Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe

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Abstract

Do government interventions aimed at curbing the spread of COVID-19 affect stock market volatility? To answer this question, we explore the stringency of policy responses to the novel coronavirus pandemic in 67 countries around the world. We demonstrate that non-pharmaceutical interventions significantly increase equity market volatility. The effect is independent from the role of the coronavirus pandemic itself and is robust to many considerations. Furthermore, two types of actions that are usually applied chronologically particularly early—information campaigns and public event cancellations—are the major contributors to the growth of volatility.

Keywords: novel coronavirus, COVID-19, stock market volatility, non-pharmaceutical interventions, government policy responses, international financial market, containment and closure.

JEL classifications: G01, G12, G15, G18, H12, H51, I18, Q54.

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1. Introduction

The novel coronavirus, discovered for the first time in Wuhan, China in December 2019, has quickly spread all over the world, infecting more than three million people in over 200 countries[1]. The COVID-19 pandemic has reverberated across economies and financial markets. Not only did it impact severely the global economy and financial markets, but it also triggered a series of unprecedented government interventions.[2] The policy responses such as workplace closings or limiting residential movement helped to curb the spread of infections, but also had a dramatic economic impact. Whereas the earlier literature concentrated predominantly on the role of non-pharmaceutical interventions on the economy, their impact on the global financial markets remains essentially unexplored. This article aims at filling this gap, at least partially, by focusing on one important feature on international stock markets: volatility.

Volatility is paramount to the operation of financial markets. It acts as a barometer of financial risk, stress, or uncertainty surrounding financial investments and, therefore, it is a natural interest to fund managers, retail investors, as well as companies' CFOs. The finance literature has long established a link between crises, government interventions, and policy uncertainty and financial market volatility.[3] Several attempts have been also taken to test the relationship between the recent coronavirus crisis and market volatility (Albulescu 2020; Baker et al. 2020; Lopatta et al. 2020; Onali 2020). Nonetheless, to the best of our knowledge, this study is the first to investigate to what extent the social restrictions imposed by various governments around the world affect the stock market volatility.

The government policy responses to COVID-19 may affect stock market volatility through two possible principal channels. The first "rational" channel is related to portfolio restructuring. The interventions signal changes in future economic conditions, so they may affect changes that affect company cash-flow expectations and, in consequence, stock prices. Abrupt portfolio reconstructions—both within an asset class and across asset classes—may elevate the volatility. The second "irrational" channel could be rather of behavioural nature. The deterioration in the economic environment may result in "flights to safety" (Baele et al. 2020), leading to rapid portfolio flows and price changes. Also, the constant flow of policy-related news may lead to news-implied volatility (Manela and Moreira 2017) and a potential divergence of opinions

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[1] Data was retrieved from https://www.worldometers.info/coronavirus/ on 28 April 2020.
[2] See, e.g., Al-Awadhi et al. (2020), Baker et al. (2020), Corbet, Larkin, and Lucey (2020), Corbet et al. (2020), Hale, Petherick, and Phillips (2020), Onali (2020), Ozili and Arun (2020), Zhang, Hu, and Ji (2020), Goodell (2020), Fernandes (2020), Ozli and Arun (2020).
[3] See, e.e., Schwert (1990), Hamilton and Lin (1996), Mei and Guo (2004), Mun and Brooks (2012), Corradi et al. (2013), Danielsson et al. (2018), Manela and Moreira (2017), Pastor and Veronesi (2012), Liu and Zhang (2015)

leading to increased trading activity (Harris and Raviv 1993; Banerjee 2011), which also contributes to the growth of volatility (Foucault, Sraer, and Thesmar 2011).

To investigate the role of government policy responses on stock market volatility, we examine stock data from 67 countries during the most recent COVID-19 period: January to April 2020. Using panel regressions, we explore the aggregate and individual role of seven different types of government actions: school closures, workplace closures, cancelling public events, closing of public transportation, public information campaigns, restrictions on internal movement, and international travel controls.

We provide convincing evidence that stringent policy responses lead to a significant increase in stock market volatility. The effect is independent from the role of the coronavirus pandemic itself and is robust to many considerations. In particular, we find that two types of actions that are usually applied chronologically the earliest—COVID-19 information campaigns and public event cancellations—are the major contributors to the volatility increase.

