and volatility connectedness. For example, we observe visibly low levels of connectedness around December 8th, 2020, when GameStop reported disappointing financial results, which revealed a quarterly loss of USD 63 million. The following day brought a share price decline by nearly 20%. Moreover, the appointment of three new directors to its board, including the Chewy.com founder, on January 11th, 2021, was followed by relatively high levels of both the return and volatility connectedness. The Twitter *ad hominem* attack on GameStop buyers by Citron Research, a stock research firm run by a famous short-seller Andrew Left, on January 19th, 2021, was again followed by an increase in the return and volatility connectedness.[10] A similar effect can be observed around January 26th, 2021, when the GameStop stock price surged by 92.7%. However, when Robinhood restricted trading in

[10] For details, please see https://www.reuters.com/article/us-retail-trading-gamestop-timeline-idUSKBN2AI0IQ. Accessed on May 19th, 2021.

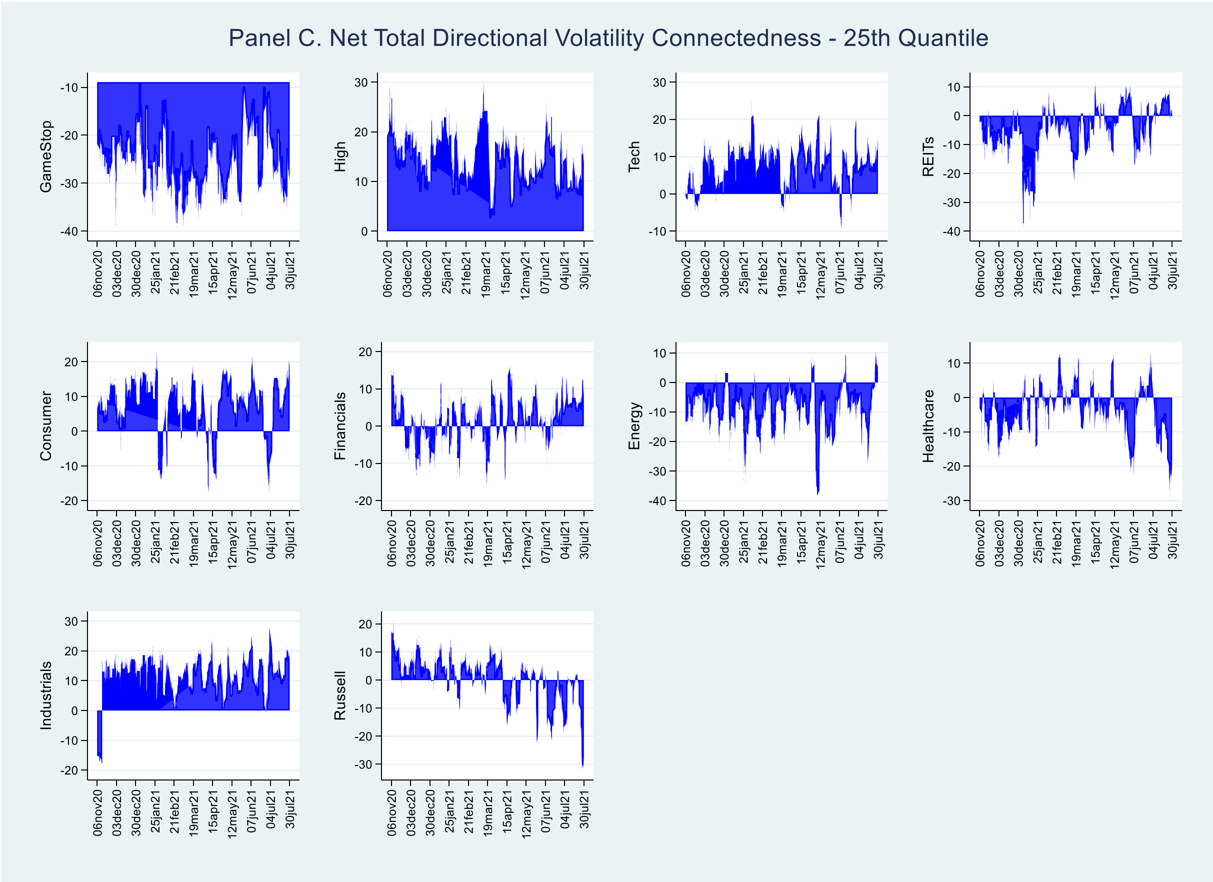

Fig. 3b. (*continued*).

