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Analyzing the Impact of Government Interventions on Stock Market Volatility During the COVID-19 Pandemic

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Abstract

This study investigates the relationship between government interventions aimed at curbing the spread of the novel coronavirus (COVID-19) and stock market volatility across 67 countries. Using panel regression analysis, we examine how various non-pharmaceutical interventions influence financial market uncertainty. Using panel regression analysis, we examine how various non-pharmaceutical interventions influence financial market uncertainty. Our findings reveal that stringent policy responses significantly increase stock market volatility, independent of the direct impact of the pandemic itself. Specifically, information campaigns and public event cancellations are identified as major contributors to this phenomenon. These results highlight the dual role of government actions: mitigating health risks while simultaneously amplifying financial instability.

Keywords: COVID-19, Government Interventions, Stock Market Volatility, Non-pharmaceutical Interventions, Panel Regression, Financial Markets, Policy Response, Market Uncertainty

JEL Classification: G01, G14, G15, G18, H12, I18

1. Introduction: The Intersection of Public Health and Financial Markets

The global outbreak of the novel coronavirus (COVID-19), first reported in Wuhan, China, in December 2019, has had profound implications for both public health and economic stability (Zaremba et al., 2020). As governments worldwide implemented measures to control the virus's spread, such as lockdowns, travel restrictions, and social distancing policies, these actions inadvertently introduced significant disruptions into financial markets (Fernandes, 2020; Goodell, 2020). While prior studies have explored the link between crises and market volatility (Schwert, 1990; Pastor & Veronesi, 2012), little attention has been paid to the specific effects of government interventions during pandemics.

This research aims to address this gap by analyzing the impact of non-pharmaceutical interventions (NPIs) on stock market volatility. Drawing upon theories of behavioral finance and portfolio theory, we hypothesize that government actions signal changes in future economic conditions, leading to increased trading activity and heightened uncertainty among investors (Banerjee, 2011; Harris & Raviv, 1993). Furthermore, we explore whether certain types of interventions—such as information campaigns and public event cancellations—are more influential than others.

1.1 Research Objectives

The primary goal of this research is to quantify and analyze the relationship between government policy responses to COVID-19 and stock market volatility. Specifically, we aim to:

1. Determine whether the stringency of government interventions significantly affects stock market volatility, independent of the direct impact of the pandemic itself.
2. Identify which specific non-pharmaceutical interventions have the strongest influence on market volatility.
3. Analyze the mechanisms through which government actions translate into financial market uncertainty.
4. Provide evidence-based recommendations for policymakers and financial practitioners to minimize adverse economic consequences while maintaining necessary health measures.

By achieving these objectives, our study contributes to the growing body of literature on crisis management and financial stability, offering insights that can inform future policy responses during global health emergencies.

2. Literature Review: Understanding Volatility Drivers

Volatility, defined as the degree of variation in asset prices over time, serves as a critical indicator of financial risk and uncertainty (Corradi et al., 2013; Liu & Zhang, 2015). In times of crisis, volatility tends to spike due to heightened investor anxiety and reduced liquidity (Bohl et al., 2016; Talsepp & Rieger, 2010). For instance, during the 2008 Global Financial Crisis, news-related shocks and policy uncertainty were found to significantly affect market volatility (Mun & Brooks, 2012; Danielsson et al., 2018).

2.1 Historical Perspectives on Market Volatility During Crises

The relationship between economic crises and stock market volatility has been extensively documented in financial literature. Schwert (1990) examined historical patterns of market volatility during economic recessions and found that volatility tends to increase during downturns. Similarly, Hamilton and Lin (1996) established that stock market volatility is significantly higher during recessions than during expansions. These findings suggest that periods of economic uncertainty are inherently associated with greater financial market fluctuations.

Bloom (2009) developed a theoretical framework explaining how uncertainty shocks affect economic activity. His research indicates that heightened uncertainty causes firms to temporarily pause their investment and hiring decisions, leading to sharp drops in productivity and output. These economic consequences, in turn, amplify stock market volatility through feedback effects.

2.2 Policy Uncertainty and Financial Markets

Pastor and Veronesi (2012) examined how government policy uncertainty affects asset prices. They proposed that policy changes create systematic risk that cannot be diversified away, resulting in higher risk premiums and increased market volatility. Their model predicts that policy uncertainty has stronger effects during economic downturns, which is particularly relevant for pandemic scenarios.

Baker et al. (2016) introduced the Economic Policy Uncertainty (EPU) index to measure policy-related uncertainty. Subsequent research has shown strong correlations between the EPU index and various measures of financial market volatility. Liu and Zhang (2015) found that economic policy uncertainty has significant predictive power for future stock market volatility, highlighting the importance of government actions in shaping financial market dynamics.

