The Linkage between Equity Returns and Government Responses to the Disease Outbreak

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Abstract

This study examines regime switches in the empirical relation between stock market returns and government stringency indices, which reflect the extent of policy responses to the new coronavirus outbreak. The analysis is based on the Oxford Covid-19 Government Response Tracker, which reflects several indicators of governmental responses ranging from workplace and school closures, to movement restrictions, and income support. The evidence from Markov-regime switching models for the Japanese and U.S. markets suggests that the dynamics of market returns are dominated by regimes governed by mean reversion and negative correlation with changes in the model-free volatility index. The negative relationship between changes in volatility expectations and market returns seems to be robust to different Markov regimes. The relationship between returns and changes in government stringency index is more likely to be associated with the expected negative sign, but it remains rather weak. Markov regimes where the impact of government responses on market returns is found to be statistically significant, are indeed less likely to prevail. The evidence lends support to the proposition that the return-generating process is insensitive to the serious economic effects of the disease outbreak. The important question remains as to whether in addition to their impact on currency markets, quantitative and qualitative easing programs are also conducive to the impairment of the price discovery process in financial markets.

1. Introduction

The disease outbreak has taken a heavy toll in terms of lost human lives and continues to be a major source of economic uncertainty. Governments have responded to the compounded healthcare and economic crises in ways that tend to differ over time and across regions, and countries. The wide spectrum of government measures includes closures of schools and workplace, movement restrictions, social distancing, and income support. Such measures have serious implications for economic and social life as they tend to alter the dynamics of healthcare, welfare, and economic systems. Disruptions to economic activities initially caused by the disease outbreak

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and subsequent government responses to its rapid spread are bound to also affect asset prices and market expectations about future levels of volatility.

The formation of volatility expectations in financial markets is driven by economic conditions, policy responses, and the arrival to new macroeconomic information. With the onset of the healthcare crisis, which constitutes a major disruptive event that has serious implications for the real economy and the financial system, new information continues to play a key role in the formulation and coordination of government policies, and in shaping effective responses to the new economic challenges. Cantú, Cavallino, De Fiore and Yetman (2021) provide a global database on the monetary responses by central banks. It is noted that information from monetary authorities relates to interest rates, foreign exchange operations, reserve policies, and asset purchase program among others. The evidence indicates that monetary responses in advanced economies focused on lending operations and asset purchases meant to provide further liquidity to the financial system. In contrast, the focus of central banks in emerging economies was placed not so much on asset purchases as on interest rates, foreign exchange, and reserve policies. These measures are consistent with the policy recommendations of the International Monetary Fund (2020), which advocated timely and decisive actions by central banks including the provision of market liquidity and the lowering of borrowing costs for firms and households.

The recent recourse to unconventional monetary policies and exceptional measures is justified by the onset of the healthcare crisis, and the need to avoid financial instability, reduce systemic risk, and prevent economic crises. However, as argued by Barajas, Choi, Gan, Guérin, Mann, Wang and Xu (2021), loose monetary policies are contributive to higher leverage, and conducive to an intertemporal tradeoff where the risk to macro-financial stability is reduced in the short term but exacerbated in the medium term. Thus, it is clear that not only the speed of disease spread, but also the reactions of monetary authorities, and their immediate and longer-term effects may differ across countries. It is possible to gauge the impact of monetary policy responses on the behaviour of asset prices in financial markets using the global database of monetary responses. But the scope of the analysis would be confined in this case to the risks to financial stability. Thus, it is important to extend the study to include other non-monetary aspects of government responses to the compounded healthcare and economic crises.

It is possible to examine the reaction of financial markets to government responses using the newly developed Oxford Covid-19 Government Response Tracker. This is a composite measure developed by the Blavatnik School of Government, University of Oxford, based on some response indicators including workplace closures, school closures, restrictions on domestic and international movements, income support, and fiscal measures. It varies from zero to the maximum level of hundred, which represents the strictest lockdown measures including containment and closure policies. Given the nature of government responses, which typically lag the growth in the number of new infections, the stringency index is not a measure of policy effectiveness. It may not provide either an accurate and contemporaneous measure of the disease outbreak and spread, but as noted by Hale et al. (2021), it constitutes, nevertheless, a broad tracker of the virus spread. It is important to note that such benchmarks allow also for the measurement of variations in government responses across regions and countries.

Thus, the main purpose of the present study is to address the question of whether stock markets are sensitive to government responses to the disease outbreak. Part of these responses is to provide remedies to the disruptive effects of simultaneous shocks to the demand and supply functions, and it is important to understand the reaction of stock markets to these government measures. This is an attempt to examine the issue of whether the dynamics of stock market returns are driven by a significant correlation with government responses. The empirical approach is based on Markov-regime switching models, following the pioneering work of Hamilton (1989) on business cycles. These estimation models can be useful in capturing changes in the distribution of variables conditional on a latent state variable. As shown by Branch and Evans (2010), the beliefs of agents and asset prices can be jointly determined, under the assumption of bounded rational expectations, by multiple equilibria with endogenous shifts between regimes characterized by distinct mean and variance terms. Also, regime switching models can provide useful insights on the dynamics of interest rates as shown by Bekaert and Ang (2002), and real exchange rates as suggested by Bergman and Hansson (2005).