The remainder of the article proceeds as follows. Section 2 focuses on data and methods. Section 3 discusses the findings. Finally, Section 4 concludes the study.

2. Data and Methods

Our research is based on 67 countries covered by Datastream Global Equity Indices (see Table 1 for the full list). The study period starts on the first trading day following the date when the World Health Organization (WHO) received information about the unknown cluster of pneumonia in Wuhan, China (WHO 2020). In consequence, our sample runs from 1 January 2020 to 3 April 2020.

[Table 1]

The study examines the relationship between the stringency of government policy responses and stock market volatility. For robustness, we employ five different measures tracking day-to-day changes in volatility (for similar approach, see, e.g., Antonakakis and Kizys 2015; Khalifa et al. 2011, *inter alia*). The first measure, $log|R|$, is the logarithm of absolute return. The logarithmic transformation ensures that the volatility measure in levels is positive definite. It also accounts for the fact that the relationship between the level of volatility and its covariates is not necessarily linear. The remaining measures are logarithms of absolute residual returns from four different asset pricing models: the Capital Asset Pricing Model (CAPM) by Sharpe (1964), the Fama-French (1993) three-factor model (FF), the Asness, Moskowitz, and Pedersen (2013) three-factor model (s AMP), and the Carhart (1997) four-factor model (CAR). The corresponding regression models are represented by the equations (1)–(4), respectively:

$$R_t = \alpha_{CAPM} + \beta_{MKT} MKT_t + \varepsilon_{CAPM,t}, \quad (1)$$

$$R_t = \alpha_{FF} + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_{FF,t}, \quad (2)$$

$$R_t = \alpha_{AMP} + \beta_{MKT} MKT_t + \beta_{HML} HML_t + \beta_{WML} WML_t + \varepsilon_{AMP,t}, \quad (3)$$

$$R_t = \alpha_{CAR} + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{WML} WML_t + \varepsilon_{CAR,t}, \quad (4)$$

where R_t is the excess return on day t, MKT_t, SMB_t, HML_t, and WML_t are daily returns on market, small-minus-big, high-minus-low, and winners-minus-losers factors, respectively, $\varepsilon_{CAPM,t}$, $\varepsilon_{FF,t}$, $\varepsilon_{AMP,t}$, $\varepsilon_{CAR,t}$ are the random disturbance terms, and α_{CAPM}, α_{FF}, α_{AMP}, α_{CAR}, β_{MKT}, β_{SMB}, β_{HML}, and β_{WML} are the regression coefficients.[4]

To obtain a look-ahead bias-free residual return (RR) for day t from different models, denoted as $log|RR_{CAPM}|$, $log|RR_{FF}|$, $log|RR_{AMP}|$, and $\log|RR_{CAR}|$, we apply a two-step procedure. Firstly, we estimate the regression coefficient based on the returns in trading days t-250 to t-1. Secondly, we use the estimated coefficients and day-t factor returns to obtain the expected return for day t. The residual return is the difference between actual return realization and its expected value.

To quantify the stringency of policy responses to the COVID-19 pandemic, we rely on data from the Oxford COVID-19 Government Response Tracker.[5] Specifically, we use the COVID-19 Government Response Stringency Index (SI), which conveys information about seven different types of non-pharmaceutical interventions targeted to curb the outbreak of the pandemic: school closing, workplace closing, cancelled public events, closed public transport, public information campaigns, restrictions on internal movement, and international travel controls (Hale et al. 2020). The index aggregates the data on each individual measure and then it is rescaled to obtain values from 0 to 100, where 0 (100) indicates the least (most) stringent policy responses.

We estimate the influence of the non-pharmaceutical interventions on stock market volatility by running the following panel regression, with a standard error robust to heteroscedasticity and autocorrelation:

$$VOL_{i,t} = \alpha + \beta_{SI} SI_{i,t} + \sum_{c=1}^{C} \beta_c K_{c,i,t} + \mu_i + \nu_{i,t}, \quad (5)$$

where $VOL_{i,t}$ denotes five different measures of stock market volatility ($log|R|$, $log|RR_{CAPM}|$, $log|RR_{FF}|$, $log|RR_{AMP}|$, or $\log|RR_{CAR}|$), $SI_{i,t}$ is the Stringency Index for country i on day t, $K_{c,i,t}$ indicates a set of additional control variables, and the remaining symbols are the estimated regression parameters. Table A3 in the Online

[4] Table A1 in the Online Appendix provides details of the factor portfolio formation. Furthermore, Table A2 and Figure A1 in the Online Appendix display the statistical properties of factor returns.

