WPS No. EC-22-64

INDIAN INSTITUTE OF FOREIGN TRADE

WORKING PAPER

THE EFFECT OF CORONAVIRUS PANDEMIC ON THE RUPEE DOLLAR EXCHANGE RATE

Ranajoy Bhattacharyya
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Printed and published by

Indian Institute of Foreign Trade

Delhi Centre: IIFT Bhawan, B-21, Qutab Institutional Area, New Delhi – 110016
Kolkata Centre: 1583 Madurdaha, Chowbagha Road, Ward No 108, Borough XII, Kolkata 700107

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The Effect of Coronavirus Pandemic on the Rupee Dollar Exchange Rate

Ranajoy Bhattacharyya♣ and Ripudaman Bhardwaj♠

Abstract

In this paper, we use the "news" (unanticipated information) model of short-term exchange rate fluctuations (Frenkel, 1994) to determine the effect of the Coronavirus pandemic on the rupee-dollar exchange rate. We analyse the exact nature of the pandemic's impact by incorporating the news model in a Markov Switching regression setup and comparing them with (a) the pre-pandemic and (b) the post-onset of the pandemic data without news. Our main result suggests that the pandemic induced a transition from a lower mean and volatility rupee/dollar regime to a higher mean and volatility regime. Other significant observations include (1) the news of the pandemic played a statistically significant role both in the evolution of the series during the pandemic and as control variables in the regime estimates (2) the expected duration of the regimes was reduced significantly (by 166 and 26 days) during the pandemic with marginal changes in transition probabilities and (3) inclusion of the statistically significant news controls change these durations almost to pre-pandemic levels. Results (2) and (3) and regime transition graphs suggest that the pandemic affected the evolution of the series through a few episodic interventions in its mean–volatility regimes.

Keywords: Coronavirus, rupee-dollar exchange rate, news model, regime change.

JEL Classification: F310, G140

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The Effect of Coronavirus Pandemic on the Rupee Dollar Exchange Rate

1. Introduction

It is now well known that the coronavirus pandemic made asset markets unstable[1]. In particular, currency markets around the world witnessed extraordinary movements[2]. With increased uncertainty regarding economic outcomes, capital started to flow out of countries perceived as relatively unsafe to countries perceived as relatively safe, weakening the former's currencies and strengthening the latter's currencies. For instance, the Australian dollar (AUD) fell to a 17-year low of $0.59215, and the New Zealand dollar to an 11-year low of $0.5850. On the other hand, the Swiss Franc (CHF) rose to US$ 0.9598 per CHF (Aslam et al., 2020). In particular, emerging market currencies witnessed significant depreciation and volatility (RBI, 2020; Smith, 2020; Aquilante et al., 2022; Jamal and Bhat, 2022).

India declared its first lockdown due to the Covid-19 Pandemic on March 24, 2020. The lockdown was extended twice up to May 31 (on May 1 and 17) before a long period of "unlock" was initiated from June 1, 2020. Between January 15 and March 11, 2020, the Indian rupee depreciated with respect to the dollar by 4.2% percent. Further 2.5% percent depreciation followed between 16th and 25th March 2020. In contrast to the pre-pandemic levels, however, these fluctuations led to a general appreciation rather than the rupee depreciation (see trend lines in Figure 1)[3]. From March 25 to June 19, the exchange rate narrowly fluctuated around 74 rupees to the dollar. This sudden stabilization of what was a free fall of the rupee was caused by a series of interventions by the Reserve Bank of India (RBI) in the forex market. As we can see from Figure 2, the first wave of infections in February and March, 2020 exactly coincided with a high volatility (mainly depreciation) period in the dollar. Though subsequent excess infection points did not always coincide with depreciations, in some phases, like in end of December, 2020, high level of infections were associated with high level of volatility of the exchange rate. It appears from Figure 2 that infections may have been one of the causes that made the exchange rate volatile and a further investigation on their possible relationship is worth a look..

[1] For example, see Havva (2021), Zhou et al. (2021), Hong, Bian and Lee (2021).

[2] For example, see Rizvi et.al. (2020), Li et.al. (2021), Phiri (2022), and Sharma et.al. (2022).

[3] Appearing to suggest that the rupee had overshot its long run trend during the sharp depreciation prior to the lockdown.

The reason for the rapid depreciation of the rupee during the initial period of the Pandemic was capital outflows, especially outflows of Foreign Portfolio Investment (FPI). For example, there was an FPI outflow of US$15.92 billion in March 2020[4] . The risk profile of Indian (and other emerging market) portfolios increased due to global economic uncertainty leading to a risk-off scenario (Figure 3). It is natural to think that the stabilization of the value of the rupee after March 25, 2020, was due to interventions by the RBI[5] throughout March 2020 and later. These interventions possibly cushioned off the potential depreciation of the rupee immediately after the announcement of the lockdown in India on March 24, 2020. The announcement perse had no significant visual effect on the exchange rate graph[6] (also evident from figure 2): a search for endogenous structural breaks around the lockdown date using the Bai – Perron (2003) method figures out March 19, 2020, as the exact date when the break happened. Since this date is before the date of lockdown, the turmoil in the market was controlled by the time people became fully aware that a pandemic was on the prowl.

Interestingly, however, this date also coincides with the day the total infections curve for the world took off (Figure 2), and the U.S. imposed the first lockdown[7]. A surge in reported cases in India, the U.S., and worldwide (see Figure A1) began in late March 2020. Unanticipated information (which, in this paper’s context, is labeled news) gathering and dissemination processes became more and more efficient, and daily information on the progress of the Pandemic became readily available to all individuals, including the foreign exchange traders. The central hypothesis in this paper is that this daily new infection information affected the series' evolution. This assumption of market efficiency of the rupee has some empirical support in the literature (see, for example, Bhattacharyya and Datta, 2019; Datta and Bhattacharyya, 2018). It also appears to be validated for the pandemic period. News on the outbreak of the Covid-19 disease in China started to filter through media in December 2019. The World Health Organization (WHO) declared Covid-19 a Public Health Emergency of International

[4] See the Reserve Bank of India Bulletin of December, 2020.

[5] See the Reserve Bank of India Bulletin of December, 2020.

[6] The alternative conjecture is that the news of the lockdown had no new information content to the market – the market acted efficiently, internalizing and hence adjusting to the incremental information of the disease as and when they were available, prior to the announcement, leading it to fully anticipate the news of the lockdown. Going deeper into this market interventions vs market efficiency debate to model the behaviour of the rupee during this period goes beyond the scope of this paper but appears to be an interesting project for future research.