Further empirical evidence on stock returns and market volatility includes the earlier study by Holmes and Maghrebi (2002), which examines the existence of nonlinearities in terms of regime shifts in the relation between equity and currency markets. The evidence from Markov-regimes switching models by Maghrebi, Holmes and Oya (2014) suggests that past information may not provide useful guidance about the dynamics of volatility expectations during financial crises. Forward-looking macroeconomic information and monetary policy are more likely to shape volatility expectations.[1] The empirical literature on the dynamics of stock market returns, and their relationship with volatility expectations remains however scant. To the best knowledge of the author, this is also the first attempt to examine the empirical relationship of market returns with the newly developed government stringency index using Markov regime switching models.

The remainder of the paper is organized as follows. The next section discusses the Markov-regime

[1] Maghrebi, Kim and Nishina (2007) provide further evidence of regime switching in the behaviour of implied volatility in the Korean stock markets. It is possible to examine also the nonlinear adjustment mechanism following forecast errors in the dynamics of volatility expectations as shown by Nishina, Maghrebi and Holmes (2012), *inter alia*.

switching modelling of the empirical relation between stock market returns and the benchmark for government responses to the disease outbreak. Section 3 describes the government stringency index, the time-series of stock market returns, and implied volatility indices, as well as their distributional properties. Section 4 discusses the empirical results and the nature of regimes governing the price dynamics in the Japanese and U.S. equity markets. Section 5 concludes the paper.

2. Markov-regime modelling of stock market returns and government responses

Markov regime models can be useful in understanding the properties of the return-generating process and in capturing the inner dynamics of its relationship with risk factors. These properties can be reflected by the significance of long-term drift terms, autoregressive effects, and correlation structure. It is possible to describe the return dynamics according to Equation [1], where regimes are function of the significance of the drift term μ, as well as the autoregressive term δ that reflects the mean reversion process, or speed at which shocks tend to be absorbed over time.

$$r_t = \mu + \delta r_{t-1} + \gamma G_{t-1} + \vartheta \Delta v_{t-1} + \varphi \Delta v_t + \zeta_t \qquad [1]$$

This Markov regime model specification describes the return dynamics as a function also of the correlation with changes in government responses. The estimated coefficient γ describing this relationship is expected to be associated with the negative sign as the level of the Oxford Covid-19 Government Response Tracker G_t is, by definition, bound to rise under more stringent government measures. Indeed, an increase in the stringency index is indicative of perceptions of rising concerns about the speed of disease spread and severity of the healthcare crisis. Thus, with increasing concerns about the government stringency index are also reflective of greater uncertainty, and increasing concerns about weaker economic growth and diminishing returns.

It is also noted that the anticipated levels of uncertainty can be measured by the model-free volatility index v_t, which provides a gauge of investors' fear and market sentiment.[2] The benchmark of volatility expectations can be useful for forecasting purposes, and in understanding the reaction of financial markets to the arrival of new economic information, including policy measures.[3]

[2] The Chicago Board Options Exchange methodology used in the calculation of the model-free VIX index is based on the approximations of one-month variance swaps on the underlying asset. Reference can be made to Demeterfi et al. (1999) and Britten-Jones and Neuberger (2000) for a theoretical analysis of variance swaps. Fukasawa et al. (2011) propose a new method for approximating the expected quadratic variations using an interpolation scheme for the volatility surface that is consistent with arbitrage bounds. Thus, forward-looking volatility indices represent ex ante measures of short-term volatility implicit in the market prices options written on the underlying index.

[3] There is indeed evidence from Neely (2005) and Fornari (2004), that implied volatility tends to increase prior to the release of macroeconomic information and ahead of monetary policy meetings. Maghrebi (2020) provides further evidence about the information content of volatility expectations based on the behaviour of the Nikkei 225 implied volatility index around the monetary policy meetings of the Bank of Japan.

Thus, higher levels of volatility expectations are indicative of perceptions of higher economic uncertainty, which is negatively correlated with market returns. This dynamic linkage is captured in equation [1] by the model coefficients ϑ and φ, which describe the reaction of market returns to past changes Δv_{t-1} and contemporaneous changes Δv_t in volatility expectations, respectively. It is noted finally that the error terms in equation [1] are distributed as $\zeta_t \sim i.i.d.\ N(0, \sigma_\zeta^2)$., and that on aggregate, market returns are assumed to be driven by Markov regimes governed by different speeds of mean reversion or memory process and different levels of significance in the anticipated negative relationships with both government stringency and implied volatility benchmarks.[4]

It is assumed that the regression parameters follow a first-order Markov process, where the current state s_t depends only on the previous state s_{t-1}. The regimes are not path-dependent as the transition probabilities, which are conditional on past information, can be expressed as follows.

$$\Pr(s_t = i | s_{t-1} = j) = \Phi(z_t \cdot r_{ij}) \quad [2]$$

where Φ denotes the standard normal cumulative distribution. The cumulative density function depends on the stochastic process $s_t = (1 - p_{11}) + \eta\ s_{t-1} + \omega_t$, where $\eta = p_{11} + p_{22} - 1$, and ω_t are disturbance terms normally distributed conditional upon the set of available information Ω_{t-1}. Thus, the likelihood for market returns to shift from regime $s = i$ at time $t - 1$ to an alternative regime $s = j$ at time t is defined as $p_{ij} = 1 - p_{ii}$, where p_{ii} represents the probability of remaining in the same $s = i$ regime.[5]

It is possible to estimate the conditional density of returns from the joint density and the state variable s_t.

$$f(r_t | s_t; \Omega_{t-1}, \psi) = \sum f(r_t | s_t = i; \Omega_{t-1}, \psi) \cdot \mathrm{P}(s_t = i | \Omega_{t-1}, \psi) \quad [3]$$

where ψ represents the vector of parameters included in the Markov-regime switching model defined in equation [1]. The maximum likelihood estimates of transition probabilities can be expressed following Hamilton (1990) as

$$\hat{p}_{ij} = \sum_{t=2} \Pr\big(s_t = j, s_{t-1} = i | \Omega_T; \hat{\psi}\big) / \sum_{t=2} \Pr\big(s = i | \Omega_T; \hat{\psi}\big) \quad [4]$$

where $\hat{\psi}$ denotes the maximum likelihood estimates of model parameters. The estimation is based on an iteration process using initial values of the vector of parameters $\hat{\psi}_0$ and smoothed inferences of regime probabilities. The iteration process is conducive to an increase in the likelihood function, and convergence is associated with the maximum likelihood estimates of parameter estimates.