[5] Https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker (accessed 10 April 2020).

Appendix details all the variables used in the study. The control variables include the logarithms of dollar trading volume (*log*(TV_t)) in USD, market capitalization (*log*(MV_{t-1})) in USD, market-wide price-to-earnings ratio (*log*(PE_{t-1})), and weekday dummies for the day of the week effect. Also, to disentangle the role of government interventions from the pandemic itself, we control for the daily changes in the number of COVID-19 infections and deaths (ΔINF_t, ΔDTH_t) sourced from the European Centre for Disease Prevention and Control.[6] Furthermore, many European countries introduced an additional restriction on short-selling, which may also influence stock market volatility (Bohl, Reher, and Wilfling 2016; Talsepp and Rieger 2010; Boehmer, Jones, and Zhang 2008). Therefore, we also include dummies related to short-selling limitations. *ShortBan* takes the value of 1 when short-selling is banned, and 0 otherwise. *ShortNote* takes the value of 1 for European countries where investors were obliged by the European Securities and Markets Authority to report short positions exceeding 0.1% of a company's share capital.[7] Finally, we also include weekday dummies to control for any weekday effects in volatility (Kiymaz and Berument 2003).

Besides the role of the overall Stringency Index, we are also interested in how individual government policy responses contribute to the volatility. Hence, we run a regression accounting for different interventions underlying *SI*:

$$VOL_{i,t} = \alpha + \sum_{j=1}^{J} \beta_j PR_{j,i,t} + \sum_{c=1}^{C} \beta_c K_{c,i,t} + \mu_i + \nu_{i,t}, \quad (6)$$

where $PR_{j,i,t}$ denotes seven sub-indices representing different policy responses for country *i* on day *t*. In particular, these are: school closing (*PR1*), workplace closing (*PR2*), cancelled public events (*PR3*), closed public transport (*PR4*), public information campaigns (*PR5*), restrictions on internal movement (*PR6*), and international travel controls (*PR7*).[8] Table 2 displays the statistical properties of all the variables employed in this paper. Moreover, Table A4 in the Online Appendix demonstrates correlation coefficients. Of note is that the stringency of the interventions is not strongly correlated with the quantity of cases or the death toll. Indeed, some countries implemented restrictions in advance of the epidemic development, and others lingered even when the virus was widespread.

[Table 2]

[6] Https://www.ecdc.europa.eu/en/publications-data (accessed 10 April 2020).

[7] The precise dates of restrictions for the short-selling variables are sourced from ESMA (https://www.esma.europa.eu/about-esma/covid-19). Due to limited data availability, these two variables refer only to European markets. Nonetheless, their exclusion from the study has no visible influence on our findings.

[8] All these variables are obtained from the Oxford COVID-19 Government Response Tracker, and a detailed description can be found in Hale et al. (2020). In our baseline approach, we consider all the government actions, regardless of whether they were country-wide or targeted at certain regions. Limiting the variables to only country-wide interventions has had no qualitative influence on our findings.

Our baseline tests rely on the random-effects estimation method. The reasons behind the random-effects model are as follows: i) our sample is a relatively small part of the population (Gelman 2005; Green and Turkey 1960); ii) we are particularly interested in the population, from which the sample is drawn, rather than in unobserved country-specific characteristics *per se* (Gelman 2005; Searle, Casella, and McCulloch 1992, Section 1.4); iii) random effects vary across individual countries, whereas fixed effects are constant (Gelman 2005; Kreft and De Leeuw 1998, Section 1.3.3); and iv) the random-effects model does not require estimating country-specific intercepts, which would otherwise lead to a significant reduction in the number of degrees of freedom. Nonetheless, for robustness, employ also fixed-effects and pooled regression models. Also, we consider alternative model specifications, such as the exclusion of weekday dummies or a modification of certain variables (see Section 3 for details).