[7] Refer to: First Day of Stay-at-Home Order in the United States (timeanddate.com)

Concern (PHEIC) on January 30, 2020, and a pandemic on March 11, 2020. The last date coincides with the day the second phase of depreciation of the rupee started.

The primary objective of this paper is to analyze the effect that the pandemic news played in influencing the fluctuations in the rupee-dollar exchange rate by determining the nature of changes during the pandemic period and comparing them with the pre-pandemic levels. We reach a Markov regime-switching model that breaks down the dynamics into potentially multiple mean and volatility values, each corresponding to a particular regime. Our second objective is to determine whether the Pandemic played any significant role in this process of regime fluctuations. We do this (a) by determining which of the Coronavirus news components play a significant role in defining the short-term dynamics of the exchange rate and (b) analysing the nature of their effect in determining the observed changes in the regime parameters. We achieve this by incorporating the information through Frenkel's (1984) news model of exchange rate fluctuations in the switching regressions and comparing them with the pre-pandemic and the post-pandemic regime without news. We hypothesize that if some of these coronavirus news variables are statistically significant and the regime parameters in the pre- and post-pandemic periods tend to converge after using them as controls, then the Pandemic can be identified as the causal factor behind the observed changes in the two periods.

The rest of the paper is arranged as follows: Section 2 reviews the literature on the effect of the news on economic variables and, in particular, the impact of the Pandemic on exchange rates. Section 3 sets out the methodology, section 4 reports the main results, and section 5 conducts some robustness and sensitivity analysis. Finally, section 6 concludes the paper.

2. Literature Review

Since the beginning of the floating exchange rate era, there has been emerging literature on explicating the behavior of exchange rates (Cheung and Erlandsson, 2005). There is an extensive literature on the role of unanticipated information in explaining short-term fluctuations in exchange rates (see, for example, Edwards, 1983; Hodrick, 1989; McDonald and Taylor, 1992; Napolitano, 2000; Ehrmann and Fratzscher, 2005; Roy Trivedi, 2018; Narayan et al., 2018; 2021). Macroeconomic surprises influence both the conditional mean returns and volatilities of the exchange rates (Anderson et al., 2003, Almeida et al., 1998; Pearce and Solakoglu, 2007; Evans and Lyons, 2008; Hutchison and Sushko, 2013; Vortelinos, 2015; Omrane and Hafner, 2015; Narayan et al., 2021). Evans and Lyons (2008) show that the arrival of macroeconomic news affects currency prices directly and indirectly via order flow.

News triggers the trading of incremental information, thus affecting currency prices. And these results are also supported by Bergemann et al. (2015), Zhang et al. (2016), Anifowose et al. (2018), and Firouzi and Wang, 2019. Both scheduled[8] and unscheduled[9] news has significantly impacted the financial markets (Fornari et al., 2002). For instance, Bauwens et al. (2005) show that expected information increases pre-announcement fluctuations. In comparison, Fornari and Mele (2000) find the limited role of news in changing expectations over horizons longer than one day. Fornari et al. (2002) find that anticipated news effects are short-lived. Almedia et al. (1998) find that the impact of most announcements on exchange rate movement does not live longer than 15 minutes. There is ambiguous evidence of exchange rate responses to surprises in macroeconomic variables like trade balance, inflation, money supply, industrial production, producer price announcements, etc. Agarwal and Schirm (1992) show that U.S. exchange rates are sensitive to anticipated information about the trade balance. In comparison, Hardouvelis (1988) find no such evidence. Ito and Roley (1987) and Cheung et al. (2019) find that Yen/dollar exchange rates are more sensitive to economic surprises in the U.S. than domestic surprises. Cai et al. (2009) show a similar result for nine developing countries.

A lot of papers have examined the linkage between epidemics and macroeconomic variables. For example, Bloom & Mahal (1997); Kauffman and Weerepanna (2009) study the effects of the AIDS epidemic on economic variables like per-capita income and exchange rates. Chen et al. (2007) and Keogh et al. (2008) have examined the effects of the SARS pandemic on various economies. Hoffman et al. (2020), Kouam (2020), and Fernandes (2020) have estimated the impact of COVID-19 on varied sectors of different economies. Like other epidemics, novel coronavirus has also had significant economic consequences (Ozturk and Cavdar, 2021). Since the virus spread created uncertainty in the economy and panic among the investors, markets became more volatile during the Pandemic (Sharma, 2020). Narayan (2020) studies the changes in exchange rate resilience in response to the COVID pandemic. Narayan, Devpura, and Wang (2020) show that exchange rates influence stock returns more intensely due to Coronavirus. Corbet et al. (2020) find a significant and positive impact of COVID-19 on

[8] News whose release is anticipated by the market. For example, macroeconomic data released on dates and times known by market participants.

[9] News that is not anticipated or whose time of release is uncertain. For example, unexpected declarations made by ministers or government officials, economic shocks, disease outbreaks etc.

exchange rate volatility. Iyke (2020) demonstrates the importance of COVID-19 announcements on exchange rate returns and volatility.

Characterization of regime shifts in economic time series (Markov switching models (MSM)) were popularized by the seminal work of Hamilton (1989; 1990). MSM introduces an ‘unobservable’ state variable that follows a Markov chain process to represent the multiple regimes. Later Engel and Hamilton (1990), Engel (1992), and Marsh (2000), for the first time, applied MSMs in the foreign exchange market. They showed that MSM is superior to both structural and time series models. Caporale & Spagnolo (2004), Walid et al. (2011), and Basher et al. (2016) have also fairly investigated exchange rates through MSM. The work closest to our approach is by Konstantakis et al. (2021). They use the method of Markov-switching estimation to analyse how the Covid-19 Pandemic changed the dynamics of the euro to the dollar exchange rate. They find that the exchange rate volatility in the Covid-19 era has doubled, from almost 3 to approximately six days, compared to the pre-Covid-19 period. They do this exercise in two parts. In the first part, they check whether the Pandemic has a statistically significant relationship with the exchange rate. In the second part, they independently search for regime shift coinciding with the Pandemic.

By adopting the news model and incorporating it in the switching regression, we pose a more comprehensive question on the effect of the Pandemic on regime shift. If a regime change has indeed happened in the rupee-dollar exchange rate coinciding with the occurrence of the Pandemic, was the Pandemic a statistically significant causal factor in accounting for this regime change? We seek an answer to this question by comparing the post-pandemic regime shift data with and without the news controls to the pre-pandemic data. We hypothesize that, if there is a regime shift and the Pandemic causes it, then the post-pandemic regime shift results with news control should resemble the pre-pandemic regime shift results. Additionally, we adopt a simple but intuitively appealing method to capture the one-period lagged information set for the news variables.