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[4] It is possible to estimate, in addition to this unrestricted Markov-regime model described by equation [1], alternative restricted versions can be estimated, where returns are regressed on the drift and autoregressive terms as well as the government stringency index or the volatility index.

[5] It is noted also that the transition probabilities should satisfy the condition of non-negativity and the restriction that $p_{ii} + p_{ij} = 1$.

It is finally noted that the maximum likelihood estimation of Markov-regime switching models is complicated by the fact that the probability of a given state depends only on the state prevailing one period earlier. Standard regularity assumptions for inferences based on the likelihood estimates may, thus, be violated.[6] Indeed, inferences about Markov-regime probabilities can be affected by the violation of the normality assumption. Thus, Markov-regime shifts in the return dynamics are estimated using initial probabilities from ergodic solutions and Huber-White robust standard errors and covariances.

3. Data description and distributional properties

The empirical analysis is based on the time-series of government stringency indices, stock market returns, and implied volatility benchmarks for the Japanese and U.S. financial market over the sample period from January 1, 2020 to June 30, 2021. Following the emargence of the new coronavirus in December 2019, governments around the world have taken unprecedented measures to lockdown populations, and impose social distancing restrictions to prevent the spread of the disease. The development of new vaccinations holds the promise of decreasing the speed of spread, but the emergence of new variants has added new layers of complexity to the healthcare crisis. Naturally, government responses are, to a large extent, dictated by the dynamics of the disease outbreak, and by economic and social constraints. Thus, insofar that government measures can be explained only by new information about the disease outbreak, the time-series of the Oxford Covid-19 Government Response Tracker developed by the Blavatnik School of Government, University of Oxford, can be reflective of perceived levels of uncertainty. The time-series of government stringency indices, stock price averages, and implied volatility benchmarks for the Japanese and the U.S. markets are obtained from the Thomson-Reuters economic and financial database.

Figure 1 describes the behaviour of the government stringency indices and equity returns for the Japanese and U.S. markets. The benchmark for the Japanese government responses has increased gradually in the early months of 2020, receded to lower levels afterward before resurging to higher peaks beyond the threshold value of 50, which represents the middle point of stringency measures. The sharp decrease in the Nikkei 225 stock prices, which coincides in part with the rise in government stringency index, is followed by a steady upward movement from the lowest level in March 2020 to the highest level in February 2021. It seems that despite a more volatile market, the Nikkei 225 index remained at higher levels associated with increased government stringency measures.

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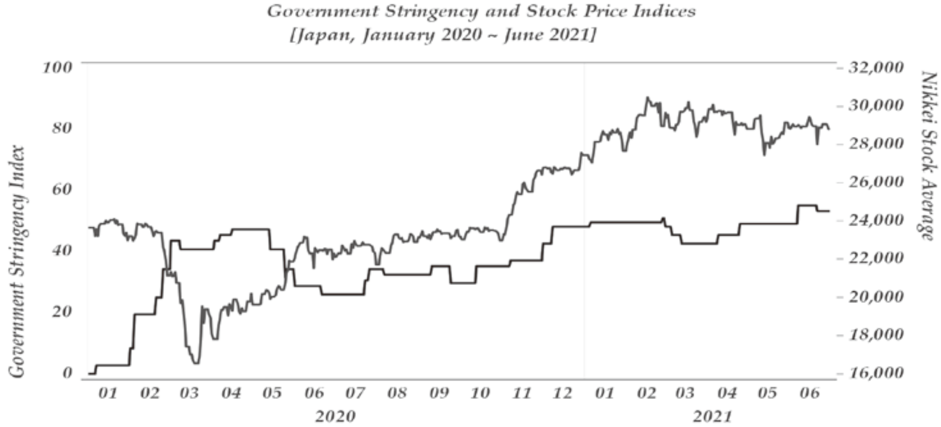
[6] It is noted that the violation of regularity conditions that underlie likelihood-based parametric inference may be conducive to boundary problems, singular information matrix and indeterminate parameters, among other issues.

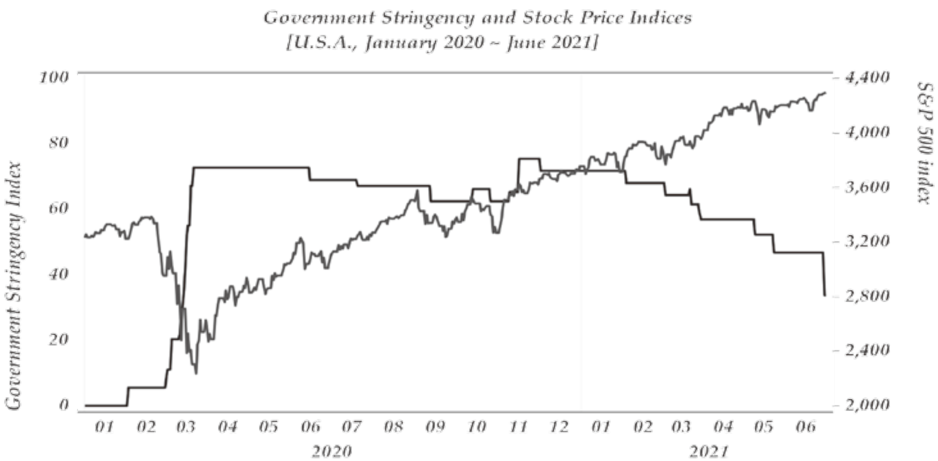
Figure 1. Japanese government stringency index and stock market prices