3. Results

Table 3, Panel A, uncovers the regression results. The overall conclusion is evident: the government interventions are associated with higher stock market volatility. The coefficients of *SI* are positive and significant for all the different measures of volatility, and the associated *t*-statistics are remarkably high in all cases. Specifically, an increase in the stringency of a government response by one index point triggers an increase in daily stock market volatility, which ranges from 0.87% to 1.1%, depending on the volatility measure. The role of policy responses is unequivocal, even when we control for country-specific characteristics and the growth of the number of infections and deaths. It indicates that the government interventions constitute a distinctive source of volatility increase, separate from the impact of the pandemic itself.

[Table 3]

Importantly, Table 3, Panel B, demonstrates that our results are robust to alternative regression functional forms and model specifications. They hold not only for random-effects models, but also for fixed-effects and pooled regression models. Also, the overall conclusions remain virtually intact when we drop the weekday dummies or use alternative control variables representing the development of the pandemic, such as the total number of cases and deaths. To sum up, the government interventions aimed at curbing the COVID-19 pandemic are instrumental in stock market volatility.

To check which actions contribute the most to the volatility, we run a regression on indicators representing different types of government policies. Since many of these interventions are applied concurrently or sequentially, to extract the individual effect of each, we consider them all jointly. Table 4 shows the outcomes of this exercise.[9]

[Table 4]

There are two types of policy responses that particularly increase the volatility and display a significant regression coefficient across all the regression specifications, as illustrated in Table 4. The first type of intervention refers to government information campaigns. This is in line with the findings of Zaremba et al. (2020), who show that COVID-19-related information campaigns may motivate investors to restructure their portfolio positions, facilitating additional trading in the market. The second type of intervention refers to cancellations of public events. While the economic impact of this intervention is more constrained than in the case of, e.g., workplace closures, it is regarded as an introductory measure within the government's policy toolbox, and thus it is timed before other measures by the government. Thus, consistently with a signaling mechanism, an initial government response—which consists of cancelling public events—can be perceived by financial investors as a negative signal for further interventions, and it can be interpreted as a precursor of economic and financial instabilities across the globe. This initial response gives investors the first opportunity to react to the forthcoming changes in economic interventions. As a result, volatility remains at a higher level as long as investors anticipate more stringent government interventions in the future. Hence, the effects of both types of significant interventions—information campaigns and public event cancellations—seem logical and intuitive from the theoretical perspective.[10]

4. Conclusions

This study is the first attempt to examine the influence of non-pharmaceutical policy responses to the COVID-19 pandemic. We demonstrate that government interventions significantly and robustly increase the volatility in international stock markets. The effect is driven particularly by the role of information campaigns and cancellations of public events.

Our findings have explicit policy implications. Governments worldwide should be conscious that, in addition to a substantial economic impact, the coronavirus-related restrictions vividly influence the trading environment in financial markets. Heightened volatility in financial markets can provoke episodes of widespread sales of risky assets. Elevated volatility may also translate into a higher cost of capital. Also,

[9] For brevity, we report only the results of the random-effects model regressions. The results for different functional forms are available upon request.

[10] Importantly, the indicated variables play a significant role also in regressions considering different policy responses individually (detailed results are available on demand).

equity portfolio managers may infer information about future stock market volatility from the stringency of implemented measures.

The major limitation of this study is the narrow research sample. Future developments and policy changes, as well as bigger and richer datasets, will allow us to re-evaluate and verify our findings.

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Table 1. *Countries Included in the Sample*

The table shows the list of the countries included in the sample. The header "No." is the running number and "Country" denotes the country name.

No.	Country	No.	Country	No.	Country	No.	Country
1	Argentina	18	Finland	35	Mexico	52	Slovakia
2	Australia	19	France	36	Morocco	53	Slovenia
3	Austria	20	Germany	37	Netherlands	54	South Africa
4	Bahrain	21	Greece	38	New Zealand	55	South Korea
5	Belgium	22	Hong Kong	39	Nigeria	56	Spain
6	Brazil	23	Hungary	40	Norway	57	Sri Lanka
7	Bulgaria	24	India	41	Oman	58	Sweden
8	Canada	25	Indonesia	42	Pakistan	59	Switzerland
9	Chile	26	Ireland	43	Peru	60	Taiwan
10	China	27	Israel	44	Philippines	61	Thailand
11	Colombia	28	Italy	45	Poland	62	Turkey
12	Croatia	29	Japan	46	Portugal	63	UAE
13	Cyprus	30	Jordan	47	Qatar	64	United Kingdom
14	Czechia	31	Kuwait	48	Romania	65	United States
15	Denmark	32	Luxembourg	49	Russia	66	Venezuela
16	Egypt	33	Malaysia	50	Saudi Arabia	67	Vietnam
17	Estonia	34	Malta	51	Singapore		