3. Methodology

3.1 Defining Regime Change in a Model with Unanticipated Information or “News.”

It is clear from the discussion so far that our core objectives are two-fold. First, we intend to see whether the spot rate has experienced any structural break and regime change due to the onset of the Pandemic; second, whether the news regarding the Pandemic affected this regime change and, if so, in what sense. Accordingly, in what follows, we view the spot exchange rate as the sum of a stochastic trend component following a two-state Markov property and a state-dependent sub-process with the same property. We maintain the assumption of two regimes (Frenkel and Hamilton, 1990; Cheung and Erlandsson, 2005). This sub-process follows the "news" model of Frenkel (1981):

$$\boldsymbol{S_t = \delta_{st} + N_t\beta_{st} + v_{st}} \quad (1)$$

$$\boldsymbol{\delta_{st} = \alpha_1 M_t + \alpha_0 + S_{t-1}} \quad (2)$$

$$\boldsymbol{\beta_{st} = \beta_1 M_t + \beta_0} \quad (3)$$

$$\boldsymbol{N_t = C_t - E_{t-1}C_t} \quad (4)$$

Where S_t is the spot exchange rate, δ_t is the trend component of S_t, N_t is the vector of coronavirus news variable arriving in period t, M_t = 0 or 1 represents the unobserved state of the system. M_t is assumed to be aperiodic, with the transition between the states being governed by a first-order Markov process and v_{st} is the error term that is $iid \sim(0, \sigma_s^2)$. M_t allows us to divide the fluctuations in the exchange rate in two different regimes separating periods of slower depreciation with those of higher depreciation of the rupee (through changes in mean/intercept) as well as higher and lower estimated heteroscedasticity (regime-specific error variances). Equation (2) and (3) defines the regime changes in the spot rate, and equation (4) models the news variables with respect to a vector C_t that conveys some information relevant to the spot rate (the interest rate differential for Frenkel (1981)) and E_{t-1} is the information set available in period t-1. Thus, S_{t-1} is the "anticipated" and $(C_t - E_{t-1}C_t)$ or the difference between the actual value of C_t and its expected value in the previous period is the "unanticipated" part of the exchange rate process. If the news components are assumed to be non-switch, then M_t is assumed to be zero in (3). It is important to carefully understand the implication of the signs in the right-hand side of (4). Since the dependent variable in (4) is the rupee per dollar exchange rate, we assume that a positive unanticipated coronavirus news shock depreciates the rupee. Putting (2) and (3) in (1):

$$\Delta \boldsymbol{S_t = (\alpha_0 + \alpha_1 M_t) + N_t(\beta_0 + \beta_1 M_t) + v_{st}} \quad (5)$$

$$\Leftrightarrow \Delta \boldsymbol{S_t = \mu_{st} + \alpha_{st} z_t + v_{st}} \;\; \boldsymbol{; s_t = 1, 2}$$

(5) is the regime shift version of the exchange rate process[10] , implying that the exchange rate change varies between two constant values according to a first-order Markov process. S_t is a dependent variable, μ_{st} is a state-dependent intercept, z_t is a vector of state-dependent exogenous variables, and α_{st} is a vector of the state-dependent coefficients and $\boldsymbol{v}_{st} iid{\sim}(0, \sigma^2)$ are the state-dependent error terms characterized by a state-dependent variance. We also allow for switching variance across regimes. Literature on international macroeconomics cannot connect exchange rate movements to movements in fundamentals[11]. There is consensus that the fundamental variables struggle to explain short-term exchange rate movements and even much of the longer-term trends. A significant and burgeoning strand of the literature has focused on addressing this shortcoming of exchange rate models by allowing the effects of fundamentals to vary over time (Stillwagon and Sullivan, 2020). We address this problem by allowing "news" variables to be regime regressors.

The probability of switching is captured in the matrix of the transition probabilities φ:

$$\varphi = \begin{bmatrix} p_{1/1} & p_{1/2} \\ p_{2/1} & p_{2/2} \end{bmatrix};$$

where $p_{i/j}$ is the probability of being in state i next period conditional on being in state j this period.

3.2 Modelling the Expectation Formation Component of the News on Pandemic

We assume that the expectation of C_t is dependent on their lags and hence follows the following A.R. (j) process with drift:

$$\boldsymbol{E_{t-1}C_t = \vartheta + \sum_{j=1}^{n} C_{t-j}\theta_j + \epsilon_t} \tag{6}$$

Where ϵ_t is the part of expectation formations unexplained by the news variables. Equation (6) has the following rationale: since information on the progress of the Covid-19 disease is well reported on several websites (and through them to news channels closely followed by the public), the set of variables in C_{t-j} should capture all the prior information (news) on a possible disease state soon for the market to internalize. Thus, if the market is efficient with news, all θ's should be statistically zero and ϵ_t should be $I\,(0)$ with exponential decay of the

[10] S_t is assumed to be I (0). (Please see, you had written I(1), which is not true).

[11] The variables which should determine the exchange rate in theory.

autocorrelation function. Additionally, the statistical significance of particular variables in C_{t-j} will provide the kind of news that is relevant for deviations from market efficiency to news.

Incorporating (4) and (6) in (5), we get:

$$\boldsymbol{\Delta S_t = (\alpha_1 M_t + \alpha_0) + (C_t - \vartheta + \textstyle\sum_{j=1}^{n} C_{t-j}\theta_j)(\beta_1 M_t + \beta_0) + \sigma_t} \qquad (6a)$$

Where $\sigma_t = (\beta_1 M_t + \beta_0)\epsilon_t - v_t$ shows the possibility of the regime change in error variances. (6a) is the estimated equation for regime change after incorporating the news variables.

3.3 The Relationship between the Exchange rate and Coronavirus News

To cast the model as in Frenkel (1981), we replace δ_{st} and β_{st} without its regime shift components[12] in equation (1) to get:

$$\boldsymbol{S_t = \alpha + \beta F_{t-1} + (C_t - E_{t-1}C_t)\gamma + u_t} \qquad (7)$$

Putting (6) in (7) and writing in expanded form for clarity of notation, we get:

$$\boldsymbol{S_t = (\alpha_1 - \gamma\vartheta) + \beta F_{t-1} + \gamma C_t - \textstyle\sum_{j=1}^{n} C_{t-j}\theta_j + \tau_t} \qquad (8)$$

Where $(\tau_t = u_t - \gamma\epsilon_t)$. Since the error in (8) is a composite of the errors in (6) and (7), a strategy has to be found to recover ϵ_t from (8). We do this by estimating (6) with several possible instruments[13] for $E_{t-1}C_t$. This will also potentially take care of the possibility of endogeneity in (8) sipping in through (6).