Notes: The time-series of the Japanese government stringency index is derived from the Oxford Covid-19 Government Response Tracker developed by the Blavatnik School of Government, University of Oxford

In contrast, the U.S. government responses to the crisis seem to follow distinct trends as suggested by Figure 2. There is a tendency for the stringency index to remain at high levels for a prolonged period of time following a sharp and belated increase in February 2020. There is however a monotonous decrease starting from January 2021, reflecting a tendency for less stringent measures. The behaviour of the S&P 500 index is similar to that of the Nikkei 225 index, except for the later period where stock prices and stringency indices tend to move in opposite directions. It seems that the upward movement of the U.S. equity market is insensitive to clear shifts in the government stringency index.

Figure 2. U.S. government stringency index and stock market prices



Notes: The time-series of the Japanese government stringency index is derived from the Oxford Covid-19 Government Response Tracker developed by the Blavatnik School of Government, University of Oxford

Table 1 reports the distributional properties of changes in the government stringency index and stock market returns as well as changes in the implied volatility index. In order to assess the impact of the healthcare and economic crises, the full sample period is divided into two equal subperiods-A from January to September 2020 and subperiod-B from October 2020 to June 2021. There is evidence of positive average stock returns for both stock markets, particularly during subperiod-B, which tends to be associated with lower standard deviations.

Changes in market volatility expectations, proxied by the VIX and VXJ model-free volatility indices, are found to be, on average, positive and relatively higher during subperiod-A. The evidence of increasing volatility expectations is consistent with the observation of higher levels of realized volatility during the initial period. This is also consistent with the higher averages of changes in the government stringency index, which are suggestive of increasingly levels of uncertainty stemming from the disease outbreak. It is finally noted that the distributions of returns, and daily changes in implied volatility and stringency indices are found to approach the normal distribution, as suggested by Jarque-Bera statistics. Also, the Augmented Dickey-Fuller tests provide evidence of stationarity series for the various time series. It is noted that the stationarity tests tend to be performed with both intercept and trend terms for changes in government stringency indices, and with neither intercept nor trend terms for returns in the Japanese and U.S. markets.

Table 1. Distributional moments of daily market returns and changes in government stringency and implied volatility indices

Distributional properties	Mean	Std. Dev.	Skew-ness	Kurtosis	Jarque Bera	ADF test
	Daily returns on stock market index					
Japan- Full period	0.0004	0.0123	0.340	10.982	1459.95	-14.331***c
Subperiod-A	0.0000	0.0148	0.489	9.850	544.56	-15.303***c
Subperiod-B	0.0008	0.0093	-0.168	5.874	95.24	-17.769***b
U.S.A.- Full period	0.0006	0.0153	-0.697	20.222	6792.08	-6.226***c
Subperiod-A	0.0004	0.0203	-0.543	13.031	1158.08	-21.856***c
Subperiod-B	0.0009	0.0076	-0.394	5.936	105.10	-16.965***a
	Daily changes in government stringency index					
Japan- Full period	0.0086	0.1085	14.931	251.594	1410546.97	-8.918***b
Subperiod-A	0.0149	0.1527	10.709	128.106	179226.54	-6.221***b
Subperiod-B	0.0023	0.0205	5.790	46.363	22913.89	-16.679***a
U.S.A.- Full period	0.0047	0.0547	9.476	126.304	333306.55	-3.783 **b
Subperiod-A	0.0122	0.0755	7.642	70.739	48422.34	-3.825 **b
Subperiod-B	-0.0020	0.0230	-5.822	87.519	82799.06	-17.032***b
	Daily changes in implied volatility index					
Japan- Full period	0.0023	0.0653	1.583	9.363	1149.10	-24.183***c
Subperiod-A	0.0043	0.0743	1.617	8.393	449.82	-17.338***c
Subperiod-B	0.0002	0.0549	1.242	9.030	483.74	-16.617***c
U.S.A.- Full period	0.0031	0.0803	2.713	17.517	5464.43	-26.059***b
Subperiod-A	0.0058	0.0875	2.569	13.521	1559.44	-18.957***b
Subperiod-B	0.0005	0.0725	2.832	24.020	5391.04	-17.724***c

*Notes: The sample period covering the disease outbreak runs from January 1, 2020 to June 30, 2021. Subperiod-A includes daily observations from January to September 2020, and subperiod-B includes the subsequent observations from October 2020 to June 2021. ADF tests with intercept only, with both intercept and trend terms, and with neither intercept nor trend terms are denoted by superscripts a, b, and c, respectively. Superscripts *** and ** indicate significance at the 1%, and 5% levels, respectively. Jarque-Bera statistics for normality tests are distributed as χ^2 on the null.*

4. Empirical Evidence on Regime Shifts in Volatility Expectations

The estimation results of Markov-regime switching models described by Equation [1] for the full sample period are reported in Table 2. With reference to the Japanese stock market, it appears that returns can be described by Markov-regime parameters associated with different signs and various degrees of statistical significance. The evidence suggests that regime-1 is governed by a positive drift μ_1, long memory based on the positive autoregressive term δ_1, and positive relationship with changes in the government stringency index γ_1. This regime is also characterized by positive correlation with past changes in volatility expectations ϑ_1 but negative correlation with contemporaneous changes φ_1. These coefficients are found to be statistically significant at the 1% level. In contrast, the alternative regime-2 is characterized by a negative relationship between market returns and contemporaneous changes in volatility expectations, but the coefficients associated with the drift and autoregressive terms are found to be statistically insignificant.[7] There is a tendency for the regime parameters to be associated with the negative sign, except for past changes in the government stringency index.