2.3 Market Reactions to Pandemic Events

Previous pandemics offer valuable insights into how financial markets respond to global health crises. Nippani and Washer (2004) studied market reactions to the 2003 SARS outbreak and found temporary negative effects on affected countries' stock markets, but these effects dissipated once the outbreak was contained. Similarly, Ichev and Marinč (2018) analyzed market responses to the 2014 Ebola outbreak and documented that media attention to the crisis had significant effects on market volatility, particularly for companies with greater exposure to affected regions.

Del Giudice and Paltrinieri (2017) examined the impact of the 2009 H1N1 (swine flu) pandemic on global financial markets. They found that markets experienced increased volatility following pandemic announcements, but the effects were relatively short-lived compared to financial crises. Their research suggests that market participants tend to overreact initially to pandemic news but adjust their expectations as more information becomes available.

2.4 Early Studies on COVID-19 and Financial Markets

Recent studies examining the COVID-19 pandemic underscore its unprecedented impact on financial markets. Albulescu (2020) documents a sharp rise in volatility following the onset of the pandemic, while Baker et al. (2020) attribute much of this increase to government-imposed restrictions. Al-Awadhi et al. (2020) found that daily growth in COVID-19 confirmed cases and deaths had significant negative effects on stock returns across all companies in the Chinese market.

Zhang et al. (2020) analyzed global financial markets during the early stages of the

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COVID-19 pandemic and documented unprecedented levels of risk, with significant increases in volatility across major stock markets worldwide. They noted that government interventions played a crucial role in shaping market responses, although they did not distinguish between different types of interventions.

Onali (2020) focused specifically on US stock markets and found that the number of COVID-19 cases and deaths in countries other than China affected US stock market returns and volatility. This suggests that international spillover effects are significant during global health crises, highlighting the interconnected nature of financial markets.

2.5 The Gap in Current Knowledge

Despite the growing body of literature on COVID-19 and financial markets, the precise mechanisms through which specific government interventions influence market volatility remain underexplored. Most studies have focused on the aggregate impact of the pandemic or have used broad measures of government responses without dissecting individual policy components.

This study contributes to the literature by isolating the effects of individual policy measures and assessing their relative importance. By employing a comprehensive panel dataset spanning 67 countries and multiple volatility measures, we provide a more nuanced understanding of how different non-pharmaceutical interventions affect financial market uncertainty. This approach allows us to identify which specific policy actions trigger the strongest market reactions, offering valuable insights for policymakers seeking to balance public health objectives with financial stability.

3. Methodology: Empirical Framework and Data Description

3.1 Data Sources

Our dataset comprises daily stock market indices from 67 countries, sourced from Datastream Global Equity Indices (Zaremba, 2019). The sample period spans January 1, 2020, to April 3, 2020, encompassing the early stages of the pandemic. Additionally, we utilize the Oxford COVID-19 Government Response Tracker (Hale et al., 2020) to measure the stringency of government interventions, including school closures, workplace restrictions, public event cancellations, and international travel bans.

3.2 Empirical Model

To quantify the relationship between government interventions and stock market volatility, we employ a panel regression framework:

$$VOL_{i,t}=\alpha+\beta_1 SI_{i,t}+\sum_{j=1}^{J}\beta_j PR_{j,i,t}+\gamma X_{i,t}+\epsilon_{i,t}$$

Where:

$VOL_{i,t}$: A measure of stock market volatility for country i on day t, calculated using five alternative metrics (e.g., logarithm of absolute returns).

$SI_{i,t}$: The Stringency Index, reflecting the overall level of government intervention.

$PR_{j,i,t}$: Sub-components of the Stringency Index, representing specific policy measures.

$X_{i,t}$: Control variables, including trading volume, market capitalization, price-to-earnings ratios, and daily infection/death counts.

$\epsilon_{i,t}$: Error term capturing unobserved heterogeneity.

We estimate this model using random-effects, fixed-effects, and pooled regression approaches to ensure robustness. The Hausman test is applied to determine the most appropriate specification between fixed-effects and random-effects models.

While our main analysis uses this panel regression framework, we also consider alternative volatility modeling approaches. Specifically, we explored GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models as developed by Bollerslev (1986, https://doi.org/10.1016/0304-4076(86)90063-1) to capture the time-varying nature of volatility. Recent research by Malik and Umar (2019) has demonstrated the empirical performance of GARCH models with heavy-tailed innovations, particularly in crisis periods. However, given our focus on cross-country comparisons and the direct impact of government interventions rather than the time-series properties of volatility, we found the panel regression approach more suitable for our research objectives.

3.3 Key Variables

3.3.1 Dependent Variable: Stock Market Volatility

We employ five alternative measures of daily stock market volatility:

1. **Absolute Returns (log|R|)**: The logarithm of the absolute value of daily stock returns.
2. **CAPM Residuals (log|RRCAPM|)**: The logarithm of the absolute value of residual returns derived from the Capital Asset Pricing Model.
3. **Fama-French Residuals (log|RRFF|)**: The logarithm of the absolute value of residual returns derived from the Fama and French three-factor model.
4. **AMP Residuals (log|RRAMP|)**: The logarithm of the absolute value of residual returns derived from the Asness, Moskowitz, and Pedersen three-factor model.
5. **Carhart Residuals (log|RRCAR|)**: The logarithm of the absolute value of residual returns derived from the Carhart four-factor model.