Collecting the C_t terms, the error correction version of (8) is:

$$\boldsymbol{\Delta S_t = \rho + \partial \Delta F_{t-1} \pm \textstyle\sum_{j=1}^{n} \Delta C_{t-j}\gamma_j + \pi(\tau_{t-1}) + \tau_t} \qquad (9)$$

Where π is the rate of information assimilation for the return series (rate of depreciation) and the $\pm$ sign indicates "+ or -," whichever is appropriate[14]. Writing the error correction term (9)

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[12] Assuming the one period lagged spot rate as a proxy for the forward rate this simply reduces to equation (2) minus the switching component M_t.

[13] There is data on several highly correlated indicators of the pandemic that can do this job. In the empirical part we only use three variables: Infection levels in India, USA and the world. For example, the number of hospital beds occupied in these places can be used as instruments for these.

[14] Note that due to (4) and (6) the instantaneous effect of C enters with appositive sign in (8) while the lagged effects enter with a negative sign.

in its free form and replacing lagged forward rate with the lagged spot rate,[15] we have the following Auto Regressive Distributed Lag (ARDL) $(1, k, .., k)$ model that can be estimated:

$$\Delta S_t = \mu + \beta S_{t-1} + \sum_{j=1}^{n} \gamma_j C_{t-j} + \pi \Delta S_{t-1} + \sum_{j=1}^{n} \omega_j \Delta C_{t-j} + \epsilon_t \quad (10)$$

3.4 Data Sources and the Empirical Strategy

The data for the daily rupee-dollar exchange rate (₹/$) used in our analysis was calculated via the SDR route and downloaded from IMF[16]. The Covid-19 infections and deaths data were downloaded from Our World in Data[17]. Our empirical strategy is first to run (10) to identify which coronavirus news components significantly affected the exchange rate. Once these have been identified, we include them as the news components in the Markov model in (5) to explore their implication for regime changes. Note that there is no role of news in the pre-pandemic period. Thus, for estimation purposes, the pre-pandemic version of (5) is:

$$\Delta S_t = \alpha_0 + N_t \beta_0 + v_t \quad (11)$$

This is also the estimated equation for the post-pandemic period without news. In the post-pandemic period, a comparison of (5) and (11) will give us the difference that the news component makes to the nature of regime changes in mean and estimated regime heteroscedasticity. This is the central concern of this paper.

We use three proxies for the progress of the coronavirus pandemic as the possible "news" components of the model: Infections in India (Inf^{IND}), Infections in the U.S. (Inf^{USA}) and Infections in the world (Inf^{WLD}). It was found that the INR-Dollar exchange rate and infections in India and the world are stationary. In contrast, infection in the U.S. and the interest rate differential are stationary at first difference[18]. Hence the ARDL specification (11) is a natural choice for estimation purposes.

4. Results

4.1 Evidence of Regime Shift during the Pandemic

[15] On the assumption that they are highly correlated (see, for example McPherson and Vilasuso, 2005).

[16] [16] https://www.imf.org/external/np/fin/ert/GUI/Pages/CountryDataBase.aspx

[17] https://github.com/owid/covid-19-data/blob/master/public/data/README.md

[18] Refer to Appendix for unit root tests.

Table 1 confirms our hunch from figure 1 and the Bai-Perron test reported in the introduction that a regime changes in mean/intercept coincided with the beginning of the Pandemic. It gives two different results: (1) the Pandemic, on average, depreciated the value of the rupee by Rs 3.70, and (2) despite the Reserve Bank of India's continuous efforts, the Pandemic increased the estimated volatility of the exchange rate by about 10 percent. Table 2 and figure 3 report the third result: the regime change was one-off, occurring at the beginning of quarter 2 of 2020 – as already noted, the Bai-Perron test pinpoints this date to April 19, 2020.

4.2 The role of Lags in Expectation Formation and the Exchange Rate

The result of the A.R. (j) process described in equation (6) is reported in Table 3[19]. The residual (ϵ_t) was saved and obtained as an $I(0)$ variable. Also, the autocorrelation function (ACF) for the series (not reported here) has a slow decay falling to zero after about 100 lags. Thus, the world infection series appears to have a long memory. The estimation results for equation (7) are also reported in Table 3. The residual (u_t) was saved and obtained to be an $I(0)$ variable. Then the composite residual term in equation (8) was saved as $\tau_t = u_t - \gamma\epsilon_t$ and found to be an $I(0)$ variable. Therefore, the exchange rate has a cointegrating relationship with (a) its own first lag, (b) the level value of world infections, and (c) a drift term.

4.3 The Effect of Pandemic "news" on the Exchange Rate

We consider four possible candidates for the "news" component to analyze the period since March 2020: total infection cases/deaths in India, the U.S., and the world, and the difference in the LIBOR and MIBOR to proxy for the interest rate differential between the two countries to account for any short-term capital movement from India. This variable is potentially crucial for two reasons. First, unlike other determinants of exchange rates like inflation differential or the difference in the trade balance, daily data is readily available on this variable. Second, as discussed in section 1, short-term capital outflow from India triggered the regime change in the exchange rate. The limitation of this proxy is that it is a risk-free rate. It is, therefore, not a good proxy at a time when risk perception of holding rupees appeared to have changed significantly.

The results of equation (10) are reported in Table 4. With the average correlation between the variables for India, the U.S., and the world infections being 0.98, only one of the infection

[19] It is a long memory series. The model fitting improved with increase in the number of lags. However, we stopped at 15 lags as majority of the lags obtained were significant and the model gave expected results.

variables is used at a time to avoid multicollinearity. The interest rate differential is also included, as in Frenkel (1981). It is clear from the table that both world infections and world death numbers are statistically significant indicators of the long-run relationship between the rupee-dollar exchange rate and the independent variables in each model. Thus, the Pandemic played an essential role in the daily dynamics of the exchange rate. Interestingly, the rate differential variable did not play any significant role in these dynamics. We investigate this further in the robustness section.

Table 5 estimates equation (6a) with and without the news variables and compares the results to the pre-pandemic dataset. The objective is to visually identify some apparent patterns in the kind of regime shift observed in the three cases. Two separate mean-volatility regimes are identified in all cases. Comparing the pre-pandemic to the pandemic period without mean,[20] we observe (1) mean, and volatility have both become higher, and (2) volatility has increased more than the mean. The exchange rate has thus depreciated and become more volatile due to the Pandemic.