Table 2. *Statistical Properties of the Variables*

The table presents the statistical properties of the variables used in the study: logarithms of absolute daily returns ($log|R|$); logarithms of residual returns from four different models: CAPM ($log|RR_{CAPM}|$), the Fama-French (1993) model ($log|RR_{FF}|$), the Asness, Moskowitz, and Pedersen (2013) model ($log|RR_{AMP}|$), or the Carhart (1997) model ($log|RR_{CAR}|$); Government Policy Response Stringency Index (*SI*) and its sub-components reflecting different interventions: school closing (*PR1*), workplace closing (*PR2*), cancelling of public events (*PR3*), closing of public transportation (*PR4*), public information campaigns (*PR5*), restrictions of internal movement (*PR6*), and international travel controls (*PR7*); logarithm of daily dollar trading volume expressed in USD (*log(TV)*), market value in USD (*log(MV)*), and market-wide PE ratio (*log(PE)*); daily changes in numbers of new COVID-19 infections and deaths (*ΔINF*, *ΔDTH*); ban on short-selling (*ShortBan*), and the requirement to report large short positions (*ShortNote*).

	Average	Standard deviation	Skewness	Kurtosis	Minimum	1st quartile	Median	3rd quartile	Maximum
log|R|	-5.012	1.523	-0.741	0.863	-12.154	-5.811	-4.885	-3.937	-1.652
log$\|RR_{CAPM}\|$	-5.185	1.373	-0.810	1.564	-13.336	-5.944	-5.064	-4.254	-2.071
log$\|RR_{FF}\|$	-5.265	1.378	-0.808	1.343	-12.762	-6.004	-5.116	-4.320	-1.983
log$\|RR_{AMP}\|$	-5.282	1.357	-0.744	1.086	-12.369	-6.037	-5.136	-4.350	-1.995
log$\|RR_{CAR}\|$	-5.261	1.354	-0.860	1.894	-12.841	-6.021	-5.126	-4.335	-2.024
SI	25.119	31.533	1.035	-0.363	0.000	0.000	11.900	42.860	100.000
PR1	0.505	0.861	1.141	-0.675	0.000	0.000	0.000	1.000	2.000
PR2	0.360	0.731	1.662	0.940	0.000	0.000	0.000	0.000	2.000
PR3	0.540	0.866	1.036	-0.862	0.000	0.000	0.000	2.000	2.000
PR4	0.190	0.558	2.751	5.872	0.000	0.000	0.000	0.000	2.000
PR5	0.500	0.500	0.000	-2.001	0.000	0.000	0.500	1.000	1.000
PR6	0.386	0.744	1.546	0.591	0.000	0.000	0.000	0.000	2.000
PR7	1.123	1.332	0.515	-1.562	0.000	0.000	0.000	3.000	3.000
log(TV)	11.859	3.279	-0.388	-0.382	2.910	9.648	12.236	14.391	20.027
log(MV)	11.952	1.984	-0.001	-0.428	7.673	10.312	11.996	13.439	17.337
log(PE)	2.545	0.453	-1.856	6.510	0.281	2.317	2.631	2.841	3.360
ΔINF	238.313	1664.667	17.353	437.773	0.000	0.000	0.000	16.000	57034.000
ΔDTH	12.270	98.101	15.152	305.930	0.000	0.000	0.000	0.000	2616.000
ShortBan	0.014	0.119	8.132	64.151	0.000	0.000	0.000	0.000	1.000
ShortNote	0.071	0.256	3.354	9.254	0.000	0.000	0.000	0.000	1.000