GameStop on January 28th, 2021, the return and volatility connectedness declined. On January 29th, 2021, when Robinhood began easing restrictions, the volatility connectedness rose again. Similar observations are found in several other peaks of the GameStop stock price around the end of March 2021, when GameStop soared 87%[11] at the end of June 2021 after a successful raise of USD 1.1 Billion.[12] Overall, the results are similar when we test for the tails of the return and volatility variables. The split into the 25th, 50th, and 75th quantiles enables us to perform a clearer inspection of the connectedness across time compared with the general results of the TVP-VAR approach.

Fig. 3 adds further insights into the dynamic connectedness between the GameStop stock and the short-interest indices. More specifically, Fig. 3a (3b) depicts the dynamic NET return (volatility) connectedness for each of the return (volatility) series; specifically, these figures enable us to determine the net total directional connectedness of the GameStop stock to the rest of the assets.

Panel A in each figure reports the TVP-VAR results, whereas panels B, C, and D report the results obtained for the 50th, 25th, and 75th quantiles, respectively. These results show that GameStop is mainly a recipient rather than a transmitter or a source for return and volatility spillovers. Interestingly, the comparison of the different quantiles hints that the magnitude of GameStop absorbing shocks is generally higher during extreme movements, as represented by the left and right tails of the distribution.

Taken together, our results seem to support Hypothesis 2, which predicts that the short-interest indices provide price discovery for a short-traded stock. It is worth noting that price discovery varies across the sectors. Figs. 3a and 3b shows that the High Short Interest index, as well as the Consumer and Industrial short-interest indices, are the key sources of the dynamic return and volatility connectedness, respectively. These indices provide price discovery for the GameStop stock in terms of information transmission. This finding is supported by Boehmer and Wu (2013), who find that short sellers' trading contributes significantly to price discovery in the stock markets. An increase in the negative dynamic connectedness indicates that institutional investors sought to close their open short positions, which triggered a rise in the demand and, thus, the price of the GameStop stock. The ensuing fluctuation in the GameStop price translated into higher return volatility.

[11] For details, please see https://www.nasdaq.com/articles/why-gamestop-stock-soared-87-in-march-2021-04-01. Accessed on August 17th, 2022.

[12] For details, please see https://www.bloomberg.com/news/articles/2021-06-22/gamestop-jumps-after-raising-1-1-billion-in-stock-sale-program. Accessed on August 17th, 2022.