3.3.2 Independent Variables: Government Interventions

The primary independent variable is the Stringency Index (SI), which measures the overall level of government intervention on a scale from 0 (least stringent) to 100 (most stringent). This index aggregates seven sub-components, each representing a specific non-pharmaceutical intervention:

1. **School Closures (PR1)**: Measures the extent of school and university closures.
2. **Workplace Closures (PR2)**: Captures restrictions on workplace operations.

3. **Public Event Cancellations (PR3)**: Reflects the cancellation of public events.
4. **Public Transportation Shutdowns (PR4)**: Measures restrictions on public transportation.
5. **Public Information Campaigns (PR5)**: Captures the intensity of public information campaigns.
6. **Restrictions on Internal Movement (PR6)**: Reflects limitations on domestic travel.
7. **International Travel Controls (PR7)**: Measures restrictions on international travel.

3.3.3 Control Variables

We include several control variables to account for market-specific characteristics and pandemic severity:

1. **Trading Volume (log(TV))**: The logarithm of daily trading volume.
2. **Market Capitalization (log(MV))**: The logarithm of total market capitalization.
3. **Price-to-Earnings Ratio (log(PE))**: The logarithm of the market-wide price-to-earnings ratio.
4. **Daily Changes in Infections (ΔINF)**: The daily increase in confirmed COVID-19 cases.
5. **Daily Changes in Deaths (ΔDTH)**: The daily increase in COVID-19-related deaths.
6. **Short-Selling Ban (ShortBan)**: A dummy variable indicating whether short-selling is prohibited.
7. **Requirement to Report Large Short Positions (ShortNote)**: A dummy variable indicating whether large short positions must be reported.

3.4 Descriptive Statistics

Table 1 presents the descriptive statistics for the key variables used in the analysis. The table provides the mean, standard deviation, minimum, and maximum values for each variable across the entire sample.

Table 1. Descriptive Statistics of Key Variables

Variable	Description	Mean	Std. Dev.	Min	Max
VOL	Log of absolute daily returns	-5.012	1.523	-12.154	-1.652
SI	Stringency Index (0-100)	25.119	31.533	0.000	100.00
PR1	School closures (0-3)	0.821	1.182	0.000	3.000
PR2	Workplace closures (0-3)	0.608	0.901	0.000	3.000
PR3	Public event cancellations (0-2)	0.540	0.866	0.000	2.000
PR4	Public transportation shutdowns (0-2)	0.157	0.470	0.000	2.000
PR5	Public information campaigns (0-2)	0.500	0.500	0.000	1.000
PR6	Restrictions on internal movement (0-2)	0.329	0.680	0.000	2.000
PR7	International travel controls (0-4)	0.831	1.153	0.000	4.000
log(TV)	Log of trading volume	9.453	2.214	3.892	15.324

Variable	Description	Mean	Std. Dev.	Min	Max
log(MV)	Log of market capitalization	11.871	1.948	7.624	16.821
log(PE)	Log of price-to-earnings ratio	2.810	0.531	1.432	4.787
ΔINF	Daily change in confirmed cases	143.215	769.872	0.000	18695.00
ΔDTH	Daily change in deaths	5.823	40.128	0.000	971.00
ShortBan	Short-selling ban (0/1)	0.012	0.109	0.000	1.000
ShortNote	Requirement to report large short positions (0/1)	0.022	0.146	0.000	1.000

The Stringency Index (SI) exhibits substantial variation across countries, ranging from 0 (least stringent) to 100 (most stringent), with a mean value of 25.119. This wide dispersion reflects the heterogeneous policy responses implemented by different countries during the early stages of the pandemic. Among the sub-component indices, public event cancellations (PR3) and public information campaigns (PR5) display considerable variation, suggesting diverse implementation strategies across the sample countries.

The volatility measure (VOL) shows substantial variation as well, with values ranging from -12.154 to -1.652. As expected, trading volume (log(TV)) and market capitalization (log(MV)) exhibit considerable cross-country differences, reflecting the diverse nature of financial markets included in the sample.

3.5 Correlation Matrix

Table 2 presents the correlation matrix for the key variables used in the analysis. This matrix helps identify potential multicollinearity issues and provides preliminary insights into the relationships between variables.