Table 2. Markov-regime switching modeling of the relation between stock market returns and government response

Model parameters	Japan		U.S.A.	
	Regime 1	Regime 2	Regime 1	Regime 2
μ	0.0093*** (0.0010)	-0.0001 (0.6760)	0.0022*** (0.0035)	0.0004 (0.5450)
δ	2.0110*** (0.0000)	-0.0673 (0.3899)	-0.7142*** (0.0000)	0.1172*** (0.0019)
γ	0.0324*** (0.0077)	0.0010 (0.5278)	0.0028 (0.8579)	-0.2529*** (0.0000)
ϑ	0.3296*** (0.0000)	-0.0056 (0.6026)	-0.0678** (0.0220)	0.0010 (0.4375)
φ	-0.2713*** (0.0000)	-0.1149*** (0.0000)	-0.0941*** (0.0000)	-0.1818*** (0.0000)
Hypothesis tests				
$\mu_1 = \mu_2$	10.6290 *** (0.0011)		2.6369 (0.1044)	
$\delta_1 = \delta_2$	220.3725 *** (0.0000)		25.2071 *** (0.0000)	
$\gamma_1 = \gamma_2$	6.6074 ** (0.0102)		85.9088 *** (0.0000)	
$\vartheta_1 = \vartheta_2$	75.3758 *** (0.0000)		5.4524 ** (0.0195)	
$\varphi_1 = \varphi_2$	57.4914 *** (0.0000)		12.0242 *** (0.0005)	
$log(\sigma)$	-5.0851 *** (0.0000)		-4.7737 *** (0.0000)	
Log Likelihood	1889.801		1677.379	

Notes: The estimated Markov-regime switching model is represented by equation [1] $r_t = \mu + \delta r_{t-1} + \gamma G_{t-1} + \vartheta v_{t-1} + \varphi v_t + \zeta_t$. *No assumption is made about heteroskedasticity, or regime-specific error variances, across regimes. The sample period extends from January 2020 to June 2021. Significance at the 1, 5 and 10 % level is denoted by ***, ** and *, respectively. The hypotheses tests for equal coefficients are based on the Wald test following the* χ^2 *distribution. Figures in round brackets represent probability values.*

[7] Even when the autoregressive terms δ are found to be positive, they do not take values larger than unity, which would be indicative of an explosive stochastic process.

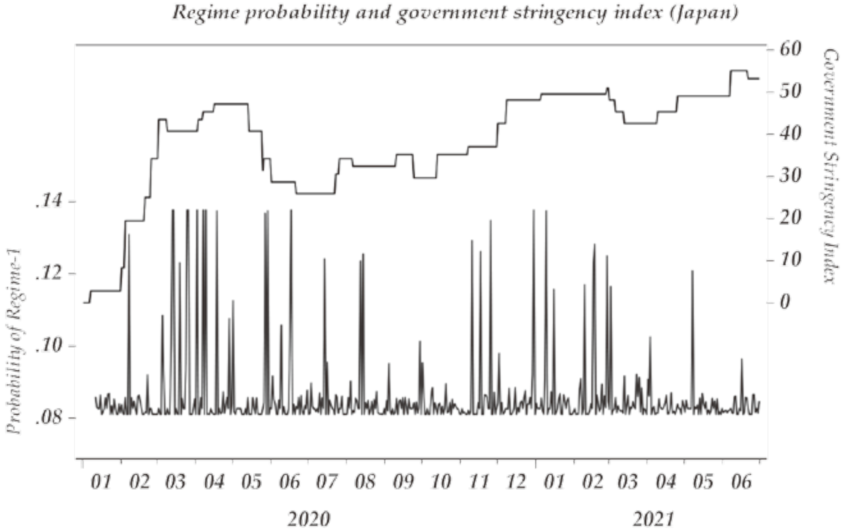
The evidence from the Markov-regime switching model estimated for the U.S. markets suggests that regime-1 can be defined by positive drift, mean reversion, and negative relationship with both past memory process, and contemporaneous changes in the VIX volatility index. The coefficient associated with the government stringency index is found to be statistically insignificant. The alternative regime-2 is characterized, however, by a long memory process, and negative relationship with contemporaneous changes in volatility expectations, and past changes in government responses. It is clear that Markov regimes of market returns may differ in terms of the sign and magnitude of drift terms, autoregressive terms, and correlation with variations in the government stringency index. It is important to note that the structure of the correlation between returns and contemporaneous changes in volatility expectations remains stable and negative irrespective of the prevailing regimes and across markets.

It is possible to examine also the relative significance of the estimated coefficients across the alternative Markov regimes. The hypothesis of equal coefficients in both regimes can be tested using the Wald statistics following the χ^2 distribution. The evidence suggests that for Japanese market returns, Markov regimes can be distinguished on the basis of statistically different drift and autoregressive terms, and correlation structures with changes in the government stringency index and volatility expectations. There are similar results with respect to U.S. market returns, which tend to be governed by regimes that differ with respect to all coefficients except the drift term.