The last two rows of the table show that the expected duration of regimes fell by 166 and 26 days during the pandemic period. The anticipated duration of regimes returns almost to the pre-pandemic level after incorporating the news variables. The exact reason for this change can be traced in figures 4-6. The figures clearly show the Pandemic's exact effect on the exchange rate. For the entire dataset and that of the pandemic period with news controls, the regime shift points are clustered around the only one-time point in the first quarter of 2020 (around February 28). But for the pandemic period without news, the number of switch points is clustered around three additional regime shift time points in the third and fourth quarters of 2020 and the second quarter of 2021. Event analysis of the Pandemic in table 5 points out that India's first regime shift recorded its second Covid-19 case (March 3, 2020) and the ‘Janta Curfew’ (Curfew of the Masses) on March 19, and the first Lockdown announcement on March 24. The second occurred at the end of August 2020. There were no significant events on the pandemic front at that time except the beginning of trials for vaccines. The third occurred at the beginning of November, when cases were rising rapidly, and India announced a financial package for the economy. The last occurred in early April 2001 when the second wave hit India. The event analysis appears to point out that regime changes happened in approximate synchronization of some significant news announcements providing further evidence that pandemic news played

[20] The value of the intercept with news is of course not comparable. Neither can it be interpreted.

a crucial role in determining the dynamics of the process. Finally, in table 5, low transition probability has decreased by a more significant amount than high to high. Also, low to high transition probability has increased more than high to low. Thus, despite RBI efforts, the Pandemic increased the series' volatility. This is also evident from the estimated coefficients of volatility.

Thus, a theoretical reason behind the statistical significance of the pandemic news terms in table 4 can be found in the regime shift analysis done subsequently: the Pandemic affected the dynamics of the exchange rate by adding three episodes of shifts from a low mean, volatility regime to a high mean volatility regime. This shortened the duration of these regimes to a considerable extent.

Table 6 replicates table 5 with the first difference in the exchange rate. Interpreting this as the returns (depreciation/appreciation rate) series, we can observe from the table that no such thing happened for this series. Figures 7 and 8 contain the time series plots of the locations of the regimes. The table, along with these figures, shows that during the Pandemic, there was an observed trend of appreciation of the rupee (figure 1). Still, this appreciation is not high enough to define regimes over means. Regimes are only defined over estimated error variances. Finally, the Pandemic was unable to affect the pattern of daily fluctuations in any significant way.

5. Robustness and Sensitivity Analysis

This section reports results with infection and death variables for India and the USA. For robustness, we include foreign portfolio investments (FPI) as an additional variable. It is clear from Tables 7 and 8 that infections in both India and USA are statistically significant indicators of the long-run relationship between the rupee-dollar exchange rate and the independent variables in each of the models. Thus, the Pandemic played an essential role in the daily dynamics of the exchange rate. However, no relationship exists between deaths in India and the rupee-dollar exchange rate. As expected, the rate differential and FPI flows variable has a long-run relationship when included alone in the model. At the same time, they become insignificant when included with 'surprising' Covid infection news. Interestingly, Covid deaths in the USA are significant. Moreover, rate differential and FPI flows also have a long-run impact, unlike in previous cases.

Table 9 shows Markov switching model estimation results with and without the news variables and compares the results to the pre-pandemic dataset. Again, two different mean-volatility regimes are identified in all cases. Comparing pre-pandemic to pandemic period without mean,[21] we observe (1) mean, and volatility have both become higher, and (2) volatility has increased more than the mean. The exchange rate has thus depreciated and become more volatile due to the Pandemic. The results are similar to M.S.'s results discussed in the previous section.

6. Concluding Comments

We find that the coronavirus pandemic affected the rupee-dollar exchange rate in three significant ways: First, it induced a structural break in the series in its initial phase. Second, in contrast to the pre-pandemic period, there was a trend of appreciation of the rupee during the Pandemic. And third, the Pandemic affected the stability of mean-volatility regimes by reducing the duration of persistence within regimes. This reduction of duration was caused by the appearance of three additional regime change episodes in an otherwise single regime change environment for the series. For this reason, the transition probabilities were marginally affected even though durations changed notably. It can be conjectured from the results that the Pandemic was a unique disruptive event as far as this exchange rate is concerned: its effect was sporadic and, in each case, short-lived. Nonetheless, these effects amounted to a statistically significant influence on the fluctuations in the series.

The reason for the rupee appreciation during the Pandemic was not researched here. However, as we have pointed out, there have been phases of appreciation in a long-run trend of depreciation for the rupee. This could have been another of them. Also, as we mentioned earlier, the appreciation episodes often coincided with global crisis episodes. Searching for commonality in patterns by comparing the behaviour of the rupee during global crises is a possible area of further research here. Thirdly the rupee could have overshot its fundamentals during the steep depreciation of the rupee during the initial phase of the Pandemic. The subsequent slow appreciation may just be a trend reverting phenomenon. This can also be pursued in further research.

[21] The value of the intercept with news is of course not comparable. Neither can it be interpreted.

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Table 1: Regime Parameters (Entire Time Period)

Parameters	Low volatility regime[1]	High volatility regime
Mean	70.55*	74.25*
Volatility[2]	1.03	1.15*

Source: Authors own calculations.

Note: (1). Regimes are defined in terms of Estimated Residual Variance. (2). Volatility is defined as the estimated residual variance and is calculated by taking the exponential of log (sigma). (3). '*' implies significant at 5% level of significance.

Table 2: Transition Probabilities and Duration (Entire Time Period)

States	Pre-COVID + COVID
Low to low	0.99
Low to high	0.001
High to low	0.001
High to high	0.99
Expected Duration (Days) **(Low volatility regime, High volatility regime)**	(507.23, 506.07)

Source: Authors own calculations.