Table 2. Correlation Matrix of Key Variables

	VOL	SI	PR1	PR2	PR3	PR4	PR5	PR6	PR7	log(TV)	log(MV)	log(PE)	ΔINF	ΔDTH
VOL	1.000													
SI	0.325	1.000												
PR1	0.203	0.798	1.000											
PR2	0.265	0.781	0.583	1.000										
PR3	0.317	0.748	0.551	0.583	1.000									
PR4	0.146	0.604	0.375	0.472	0.411	1.000								
PR5	0.298	0.521	0.349	0.375	0.506	0.234	1.000							
PR6	0.206	0.708	0.494	0.590	0.507	0.493	0.305	1.000						
PR7	0.231	0.691	0.430	0.486	0.517	0.352	0.407	0.413	1.000					
log(TV)	0.275	0.059	0.031	0.047	0.073	0.003	0.081	0.025	0.058	1.000				
log(M	-0.1	-0.0	-0.0	-0.0	-0.0	0.0	-0.0	-0.0	-0.0	0.683	1.000			

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	VOL	SI	PR1	PR2	PR3	PR4	PR5	PR6	PR7	log(TV)	log(MV)	log(PE)	ΔINF	ΔDTH
V)	64	22	10	18	43	22	48	09	22					
log(PE)	-0.049	0.028	0.026	0.017	0.036	0.025	0.021	0.031	0.013	0.039	0.087	1.000		
ΔINF	0.138	0.326	0.218	0.268	0.281	0.173	0.211	0.239	0.238	0.233	0.183	0.010	1.000	
ΔDTH	0.092	0.301	0.193	0.244	0.249	0.204	0.159	0.262	0.212	0.115	0.091	0.005	0.754	1.000

The correlation matrix reveals several important relationships:

1. Stock market volatility (VOL) is positively correlated with the Stringency Index (SI) (r = 0.325), providing preliminary evidence of a positive relationship between government interventions and market volatility.

2. Among the specific interventions, public event cancellations (PR3) and public information campaigns (PR5) show the strongest correlations with volatility (r = 0.317 and r = 0.298, respectively), suggesting these may be significant drivers of market uncertainty.

3. Trading volume (log(TV)) is positively correlated with volatility (r = 0.275), while market capitalization (log(MV)) shows a negative correlation (r = -0.164), consistent with the notion that larger markets tend to be more stable.

4. High correlations are observed between the Stringency Index and its sub-components, particularly with school closures (PR1) (r = 0.798) and workplace closures (PR2) (r = 0.781). However, these correlations are expected and do not pose multicollinearity concerns when the variables are used in separate regression models.

5. Daily changes in infections (ΔINF) and deaths (ΔDTH) are moderately correlated with the Stringency Index (r = 0.326 and r = 0.301, respectively), reflecting the tendency for governments to implement stronger measures as case numbers rise.

3.6 Hausman Test for Model Specification

In panel data analysis, determining the appropriate estimation method between fixed-effects and random-effects models is critical for obtaining unbiased and consistent results. The Hausman (1978) specification test provides a formal framework for making this decision by comparing the coefficient estimates from both models.

3.6.1 Theoretical Foundation of the Hausman Test

The Hausman test is based on the idea that under the null hypothesis of no correlation between the individual effects and the explanatory variables, both the fixed-effects and random-effects estimators are consistent, but the random-effects estimator is more efficient. However, if the null hypothesis is rejected, only the fixed-effects estimator remains consistent.

The test statistic follows a chi-square distribution with degrees of freedom equal to the number of time-varying regressors in the model. Formally, the Hausman test statistic is given by:

$$H = (\beta FE - \beta RE)'[Var(\beta FE) - Var(\beta RE)]^{(-1)}(\beta FE - \beta RE)$$

Where:

- βFE is the vector of coefficient estimates from the fixed-effects model
- βRE is the vector of coefficient estimates from the random-effects model
- Var(βFE) is the variance-covariance matrix of the fixed-effects estimator
- Var(βRE) is the variance-covariance matrix of the random-effects estimator

3.6.2 Hausman Test Results

We conducted the Hausman test on our baseline model, which includes the Stringency Index and all control variables. The results are presented in Table 3.

Table 3. Hausman Test Results

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	42.35	11	0.0000

The test yields a chi-square statistic of 42.35 with 11 degrees of freedom (corresponding to the number of time-varying regressors in our model). The associated p-value is 0.0000, which is well below the conventional significance level of 0.05.

3.6.3 Detailed Coefficient Comparison

To better understand the differences between the models that led to the significant Hausman test result, Table 4 presents a comparison of the coefficient estimates from both the fixed-effects and random-effects specifications.

Table 4. Comparison of Fixed-Effects and Random-Effects Coefficient Estimates

Variable	Fixed-Effects (βFE)	Random-Effects (βRE)	Difference (βFE - βRE)	Standard Error
SI	0.0030	0.0110	-0.0080	0.0012
log(TV)	0.3142	0.5066	-0.1924	0.0572
log(MV)	-0.5214	-0.7152	0.1938	0.0488
log(PE)	-0.2431	-0.3739	0.1308	0.0654
ΔINF	0.0000	0.0000	0.0000	0.0000
ΔDTH	-0.0004	-0.0009	0.0005	0.0001
ShortBan	0.1152	-0.0007	0.1159	0.0512
ShortNote	-0.0422	-0.0306	-0.0116	0.0093

The table reveals substantial differences in coefficient estimates between the two models, particularly for key variables such as the Stringency Index (SI), trading volume (log(TV)), and market capitalization (log(MV)). These differences suggest that the individual country-specific effects are correlated with the explanatory variables, violating a key assumption of the random-effects model.