Thus, the evidence suggests a weak relationship between market returns and government responses to the disease outbreak. The coefficient γ, which measures the impact of government stringency index, is found to be either insignificant or associated with the positive sign in regime-1 for the Japanese market, and the expected negative sign in regime-2 for the U.S. market. Thus, it seems that the reaction of equity markets to changes in government responses may be regime-dependent, but the evidence does not suggest that the relationship is necessarily associated with the expected negative sign.

With reference to Figure 3, it is clear that the probability of returns under regime-1 is rather low. This indicates that it is regime-2 that is more likely to prevail. The predominant state is governed solely by the negative relationship with contemporaneous changes in volatility expectations, given the insignificance of the remaining coefficient estimates. It is noted that the lower boundary for regime-1 probability does not exceed 10 percent, and that a potential surge, in association with increased stringency measures, is not likely to surpass the margin of 6 percent in magnitude. Thus, there is little evidence that regime probabilities are sensitive to changes in government responses.

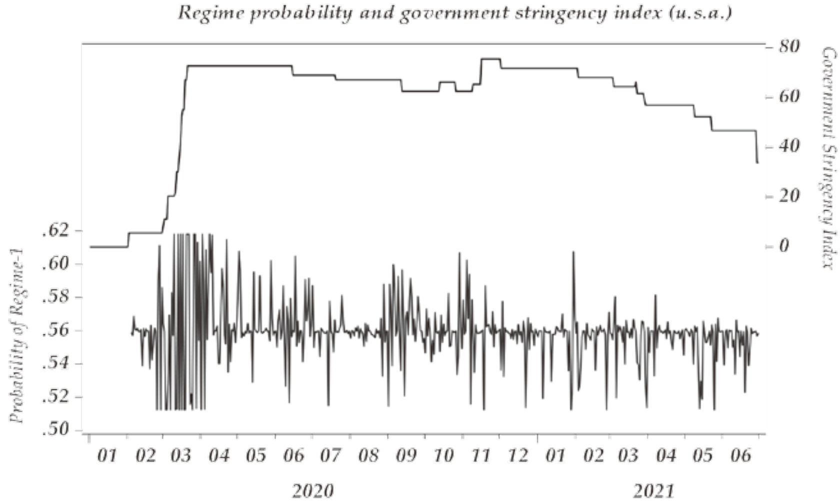
Figure 3. Inferred probabilities of market returns and variations in the Japanese government responses (regime 1)



Notes: The inferred probabilities are derived from the estimation of the Markov–regime switching model equation [2] for Japanese market returns over for the sample period from January 2020 to June 2021.

In contrast, U.S. market returns are more likely to be governed by regime-1 as suggested by Figure 4. Indeed, regime probabilities tend to vary within the range between 50% and 62%, with higher levels of fluctuations in association with a sharp increase in the government stringency index. The evidence from Table 2 suggests that the prevailing regime is characterized by long memory, and negative relationships with past changes in the government stringency index and with contemporaneous changes in volatility expectations. It is noted that the decreasing stringency measures taken toward the end of the sample period is associated with a decrease in the probability of regime-1. Convergence toward the 50 percent likelihood threshold implies that both regimes of market returns tend to become equally probable.

Figure 4. Inferred probabilities of market returns and variations in the U.S. government responses (regime 1)



Notes: The inferred probabilities are derived from the estimation of the Markov-regime switching model equation [2] for U.S. market returns over for the sample period from January 2020 to June 2021.

It is important to examine, at this point, the issue of whether market returns remain regime-dependent over different parts of the sample period. For the purposes of robustness tests, it is possible to estimate the same regime-switching model equation [1] for the Japanese and U.S. markets over subperiod-A (January 2020 to September 2020), including the earlier stages of the disease spread and over subperiod-B spanning the later stages of the healthcare and economic crises. With reference to Table 3, the estimation results for the Japanese market indicate that Markov regimes during subperiod-A can be defined in terms of the negative and significant correlation with contemporaneous changes in volatility expectations. It is also noted that regime-2 is governed by positive coefficients for autoregressive terms and correlation with past changes in volatility expectations.

With respect to subperiod-B, there is evidence that the negative correlation structure prevails with respect to changes in implied volatility, and most notably with respect to changes in the government stringency index. It is clear that returns are more sensitive to the government responses in the later stages of the disease outbreak than in its initial period. It is noted that subperiod-A is associated with higher average relative differences in the government stringency index and higher fluctuations as well. It is associated also with expectations by option market participants of higher levels of in the underlying Japanese equity market. With reference to the distributional moments reported in Table 1, it is this initial period of the disease outbreak that is characterized also by lower average returns, and increased variances, which imply expectations of higher risk premium.