Table 3: Role of Lags in Expectation Formation and the Exchange Rate

Variable	Equation (6)	Equation (7)
c	0.08^{*}	5.49^{*}
EX_{t-1}	-	0.93^{*}
Inf^{WLD}	-	-2.52^{*}
Inf_{t-1}^{WLD}	0.81^{*}	0.21
Inf_{t-2}^{WLD}	0.38^{*}	1.55
Inf_{t-3}^{WLD}	-0.07	0.67
Inf_{t-4}^{WLD}	0.25^{*}	1.97^{*}
Inf_{t-5}^{WLD}	-0.33^{*}	0.11
Inf_{t-6}^{WLD}	-0.14^{*}	-2.13^{*}
Inf_{t-7}^{WLD}	0.14^{*}	0.45
Inf_{t-8}^{WLD}	0.02	0.80
Inf_{t-9}^{WLD}	0.01	0.70
Inf_{t-10}^{WLD}	-0.13^{*}	0.34
Inf_{t-11}^{WLD}	0.04	0.90
Inf_{t-12}^{WLD}	-0.05	-0.71
Inf_{t-13}^{WLD}	-0.06	2.06^{*}
Inf_{t-14}^{WLD}	0.03	-2.09^{*}
Inf_{t-15}^{WLD}	0.07^{*}	1.04^{*}
Level of Integration for the error term	-16.93 * $\sim I\ (0)$	-16.77* $\sim I\ (0)$
$\tau_t = u_t - \gamma\epsilon_t$	-16.72* $\sim I\ (0)$	

Table 4: Long Run Effects of Coronavirus on the Rupee Dollar Exchange rate

Variable	Model I[5]	Model II[5]	Model III[5]	Model IV[5]
$\boldsymbol{Inf^{WLD}}$	-0.008*	-0.009*	-	-
$\boldsymbol{Death^{WLD}}$	-	-	-0.011*	-0.011**
C	4.44*	4.48*	4.45*	4.44*
Interest Rate Differential	-	-0.001	-	0.003
$\boldsymbol{ECT_{t-1}}$	-0.082*	-0.089*	-0.073*	-0.078*
$\boldsymbol{f}$ **- Statistics for Cointegration (Lower bound, upper bound)**	5.41 (3.62, 4.16)	4.5 (3.10, 3.87)	5.09 (3.62, 4.16)	4.42 (3.10, 3.87)

Source: Authors own calculations.

Notes: (1). Inf^{WLD} is world total infection and $Death^{WLD}$ is world total death. (2). EX is I (0). While $Inf^{WLD}$and $rate\_differential$ are I (1) variables. Thus, Auto Regressive Distributed Lags (ARDL) Estimation is used. The lag for dependent variable is fixed at one, while optimal lags are taken for independent variables. (3). All variables except $rate\_differential$ are in log form. (4). All models follow from equation (10) in section 5. **Model I:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Inf^{WLD} + \pi \Delta S_{t-1} + \gamma_2 \Delta Inf^{WLD} + \epsilon_t$, **Model II:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Inf^{WLD} + \gamma_2 RD + \pi \Delta S_{t-1} + \gamma_3 \Delta Inf^{WLD} + \gamma_4 \Delta RD + \epsilon_t$, **Model III:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Death^{WLD} + \pi \Delta S_{t-1} + \gamma_2 \Delta Death^{WLD} + \epsilon_t$, **Model IV:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Death^{WLD} + \gamma_2 RD + \pi \Delta S_{t-1} + \gamma_3 \Delta Death^{WLD} + \gamma_4 \Delta RD + \epsilon_t$6. ECT_{t-1} is the error correction coefficient in the short run equations. 7. '*' and '**'depicts statistical significance at 5% and 10% level of significance respectively.

Table 5: Comparison of Pre and During Pandemic Regime Switches in Exchange Rate and the Role of News

Variables	Parameter Estimates	Pre-COVID Estimated Coefficients		COVID Estimated Coefficient			
				Without News		With News[2]	
		Low[1]	High[1]	Low	High	Low	High
EX^3	Mean	71.28*	69.34*	73.26*	75.26*	89.47*	85.64*
	Volatility	0.37*	0.48*	0.46*	0.67*	0.54*	1.73*
Total Infections (World)	Coefficient	-		-		-0.85*	
Interest Rate Differential		-		-		-0.14	
Transition Probabilities[4]		(0.995, 0.005, 0.013, 0.987)		(0.981, 0.019, 0.020, 0.980)		(0.997, 0.003, 0.011, 0.989)	
Expected Duration (Days)		(217.03, 76.44)		(51.82, 50.02)		(301.13, 87.14)	

Source: Authors own calculations.

Note: (1). Regimes are defined in terms of the magnitude of volatility. (2). World total infections are used as a proxy for the coronavirus news. Thus, world total infections and interest rate differential are used as non-switch news variables. (3). EX is the rupee per dollar exchange rate. (4). (Low to Low, Low to high, high to low, high to high). (5). '*' depicts statistical significance at 5% level of significance.

Table 6: Comparison of Pre and During Pandemic Regime Switches in First Difference (Simple Returns) of Exchange Rate and the Role of News

Variables	Parameters	Pre-COVID		COVID			
		Estimated Coefficients		Estimated Coefficient			
				Without News		With News[2]	
		Low[1]	High[1]	Low	High	Low	High
$d(EX)$[3]	Mean	-0.001	0.008	-0.012	0.030	1.26	1.29
	Volatility	0.157*	0.296*	0.122*	0.346*	0.13*	0.34*
Total Infections (World)	Coefficient	-		-		-0.04*	
Interest Rate Differential		-		-		-0.14	
Transition Probabilities[4]		(0.915, 0.085, 0.103, 0.897)		(0.908, 0.092, 0.076, 0.924)		(0.912, 0.088, 0.078, 0.922)	
Expected Duration (Days)		(11.79, 9.73)		(10.90, 13.13)		(11.33, 12.78)	

Source: Authors own calculations.

Note: (1). Regimes are defined in terms of the magnitude of volatility. (2). World total infections are used as a proxy for the coronavirus news. Thus, world total infections and interest rate differential are used as non-switch news variables to account for ‘news’. (3). $d(EX)$ is the return or the first difference of rupee per dollar exchange rate. (4). (Low to Low, Low to high, high to low, high to high). (5). ‘*’ depicts statistical significance at 5% level of significance.

Table 7: Long Run Effects of Coronavirus on the Exchange rate with Indian Infections and Net Capital Inflow

Variable	Model I[5]	Model II[6]	Model III[7]	Model IV[8]	Model V[9]	Model VI[10]
$\boldsymbol{Inf^{IND}}$	-0.003 *	-	-0.007 **	-	-0.003	-
$\boldsymbol{Death^{IND}}$	-	-	-	-	-	-1.25E-05
$\boldsymbol{c}$	4.352 *	4.192 *	4.45 *	4.31 *	4.34	4.32 *
Interest Rate Differential	-	0.031 *	-0.013	-	0.001	-
$\boldsymbol{FPI}$	-	-	-	-4.53E-05 *	-2.86E-06	-
$\boldsymbol{ECT_{t-1}}$	-0.061 *	-0.077 *	-0.075 *	-0.035 *	-0.064 *	-
$\boldsymbol{f}$ **- Statistics for Cointegration (Lower bound, upper bound)**	5.205 (3.62, 4.16)	5.24 (3.62, 4.16)	4.33 (3.1, 3.87)	3.72 ** (3.62, 4.16)	2.28 (2.79, 3.67)	2.62 (3.62, 4.16)

Source: Authors own calculations.