3.6.4 Interpretation and Model Selection

Based on the Hausman test results, we reject the null hypothesis that the random-effects model is appropriate. This rejection indicates that there are systematic differences in the coefficients between the fixed-effects and random-effects models, suggesting that the fixed-effects specification is more suitable for our analysis. The significant test statistic provides strong evidence that country-specific unobserved heterogeneity is correlated with our explanatory variables.

The fixed-effects model accounts for this correlation by controlling for all time-invariant differences between countries, which allows us to estimate the net effect of government interventions on stock market volatility. This approach mitigates the risk of omitted variable bias that could arise from unobserved country characteristics.

However, to ensure robustness and provide a comprehensive analysis, we report results from both random-effects and fixed-effects models, as well as pooled regression estimates in our main tables. This approach allows us to assess the sensitivity of our findings to different model specifications and provides additional confidence in our conclusions if the results remain consistent across different estimation methods.

It is worth noting that while the fixed-effects model produces more consistent estimates, the coefficients of the Stringency Index remain positive and statistically significant across all specifications, albeit with different magnitudes. This consistency reinforces our main finding that government interventions significantly increase stock market volatility, regardless of the estimation technique employed.

4. Results: Quantifying the Impact of Policy Responses

4.1 Aggregate Effects

The analysis of aggregate effects reveals a strong positive association between the Stringency Index (SI) and stock market volatility. Table 5 presents the results of panel data regressions, where the dependent variable is the logarithm of daily volatility proxied by absolute daily returns (log|R|) or residual returns derived from four different asset pricing models: CAPM (log|RRCAPM|), Fama and French three-factor model (log|RRFF|), Asness, Moskowitz, and Pedersen three-factor model (log|RRAMP|), and Carhart four-factor model (log|RRCAR|).

Table 5. The Stringency of Policy Responses and Stock Market Volatility

This table presents the results of panel data regressions. The dependent variable is the logarithm of daily volatility proxied by absolute daily returns (log|R|) or residual returns from four different asset pricing models: CAPM (log|RRCAPM|), Fama and French three-factor model (log|RRFF|), Asness-Moskowitz-Pedersen three-factor model (log|RRAMP|), and Carhart four-factor model (log|RRCAR|).

The independent variables include the Government Policy Response Stringency Index (SI), trading volume (log(TV)), market value (log(MV)), price-to-earnings ratio (log(PE)), daily changes in new infections (ΔINF), daily changes in deaths (ΔDTH), short-selling ban (ShortBan), and requirement to report large short positions (ShortNote). Weekday dummies are included in all regression equations. Adjusted R^2 denotes the coefficient of determination. Numbers in parentheses are t-statistics, and asterisks (*, **, ***) indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Panel A: Baseline Results (Random-Effects Model)

Variable	log|R|	log|RRCAPM|	log|RRFF|	log|RRAMP|	log|RRCAR|
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
Adjusted R^2	0.1719	0.1364	0.1118	0.1217	0.1162

Panel B: Robustness Checks

Specification	log|R|	log|RRCAPM|	log|RRFF|	log|RRAMP|	log|RRCAR|
Fixed-Effects Regression Model	0.0030**	0.0030**	0.0029**	0.01541**	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)
Excluding Weekday Dummies	0.0101***	0.2693***	0.0089***	0.0083***	0.0085***
	(5.98)	(4.37)	(6.39)	(6.25)	(6.13)
Controlling for Total Cases/Deaths	0.0111***	0.0098***	0.0087***	0.0092***	0.0084***
	(6.80)	(7.07)	(6.27)	(6.59)	(6.32)

4.1.1 Key Findings from Table 4

Stringency Index (SI): The coefficients for the SI are consistently positive and statistically significant across all volatility measures. Specifically:

- For log|R|, the coefficient is 0.0110 (t-statistic = 6.76).
- For log|RRCAPM|, the coefficient is 0.0094 (t-statistic = 6.86).

- For log|RRFF|, the coefficient is 0.0090 (t-statistic = 6.58).
- For log|RRAMP|, the coefficient is 0.0093 (t-statistic = 6.82).
- For log|RRCAR|, the coefficient is 0.0087 (t-statistic = 6.63).

These results indicate that a one-point increase in the Stringency Index leads to an approximate increase in daily stock market volatility ranging from 0.87% to 1.1%, depending on the specific measure used.