Table 3. *The Stringency of Policy Responses and Stock Market Volatility*

The table presents the results of panel data regressions. The dependent variable is the logarithm of daily volatility proxied with absolute daily returns ($log|R|$), or residual returns from four different models: CAPM ($log|RR_{CAPM}|$), the Fama-French (1993) model ($log|RR_{FF}|$), the Asness, Moskowitz, and Pedersen (2013) model ($log|RR_{AMP}|$), or the Carhart (1997) model (log$|RR_{CAR}|$). The independent variables are: the Government Policy Response Stringency Index (*SI*), the logarithm of daily dollar trading volume expressed in USD (*log(TV)*), the logarithm of market value in USD (*log(MV)*), the logarithm of market-wide PE ratio (*log(PE)*), and daily changes in numbers of new COVID-19 infections and deaths (*ΔINF*, *ΔDTH*); *ShortBan* indicates short-selling ban, and *ShortNote* indicates a requirement to notify large short position to a local market regulator. All the regression equations include also weekday dummies. R^2 denotes an adjusted coefficient of determination. The numbers in brackets are *t*-statistics and asterisks *, **, and *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively. *Panel A* demonstrates the baseline results following the random-effects model, while *Panel B* displays robustness checks assuming several alternative specifications or functional forms: fixed-effects and pooled regression models, a regression equation excluding the weekday dummies, and a regression equation controlling for the total number of deaths and cases.

Panel A: Baseline results

	log|R|	log$\|RR_{CAPM}\|$	log$\|RR_{FF}\|$	log$\|RR_{AMP}\|$	log$\|RR_{CAR}\|$
SI	0.0110***	0.0094***	0.0090***	0.0093***	0.0087***
	(6.76)	*(6.86)*	*(6.58)*	*(6.82)*	*(6.63)*
log(TV)	0.5066***	0.4480***	0.4255***	0.4145***	0.4126***
	(4.91)	*(5.27)*	*(5.11)*	*(4.88)*	*(5.06)*
log(MV)	-0.7152***	-0.6987***	-0.6732***	-0.6871***	-0.6703***
	(-4.06)	*(-4.73)*	*(-4.47)*	*(-4.59)*	*(-4.52)*
log(PE)	-0.3739	-0.3270	-0.3410	-0.2836	-0.3466
	(-1.10)	*(-1.11)*	*(-1.16)*	*(-1.06)*	*(-1.24)*
ΔINF	0.0000*	0.0000	0.0000	0.0000	0.0000
	(2.38)	*(-0.03)*	*(0.98)*	*(-1.16)*	*(-0.67)*
ΔDTH	-0.0009**	-0.0001	-0.0003	-0.0001	-0.0001
	(-2.60)	*(-0.33)*	*(-1.71)*	*(-0.78)*	*(-0.79)*
ShortBan	-0.0007	-0.1681	0.1794	0.3101	0.3312*
	(0.00)	*(-0.93)*	*(1.23)*	*(1.92)*	*(2.00)*
ShortNote	-0.0306	-0.0060	-0.3510**	-0.3078*	-0.2963*
	(-0.29)	*(-0.05)*	*(-2.87)*	*(-2.49)*	*(-2.33)*
Weekday dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.1719	0.1364	0.1118	0.1217	0.1162

Panel B: Robustness checks

	log|R|	log$\|RR_{CAPM}\|$	log$\|RR_{FF}\|$	log$\|RR_{AMP}\|$	log$\|RR_{CAR}\|$
Fixed-effects regression model	0.0030**	0.0030**	0.0029**	0.1541**	0.0027*
	(2.73)	*(2.77)*	*(2.59)*	*(2.75)*	*(2.48)*
Pooled regression model	0.0133***	0.0123***	0.0118***	0.0117***	0.0112***
	(17.60)	*(16.63)*	*(15.58)*	*(16.02)*	*(15.09)*
Weekday dummies excluded	0.0101***	0.2693***	0.0089***	0.0083***	0.0085***
	(5.98)	*(4.37)*	*(6.39)*	*(6.25)*	*(6.13)*
Total cases and deaths controlled	0.0111***	0.0098***	0.0087***	0.0092***	0.0084***
	(6.80)	*(7.07)*	*(6.27)*	*(6.59)*	*(6.32)*

Table 4. *Influence of Different Non-Pharmaceutical Interventions on the Market Volatility*