Note: (1). Inf^{IND} is India total infection and $Death^{IND}$ is India total death. (2). EX, log of $lnInf^{IND}$ and FPI are I (0) variables. While $rate\_differential$ is I (1) variables. $Death^{IND}$ is a I (2) variable, hence, new deaths (first difference of $Death^{IND}$ which is a I (1) variable) was included in the model. (3). Auto Regressive Distributed Lags (ARDL) Estimation is used. The lag for dependent variable is fixed at one, while optimal lags are taken for independent variables. (4). EX and log of $lnInf^{IND}$ are in log form, while $rate\_differential$, FPI and $Death^{IND}$are in level form. (5). **Model I:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Inf^{IND} + \pi\Delta S_{t-1} + \gamma_2 \Delta Inf^{IND} + \epsilon_t$. (6). **Model II:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 RD + \pi\Delta S_{t-1} + \gamma_2 \Delta RD + \epsilon_t$. (7). **Model III:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Inf^{IND} + \gamma_2 RD + \pi\Delta S_{t-1} + \gamma_3 \Delta Inf^{IND} + \gamma_4 \Delta RD + \epsilon_t$ (8). **Model IV:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 FPI + \pi\Delta S_{t-1} + \gamma_2 \Delta FPI + \epsilon_t$. (9). **Model V:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Inf^{IND} + \gamma_2 RD + \gamma_3 FPI + \pi\Delta S_{t-1} + \gamma_4 \Delta Inf^{IND} + \gamma_5 \Delta RD + \gamma_6 \Delta FPI + \epsilon_t$. (10). **Model VI:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Death^{IND} + \pi\Delta S_{t-1} + \gamma_2 \Delta Death^{IND} + \epsilon_t$. (11). ECT_{t-1} is the error correction coefficient in the short run equations. (12). '*' and '**'depicts statistical significance at 5% and 10% level of significance respectively.

Table 8: Long Run Effects of Coronavirus on the Exchange Rate with Exchange rate with US Infections and Net Capital Inflow

Variable	Model I[5]	Model II[6]	Model III[7]	Model IV[8]	Model V[9]	Model VI[10]	Model VII[11]
Inf^{USA}	-0.007 *	-0.007 *	-0.011 *	-	-	-	-
$Death^{USA}$	-	-	-	-8.32E-06 *	-3.10E-06 *	-6.59E-06 *	-3.08E-06 *
c	4.42 *	4.39 *	4.48 *	4.32 *	4.20 *	4.32 *	4.20 *
Interest Rate Differential	-	0.007	-0.003	-	0.029 *	-	0.028 *
FPI	-	-	-3.76E-07	-	-	-3.11E-06 **	-4.77E-06
ECT_{t-1}	-0.053 *	-0.081 *	-0.086 *	-0.038 *	-0.081 *	-0.040 *	
f - Statistics for Cointegration (Lower bound, upper bound)	6.70 (3.62, 4.16)	4.51 (3.10, 3.87)	3.44 ** (2.79, 3.67)	5.74 (3.62, 4.16)	5.28 (3.10, 3.87)	4.88 (3.10, 3.87)	4.43 (2.79, 3.67)

Source: Authors own calculations.

Note: (1). Inf^{USA} is USA total infection and $Death^{USA}$ is USA total death. (2). EX and FPI are I (0) variables. While $rate\_differential$ and log Inf^{USA} are is I (1) variables. $Death^{USA}$ is a I (2) variable, hence, new deaths (first difference of $Death^{USA}$ which is a I (1) variable) was included in the model. (3). Auto Regressive Distributed Lags (ARDL) Estimation is used. The lag for dependent variable is fixed at one, while optimal lags are taken for independent variables. (4). EX and log of $lnInf^{USA}$ are in log form, while $rate\_differential$, FPI and $Death^{USA}$are in level form. (5). **Model I:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Inf^{USA} + \pi \Delta S_{t-1} + \gamma_2 \Delta Inf^{USA} + \epsilon_t$. (6). **Model II:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Inf^{USA} + \gamma_2 RD + \pi \Delta S_{t-1} + \gamma_3 \Delta Inf^{USA} + \gamma_4 \Delta RD + \epsilon_t$. (7). **Model III:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Inf^{USA} + \gamma_2 RD + \gamma_3 FPI + \pi \Delta S_{t-1} + \gamma_4 \Delta Inf^{USA} + \gamma_5 \Delta RD + \gamma_6 \Delta FPI + \epsilon_t$. (8). **Model IV:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Death^{USA} + \pi \Delta S_{t-1} + \gamma_2 \Delta Death^{USA} + \epsilon_t$. (9). **Model V:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Death^{USA} + \gamma_2 RD + \pi \Delta S_{t-1} + \gamma_3 \Delta Death^{USA} + \gamma_4 \Delta RD + \epsilon_t$. (10). **Model VII:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1 Death^{USA} + \gamma_2 FPI + \pi \Delta S_{t-1} + \gamma_3 \Delta Death^{USA} + \gamma_4 \Delta FPI + \epsilon_t$. (11). **Model VII:** $\Delta S_t = \mu + \beta S_{t-1} + \gamma_1, Death^{USA} + \gamma_2 RD + \gamma_3 FPI + \pi \Delta S_{t-1} + \gamma_4 \Delta, Death^{USA} + \gamma_5 \Delta RD + \gamma_6 \Delta FPI + \epsilon_t$. (12). ECT_{t-1} is the error correction coefficient in the short run equations. 13. '*' and '**'depicts statistical significance at 5% and 10% level of significance respectively.