Table 3. Japanese government responses and the dynamics of market returns

Model parameters	Subperiod A Jan. 2020 ~ Sep. 2020		Subperiod B Oct. 2020 ~ Jun. 2021	
	Regime 1	Regime 2	Regime 1	Regime 2
μ	0.0000 (0.9465)	0.0022 (0.3102)	-0.0003 (0.3060)	0.0169*** (0.0000)
δ	-0.1179 (0.2197)	1.8326*** (0.0000)	-0.0177 (0.7630)	0.0995 (0.6718)
γ	0.0010 (0.4852)	0.0009 (0.6541)	0.0157 (0.3469)	-0.0816** (0.0162)
ϑ	-0.0056 (0.6582)	0.1916** (0.0112)	0.0108 (0.3220)	-0.1286*** (0.0000)
φ	-0.1196*** (0.0000)	-0.2259*** (0.0000)	-0.1251*** (0.0000)	-0.1588*** (0.0000)
Hypothesis tests				
$\mu_1 = \mu_2$	0.7791 (0.3774)		58.6919*** (0.0000)	
$\delta_1 = \delta_2$	111.0647*** (0.0000)		0.2625 (0.6084)	
$\gamma_1 = \gamma_2$	0.0016 (0.9676)		6.3001** (0.0121)	
$\vartheta_1 = \vartheta_2$	6.5870** (0.0103)		20.9414*** (0.0000)	
$\varphi_1 = \varphi_2$	3.4069* (0.0649)		4.3765** (0.0364)	
$log(\sigma)$	-4.9302*** (0.0000)		-5.3772*** (0.0000)	
Log Likelihood	896.635		1020.538	

Notes: The estimated Markov-regime switching model is represented by equation [1] $r_t = \mu + \delta r_{t-1} + \gamma G_{t-1} + \vartheta v_{t-1} + \varphi v_t + \zeta_t$. *For the purposes of robustness tests, the sample period is divided into subperiod-A (January 2020 ~ September 2020), and subperiod-B (October 2020 ~ June 2021). Significance at the 1, 5 and 10 % level is denoted by ***, ** and *, respectively. The hypotheses tests for equal coefficients are based on the Wald test following the* χ^2 *distribution. Figures in round brackets represent probability values.*

The results reported in Table 4 for the U.S. market returns indicate that regimes are characterized by mean reversion, as reflected by the negative coefficients for autoregressive terms for both subperiods. With respect to subperiod-A, regime-1 is also characterized by a negative correlation with contemporaneous changes in volatility expectations. It is important to note that the structure of negative correlation is robust to regime shifts and variations in the sample period. This evidence is consistent with the results reported in Table 3 for the Japanese market. The results lend support to the proposition that model-free implied volatility indices are useful in measuring the level of uncertainty perceived by market participants.

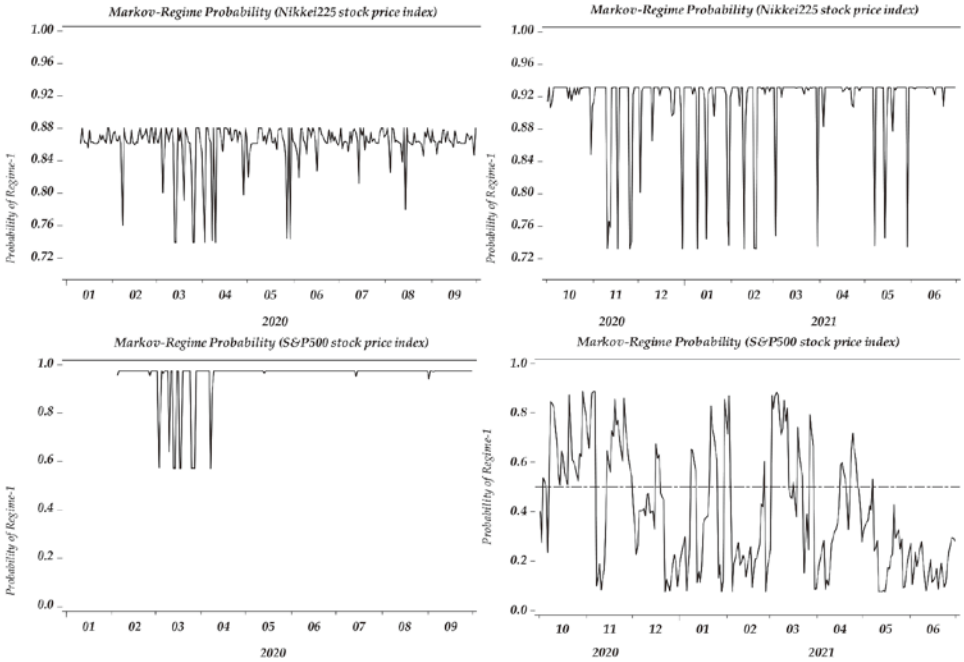
Table 4. U.S. government response and the dynamics of market returns

Model parameters	Subperiod A Jan. 2020 ~ Sep. 2020		Subperiod B Oct. 2020 ~ Jun. 2021	
	Regime 1	Regime 2	Regime 1	Regime 2
μ	0.0005 (0.4618)	0.0606*** (0.0000)	0.0009* (0.0552)	0.0010*** (0.0044)
δ	-0.1989** (0.0338)	-0.4738*** (0.0000)	-0.2153*** (0.0025)	-0.1870** (0.0323)
γ	-0.0316 (0.1179)	-0.1485*** (0.0000)	-0.0115 (0.3856)	-0.0038 (0.6051)
ϑ	-0.0185 (0.2586)	-0.1167*** (0.0003)	-0.0330*** (0.0014)	-0.0183 ** (0.0318)
φ	-0.1258*** (0.0000)	-0.3838*** (0.0000)	-0.1506*** (0.0000)	-0.0613*** (0.0000)
Hypothesis tests				
$\mu_1 = \mu_2$	85.1925*** (0.0000)		0.0531 (0.8177)	
$\delta_1 = \delta_2$	3.8651* (0.0493)		0.0719 (0.7885)	
$\gamma_1 = \gamma_2$	19.7534*** (0.0000)		0.2620 (0.6087)	
$\vartheta_1 = \vartheta_2$	7.4910*** (0.0062)		1.6917 (0.1934)	
$\varphi_1 = \varphi_2$	77.5634*** (0.0000)		62.6987*** (0.0000)	
$log(\sigma)$	-4.6090*** (0.0000)		-5.5313*** (0.0000)	
Log Likelihood	733.632		1098.171	