Trading Volume (log(TV)): Higher trading volume is associated with increased volatility, as evidenced by positive and significant coefficients across all models. For instance:

- In the log|R| model, the coefficient is 0.5066 (t-statistic = 4.91).
- In the log|RRCAPM| model, the coefficient is 0.4480 (t-statistic = 5.27).

This suggests that heightened trading activity during periods of government intervention contributes to elevated volatility.

Market Capitalization (log(MV)): Larger market capitalization tends to dampen volatility, as reflected by negative and significant coefficients. For example:

- In the log|R| model, the coefficient is -0.7152 (t-statistic = -4.06).
- In the log|RRCAPM| model, the coefficient is -0.6987 (t-statistic = -4.73).

This finding aligns with prior research suggesting that well-established firms with higher market values exhibit greater stability during turbulent times.

Price-to-Earnings Ratio (log(PE)): The relationship between the market-wide PE ratio and volatility is less pronounced, with most coefficients being insignificant. However, some models show slight negative associations, such as:

- In the log|R| model, the coefficient is -0.3739 (t-statistic = -1.10).

Daily Changes in Infections (ΔINF) and Deaths (ΔDTH): While changes in infection counts have a marginal impact, increases in daily deaths are negatively correlated with volatility in certain models:

- For ΔDTH in the log|R| model, the coefficient is -0.0009 (t-statistic = -2.60).

This may reflect investor sentiment reacting more strongly to mortality figures than infection rates.

4.1.2 Robustness Checks

To ensure the reliability of our findings, we conducted robustness checks using alternative specifications, including fixed-effects and pooled regression models, exclusion of weekday dummies, and control for total cases and deaths. The results remain consistent, reinforcing the conclusion that stringent policy responses significantly elevate stock market volatility.

As shown in Panel B of Table 4, the coefficient of the Stringency Index remains positive and statistically significant across all alternative specifications and volatility measures:

- In the fixed-effects model, the coefficient for log|R| is 0.0030 (t-statistic = 2.73), somewhat smaller than in the random-effects model but still significant.
- The pooled regression model yields a higher coefficient of 0.0133 (t-statistic = 17.60), indicating a stronger effect.
- Excluding weekday dummies results in a coefficient of 0.0101 (t-statistic = 5.98), close to our baseline estimate.
- Controlling for total cases and deaths rather than daily changes produces a coefficient of 0.0111 (t-statistic = 6.80), virtually identical to our baseline result.

These robustness tests confirm that the observed relationship between government interventions and stock market volatility is not sensitive to methodological variations. The consistency of results across different model specifications and control variable configurations strengthens the validity of our findings.

4.2 Individual Contributions

While the aggregate effects of government interventions on stock market volatility are significant, examining the contributions of specific policy measures provides valuable insights into their relative importance. Table 5 presents the results of random-effects panel data regressions that isolate the impact of seven distinct non-pharmaceutical interventions (NPIs) on volatility. These interventions include school closures (PR1), workplace closures (PR2), public event cancellations (PR3), public transportation shutdowns (PR4), public information campaigns (PR5), restrictions on internal movement (PR6), and international travel controls (PR7).

Table 6. Influence of Different Non-Pharmaceutical Interventions on Market Volatility

This table presents the results of random-effects panel data regressions. The dependent variable is the logarithm of daily volatility proxied by absolute daily returns (log|R|) or residual returns from four different asset pricing models: CAPM (log|RRCAPM|), Fama and French three-factor model (log|RRFF|), Asness-Moskowitz-Pedersen three-factor model (log|RRAMP|), and Carhart four-factor model (log|RRCAR|).

The explanatory variables represent seven non-pharmaceutical interventions (NPIs): school closures (PR1), workplace closures (PR2), public event cancellations (PR3), public transportation shutdowns (PR4), public information campaigns (PR5), restrictions on internal movement (PR6), and international travel controls (PR7). Control variables include trading volume (log(TV)), market value (log(MV)), price-to-earnings ratio (log(PE)), daily changes in infections (ΔINF), daily changes in deaths (ΔDTH), short-selling ban (ShortBan), and requirement to report large short positions (ShortNote). Weekday dummies are included in all regression equations. Adjusted R^2 denotes the coefficient of determination. Numbers in parentheses are t-statistics, and asterisks (*, **, ***) indicate statistical significance at the 5%, 1%, and 0.1% levels, respectively.

Variable	log|R|	log|RRCAPM|	log|RRFF|	log|RRAMP|	log|RRCAR|
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
Adjusted R^2	0.1911	0.1451	0.1204	0.1307	0.1231

4.2.1 Key Findings from Table 5

Public Information Campaigns (PR5): Public information campaigns emerge as one of the most influential contributors to increased stock market volatility. Across all volatility measures, the coefficients for PR5 are consistently positive and statistically significant:

- For log|R|, the coefficient is 0.3259 (t-statistic = 4.06).
- For log|RRCAPM|, the coefficient is 0.2315 (t-statistic = 3.28).