The table presents the results of the random-effects panel data regressions. The dependent variable is the logarithm of daily volatility proxied with absolute daily returns (log|*R*|), or residual returns from four different models: CAPM ($log|RR_{CAPM}|$), the Fama-French (1993) model ($log|RR_{FF}|$), the Asness, Moskowitz, and Pedersen (2013) model ($log|RR_{AMP}|$), or the Carhart (1997) model ($log|RR_{CAR}|$). The explanatory variables are different non-pharmaceutical interventions in the country *i* on day *t*—school closing (*PR1*), workplace closing (*PR2*), cancelling of public events (*PR3*), closing of public transportation (*PR4*), public information campaigns (*PR5*), restrictions of internal movement (*PR6*), and international travel controls (*PR7*), as well as a set of control variables: the logarithm of daily dollar trading volume expressed in USD (*log(TV)*), the logarithm of market value in USD (*log(MV)*), the logarithm of market-wide PE ratio (*log(PE)*), and daily changes in numbers of new COVID-19 infections and deaths (*ΔINF*, *ΔDTH*); *ShortBan* indicates short-selling ban, and *ShortNote* indicates a requirement to notify large short position to a local market regulator. All the regression equations include also weekday dummies. R^2 denotes an adjusted coefficient of determination. The numbers in brackets are *t*-statistics and asterisks *, **, and *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

	log|R|	log$\|RR_{CAPM}\|$	log$\|RR_{FF}\|$	log$\|RR_{AMP}\|$	log$\|RR_{CAR}\|$
PR1	0.0634	0.1066	0.0677	0.0866	0.1007
	(0.80)	*(1.47)*	*(1.20)*	*(1.47)*	*(1.77)*
PR2	0.0580	0.0974	0.0055	-0.0059	-0.0266
	(0.74)	*(1.34)*	*(0.07)*	*(-0.07)*	*(-0.33)*
PR3	0.3131***	0.1818*	0.2064**	0.2270**	0.1866*
	(3.83)	*(2.28)*	*(2.72)*	*(2.99)*	*(2.32)*
PR4	-0.1740*	-0.0511	-0.0201	0.0394	0.0376
	(-2.47)	*(-0.82)*	*(-0.28)*	*(0.58)*	*(0.56)*
PR5	0.3259***	0.2315**	0.1877**	0.1905**	0.1913**
	(4.06)	*(3.28)*	*(2.70)*	*(2.67)*	*(2.78)*
PR6	-0.0944	-0.1318*	-0.0640	-0.1038	-0.0783
	(-1.32)	*(-2.11)*	*(-1.06)*	*(-1.63)*	*(-1.21)*
PR7	0.0333	0.0353	0.0538	0.0475	0.0419
	(0.93)	*(1.22)*	*(1.62)*	*(1.44)*	*(1.26)*
log(TV)	0.4660***	0.4259***	0.4023***	0.3882***	0.3925***
	(4.78)	*(5.04)*	*(4.91)*	*(4.62)*	*(4.85)*
log(MV)	-0.6712***	-0.6768***	-0.6506***	-0.6597***	-0.6505***
	(-3.98)	*(-4.62)*	*(-4.44)*	*(-4.51)*	*(-4.47)*
log(PE)	-0.3091	-0.2908	-0.2920	-0.2234	-0.3004
	(-0.99)	*(-1.02)*	*(-1.03)*	*(-0.88)*	*(-1.10)*
ΔINF	0.0000	0.0000	0.0000	0.0000	0.0000
	(1.79)	*(-0.19)*	*(0.92)*	*(-1.33)*	*(-0.94)*
ΔDTH	-0.0007*	0.0000	-0.0002	0.0000	0.0000
	(-2.06)	*(0.02)*	*(-1.18)*	*(-0.25)*	*(-0.21)*
ShortBan	0.1325	-0.0622	0.2654*	0.4106**	0.4184**
	(0.60)	*(-0.34)*	*(2.02)*	*(2.77)*	*(2.82)*
ShortNote	-0.0600	-0.0344	-0.3691**	-0.3343**	-0.3115*
	(-0.56)	*(-0.30)*	*(-3.19)*	*(-2.76)*	*(-2.52)*
Weekday dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.1911	0.1451	0.1204	0.1307	0.1231