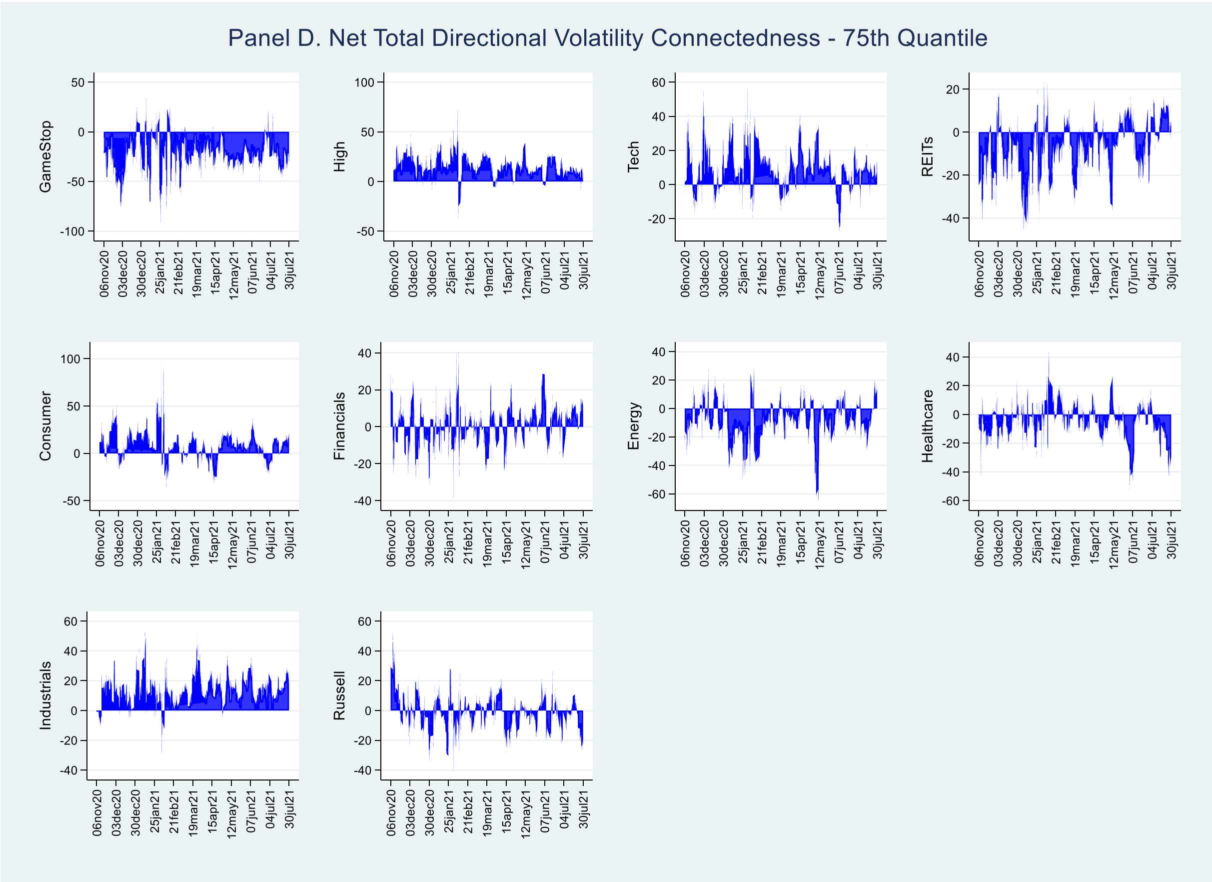

Fig. 3b. (*continued*).

We ran several robustness checks to validate our findings. First, we used 30-minute and 60-minute data to estimate the static and dynamic return and volatility connectedness. Our main results remained qualitatively similar, particularly for the 30-minute frequency (please see the Online Appendix). Second, we estimated tri-variate VARs for each short-interest index, which include: the GameStop stock, a short-interest index, and the Russell 3000 index. Again, the results remained supportive of Hypothesis 2.

5. Conclusions

In this study, we seek to ascertain whether the short-interest indices provide discovery for a short-traded stock or whether the GameStop frenzy was conducive to a rise in financial contagion across the high short-interest indices. To this end, we study the static and dynamic return and volatility connectedness among the GameStop stock, the novel market-wide and sectoral short-interest indices, and the Russell 3000 stock market index. Using the quantile connectedness approach by Ando et al. (2022), we distinguish among different parts of the return and volatility distribution (i.e., 25th, 50$^{\text{th,}}$ and 75th quantiles. This enables us to investigate the NET connectedness role of GameStop under extreme positive and negative shocks.

Using high-frequency data, we find that the GameStop stock is a net recipient of return and volatility spillovers from the short-interest indices. This result agrees with the price discovery hypothesis and rebuffs the alternative financial contagion hypothesis. The network diagrams we construct to visualize pairwise return and volatility connectedness do not agree with Hypothesis 1. Therefore, while the short squeeze orchestrated by WallStreetBets investors forced Melvin Capital to seek a bailout, we do not find evidence of an increase in financial contagion in the high short-interest indices or in the U.S. stock market. This notwithstanding, financial regulators and stock exchanges need to be concerned if speculators embark on market manipulation trading strategies over prolonged periods, which erodes the information content and efficiency, and can translate into a higher cost of equity capital.

Notably, whereas our paper finds no evidence of transmission and contagion effects from GameStop to other indices of heavily shorted stocks (or the market as a whole), it does not necessarily exclude the existence of such a relationship. While our paper constitutes a pioneer examination of a clash between the "smart" and "dumb" money, future research may be interested in exploring a pool of such short-squeeze events for a more generalized analysis.

CRediT authorship contribution statement

David A. Aharon: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Renatas Kizys:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Zaghum Umar:** Data curation, Formal analysis, Methodology, Software, Validation, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Adam Zaremba:** Conceptualization, Funding acquisition, Data curation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing.

Data availability

The authors do not have permission to share data.

Acknowledgments

We are thankful to Adam Albin (Barclays Capital) for providing invaluable support in preparing our dataset.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ribaf.2022.101803.

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