This finding aligns with prior research suggesting that information dissemination can lead to heightened investor uncertainty and portfolio restructuring (Zaremba et al., 2020). The constant flow of updates regarding the pandemic and government responses may create news-implied volatility, prompting investors to adjust their positions frequently (Manela & Moreira, 2017). Consequently, trading activity increases, driving up volatility.

Public Event Cancellations (PR3): Cancellation of public events also plays a critical role in elevating volatility. The coefficients for PR3 are significant across all models:

- For log|R|, the coefficient is 0.3131 (t-statistic = 3.83).

- For log|RRCAPM|, the coefficient is 0.1818 (t-statistic = 2.28).

Unlike other interventions, public event cancellations often serve as an early signal of impending stricter measures. Investors may interpret these actions as precursors to broader economic disruptions, leading to anticipatory behavior such as "flights to safety" (Baele et al., 2020). This behavioral response contributes to rapid portfolio flows and price adjustments, further amplifying volatility.

School Closures (PR1) and Workplace Closures (PR2): While school and workplace closures are among the most visible policy responses, their impact on volatility is less pronounced compared to information campaigns and public event cancellations. For instance:

- For log|R|, the coefficients for PR1 and PR2 are 0.0634 (t-statistic = 0.80) and 0.0580 (t-statistic = 0.74), respectively.

This muted effect could be attributed to the fact that these measures primarily affect long-term economic conditions rather than immediate financial market dynamics. Additionally, investors might already anticipate such actions during periods of widespread infection, reducing their surprise value.

Public Transportation Shutdowns (PR4): Surprisingly, closing public transportation systems appears to have a negative association with volatility:

- For log|R|, the coefficient is -0.1740 (t-statistic = -2.47).

One possible explanation is that this intervention reduces mobility and, by extension, economic activity, which may dampen trading volumes and stabilize markets temporarily. However, this effect is relatively small compared to other measures.

Restrictions on Internal Movement (PR6): Restrictions on internal movement exhibit mixed results, with generally insignificant or slightly negative coefficients:

- For log|R|, the coefficient is -0.0944 (t-statistic = -1.32).

These findings suggest that while such measures restrict physical movement, they do not necessarily translate into immediate changes in investor sentiment or trading behavior.

International Travel Controls (PR7): International travel controls show limited influence on volatility, with small and mostly insignificant coefficients:

- For log|R|, the coefficient is 0.0333 (t-statistic = 0.93).

This result indicates that global investors may perceive travel restrictions as having a more localized impact, affecting specific sectors (e.g., tourism and aviation) rather than the broader market.

4.3 Analysis of Results

The differential impacts of individual policy measures highlight the importance of understanding how investors process information about government actions. Early-stage interventions, such as public information campaigns and public event cancellations, appear to generate the most significant volatility due to their signaling effects. These measures communicate potential future disruptions, prompting preemptive reactions from market participants. In contrast, later-stage interventions like workplace closures and travel bans tend to reflect ongoing challenges rather than introducing new uncertainties.

Moreover, the findings underscore the dual nature of government interventions: while necessary for controlling the spread of the virus, they inadvertently introduce financial instability. Policymakers must carefully weigh these trade-offs when designing containment strategies. For example, targeted communication efforts could help mitigate investor anxiety without exacerbating volatility.

Finally, the results emphasize the need for comprehensive risk management frameworks in financial markets during crises. Investors should remain vigilant about the types of government actions being implemented and their likely implications for market dynamics. By understanding which interventions trigger the strongest market reactions, both policymakers and financial practitioners can better prepare for and respond to pandemic-induced volatility.

5. Discussion: Implications for Policy and Practice

Our results carry important implications for policymakers and financial practitioners. First, governments must recognize that restrictive measures, while necessary for public health, can exacerbate financial instability. Policymakers should therefore strive to balance health objectives with economic considerations, potentially through targeted fiscal stimulus or monetary easing programs (Ozili & Arun, 2020).

5.1 Policy Coordination and Communication

The strong impact of public information campaigns on stock market volatility suggests that the manner and timing of government communications are crucial. Clear, consistent, and coordinated messaging may help reduce uncertainty and prevent excessive market reactions. Policymakers could consider:

1. Establishing regular, predictable communication channels to reduce information asymmetry.

2. Providing forward guidance about potential future measures to allow markets to adjust gradually.

3. Coordinating announcements across different government agencies and international bodies to avoid conflicting messages.

5.2 Implications for Financial Market Participants

Second, investors may benefit from incorporating government response metrics into their decision-making processes. By monitoring the evolution of policy interventions, they can better anticipate shifts in market sentiment and adjust their portfolios accordingly. Specifically, market participants should:

1. Pay particular attention to early-stage interventions like public event cancellations, which serve as leading indicators of future restrictions.
2. Develop systematic approaches to tracking government policy responses across multiple jurisdictions.
3. Consider the differential sectoral impacts of specific interventions when making allocation decisions.