Notes: The estimated Markov-regime switching model is represented by equation [1] $r_t = \mu + \delta r_{t-1} + \gamma G_{t-1} + \vartheta v_{t-1} + \varphi v_t + \zeta_t$. *For the purposes of robustness tests, the sample period is divided into subperiod-A (January 2020 ~ September 2020), and subperiod-B (October 2020 ~ June 2021). Significance at the 1, 5 and 10 % level is denoted by ***, ** and *, respectively. The hypotheses tests for equal coefficients are based on the Wald test following the* χ^2 *distribution. Figures in round brackets represent probability values.*

The remaining coefficients tend to be associated with the expected negative sign, but changes in government stringency index are found to be significantly correlated with returns only under regime-2 in subperiod-A. As expected, the coefficients γ measuring the impact of government responses on returns in subperiod-B tend to be associated with the negative sign under both regimes, but they remain statistically insignificant. The results of hypothesis tests suggest that the regimes in subperiod-B can be distinguished solely on the basis of different levels of negative correlation with contemporaneous changes in implied volatility (φ_1 not equal to φ_2). Thus, returns tend to fluctuate between regimes of higher versus lower levels of negative correlation with volatility expectations, which are indicative of stronger versus weaker degrees of investors' fear. In contrast, returns in subperiod-A tend to be governed by regimes that differ with respect to all parameter estimates, including the drift and autoregressive terms, as well as the relationships with changes in government responses and volatility expectations.

Figure 5. Inferred probabilities for regime-1 during different of stock market returns



It is also possible to graphically examine the prevailing regimes judging from the time-series of inferred probabilities for the Japanese and U.S. markets during both subperiods. As shown by Figure 5, it seems that Japanese market returns are governed by regime-1 in each subperiod. As explained earlier with reference to Table 3, regime-1 in both subperiods is essentially defined in terms of the negative relation with changes in volatility expectations. There is a tendency for inferred probabilities to suddenly decrease but revert toward higher thresholds around 90 percent over the subperiods A and B, respectively.

The dynamics of U.S. market returns seem to be governed by regime-1 during subperiod-A, but tend to oscillate between regimes during subperiod-B. Indeed, whereas regime-1 tends to prevail in the first subperiod, regime switches are more frequent during the latter subperiod. It is noted that for subperiod-B, regimes are defined in terms of the degree of mean reversion and the expected negative relationship with volatility expectations. The relationship of returns with the government stringency index is associated with the expected negative sign but this linkage remains weak under both regimes. It is finally noted that the inferred probabilities tend to fluctuate below the 50 percent threshold, indicating a tendency for regime-2 to prevail over more recent periods of the disease outbreak. There are decreasing levels of the U.S. government stringency index during subperiod-2, where regime-2 tends to prevail with lower levels of mean reversion and negative correlation structures with implied volatility.

5. Conclusion

The disease outbreak has, certainly, affected human lives and livelihoods. It compelled governments to take unprecedented measures to lockdown populations and restrict economic activities. The short-term and long-run effects of the disease outbreak and government responses on the real economy are difficult to measure and quantify. The question arises, however, as to how financial markets have reacted to the onset of the healthcare and economic crises, and in turn, to government responses.

The focus of this study is placed on the linkage of equity returns with government responses to the disease outbreak. It is possible to measure variations in government responses to the new coronavirus crisis using the Oxford Covid-19 Government Response Tracker developed by the Blavatnik School of Government, University of Oxford, based on different response indicators including workplace closures, school closures, restrictions on domestic and international movements, income support, fiscal measures. The return dynamics are also examined using the model-free volatility indices, which are derived from the prices of options written on the underlying stock market index and represent a measure of investors' fear.

Markov-regime switching models are used to capture nonlinearities in the behaviour of market returns and their relationship with risk factors. The evidence from the estimated Markov-regime switching models suggests that, on aggregate, market returns are governed by regimes that tend to be defined in terms of stronger or weaker mean reversion, and negative correlation with changes in the model-free volatility index. The relationship between returns and changes in government stringency index, which tracks government responses to the crisis, is more likely to be associated with the expected negative sign, but this relationship remains rather weak. Markov regimes where the impact of government responses on market returns is found to be statistically significant, are however less likely to prevail. These empirical results suggest that the price dynamics of equity markets have not been significantly affected by government responses to a disease outbreak that has undoubtedly raised the level of economic uncertainty and has serious implications for economic growth and the future performance of firms.

It is noted that the initial impact of the disease outbreak is reflected by the sharp fall in stock prices and the unprecedented trading of oil futures at negative prices, and oil options at negative exercise prices in February 2020. The commitment of central banks to the provision of liquidity contributed to an easing of concerns about financial instability and economic uncertainty. Since these liquidity measures add to the pre-existing expansive programs of quantitative and qualitative easing programs adopted in the aftermath of the U.S. financial crisis, the unconventional role of central banks in financial markets as lender-cum-purchaser of last resort is, thereby, reinforced. Thus, it may be argued that the impact of disease outbreak and government responses may be obscured by the prolonged effects of unconventional monetary policies. The important question remains, however, as to whether in addition to their impact on currency markets, quantitative and qualitative easing programs are also conducive to the impairment of the price discovery process in financial markets.

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