5.3 Future Research Directions

Future research could extend this analysis by exploring long-term effects or investigating sector-specific impacts of NPIs. Potential avenues include:

1. Examining how the relationship between government interventions and market volatility evolves over different phases of a pandemic.
2. Investigating spillover effects across countries with varying degrees of economic integration.
3. Analyzing the impact of fiscal and monetary policy responses in mitigating the volatility induced by NPIs.
4. Exploring heterogeneous effects across different market sectors, distinguishing between essential and non-essential industries.

6. Conclusion

This study investigates the impact of non-pharmaceutical interventions (NPIs) aimed at curbing the spread of the novel coronavirus (COVID-19) on stock market volatility across 67 countries. By employing a robust panel regression framework and utilizing multiple measures of volatility, we provide compelling evidence that government policy responses significantly increase equity market volatility. This effect is independent of the direct role of the pandemic itself and remains consistent across various considerations, including alternative model specifications, control variables, and sample adjustments.

The Stringency Index (SI), which quantifies the overall level of government interventions, exhibits a strong positive relationship with stock market volatility. A one-point increase in the SI leads to an approximate rise in daily volatility ranging from 0.87% to 1.1%, depending on the specific measure used.

Trading volume positively influences volatility, while market capitalization acts as a stabilizing factor. Daily changes in deaths are negatively associated with volatility, suggesting that investors may react more strongly to mortality figures than infection counts.

Among the seven types of NPIs examined, public information campaigns (PR5) and public event cancellations (PR3) emerge as the most significant contributors to increased volatility. These early-stage interventions signal potential future disruptions, prompting preemptive reactions from market participants.

School closures (PR1) and workplace closures (PR2) have smaller but still positive effects on volatility. In contrast, public transportation shutdowns (PR4) exhibit a negative association, potentially reflecting reduced economic activity and trading volumes.

Restrictions on internal movement (PR6) and international travel controls (PR7) show limited influence, indicating that their impact is either localized or less salient to global investors.

Two primary channels underlie the observed relationship between government interventions and stock market volatility:

1. **Rational Channel**: Policy responses signal changes in future economic conditions, leading to abrupt portfolio restructuring and elevated trading activity.
2. **Behavioral Channel**: Heightened uncertainty and constant news flow create "flights to safety," resulting in rapid portfolio flows and price changes. Additionally, the divergence of opinions among investors increases trading activity, further contributing to volatility.

The findings carry important implications for policymakers, financial practitioners, and portfolio managers:

For Policymakers: Governments must recognize the dual role of NPIs in mitigating health risks while simultaneously amplifying financial instability. To minimize adverse economic consequences, policymakers should consider coordinated approaches that balance public health objectives with market stability. For instance, targeted fiscal stimulus or monetary easing programs could help offset the negative effects of stringent measures.

For Investors: Market participants can benefit from incorporating government response metrics into their decision-making processes. Monitoring the evolution of policy interventions allows investors to better anticipate shifts in market sentiment and adjust their portfolios accordingly.

For Portfolio Managers: The stringency of implemented measures serves as a valuable indicator of future stock market volatility. By analyzing these indicators, managers can refine their risk management strategies and improve portfolio performance during crises.

6.1 Limitations and Future Research Directions

While this study provides novel insights into the relationship between government interventions and stock market volatility, several limitations warrant acknowledgment:

1. **Sample Size and Time Period**: The analysis focuses on a relatively narrow timeframe (January-April 2020) and a set of 67 countries. Expanding the dataset to include more countries and longer observation periods would enhance the generalizability of the results.
2. **Heterogeneity Across Regions**: Future research could explore regional differences in the impact of NPIs on volatility. For example, developed versus emerging markets may exhibit varying degrees of sensitivity to specific interventions.

3. **Sector-Specific Effects**: Investigating how different sectors respond to government actions could yield additional insights. Certain industries, such as tourism and aviation, may be disproportionately affected by travel bans or public event cancellations.

4. **Long-Term Consequences**: This study primarily examines short-term effects; further investigation is needed to understand the long-term implications of NPIs on financial markets.

6.2 Final Remarks

In conclusion, our findings underscore the critical importance of understanding the interplay between public health policies and financial market dynamics. As governments continue to navigate the challenges posed by pandemics, it is essential to carefully weigh the trade-offs between containing the virus and maintaining economic stability. By doing so, policymakers can design more effective strategies that mitigate both health and financial risks, ultimately fostering resilience in the face of global crises.

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Authors' Contributions

Dr. Ben Mbarek Kais was responsible for the study design, data analysis, and manuscript revision. Prof. Amir Hassan contributed to the theoretical framework and interpretation of results. Dr. Fatima Al-Mansouri was responsible for data collection and validation. Dr. Ben Mbarek Kais drafted the manuscript and all authors contributed to its revision. All authors read and approved the final manuscript.

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Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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