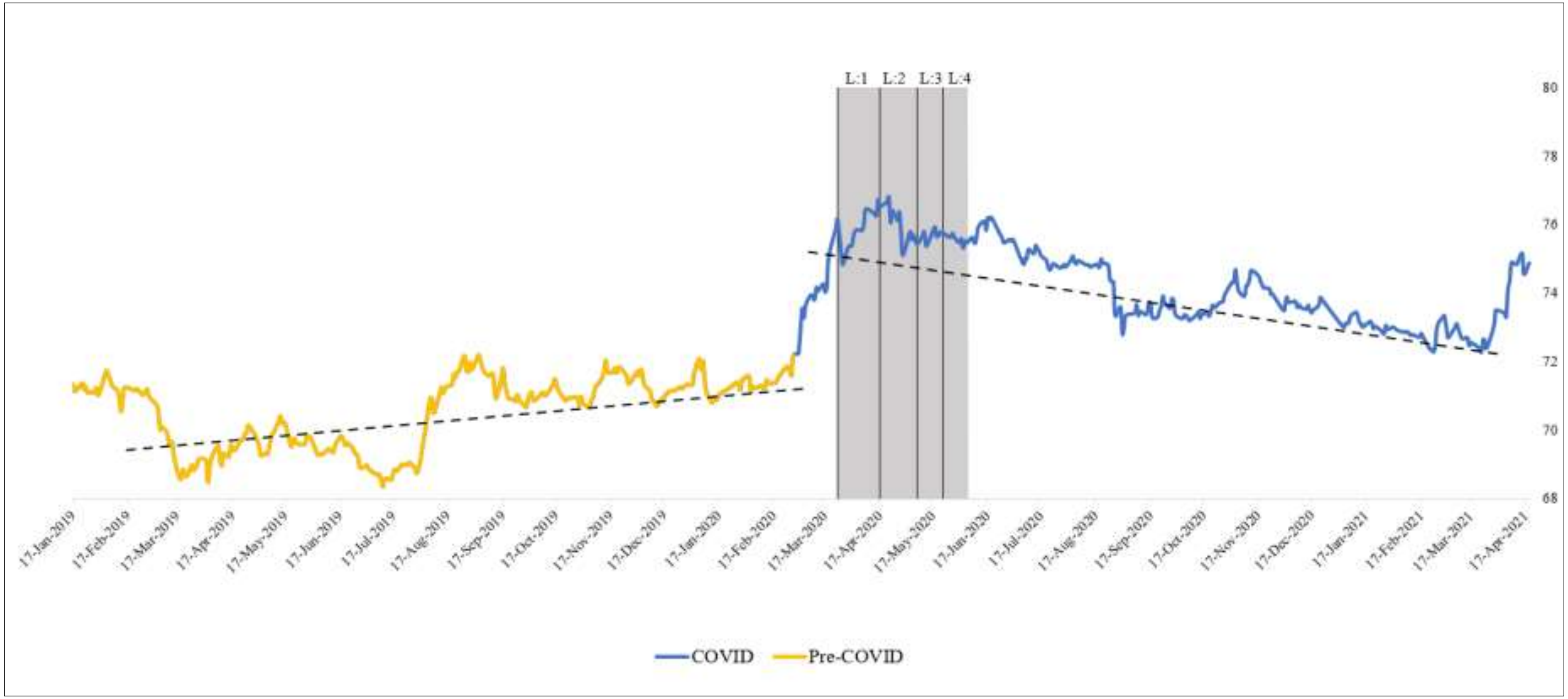
Table 9: Comparison of Pre and During Pandemic Regime Switches in Exchange Rate and the Role of News

Variables	Parameter Estimates	Pre-COVID Estimated Coefficients		COVID Estimated Coefficient					
				Without News		With News[2]		With News[3]	
		Low[1]	High[1]	Low	High	Low	High	Low	High
EX^3	Mean	71.28*	69.34*	73.26*	75.26*	72.90 *	69.48 *	91.15 *	86.65 *
	Volatility	0.37*	0.48*	0.46*	0.67*	0.62 *	0.89	0.44 *	5.04 *
Total Infections	Coefficient	-		-		-0.249 *		-1.01 *	
Interest Rate Differential		-		-		1.364 *		-0.25 *	
Transition Probabilities[4]		(0.995, 0.005, 0.013, 0.987)		(0.981, 0.019, 0.020, 0.980)		(0.997, 0.003, 0.011, 0.989)		(0.992, 0.008, 0.015, 0.985)	
Expected Duration (Days)		(217.03, 76.44)		(51.82, 50.02)		(304.30, 87.65)		(131.16, 65.81)	

Source: Authors own calculations.

Note: (1). Regimes are defined in terms of the magnitude of volatility. (2). India total infections are used as a proxy for the coronavirus news. (3). USA total infections are used as a proxy for the coronavirus news. (4). EX is the rupee per dollar exchange rate. (5). (Low to Low, Low to high, high to low, high to high). (6). '*' depicts statistical significance at 5% level of significance.

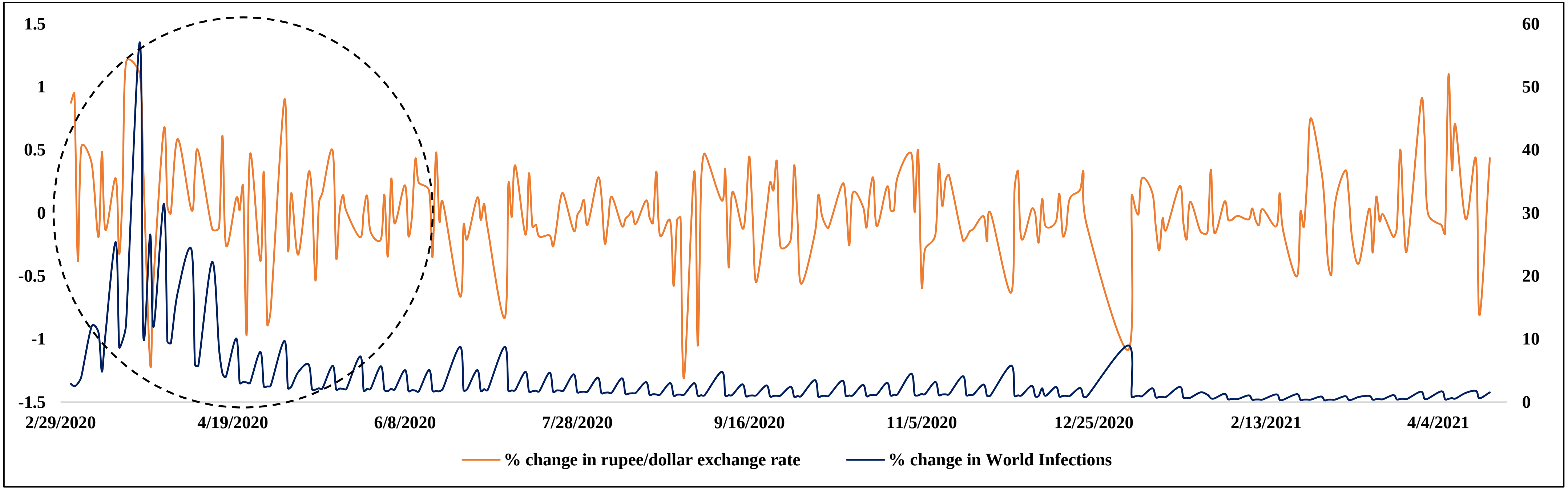
Figure 1: Time series graph for rupee/dollar exchange rate fluctuations



Source: Authors construction

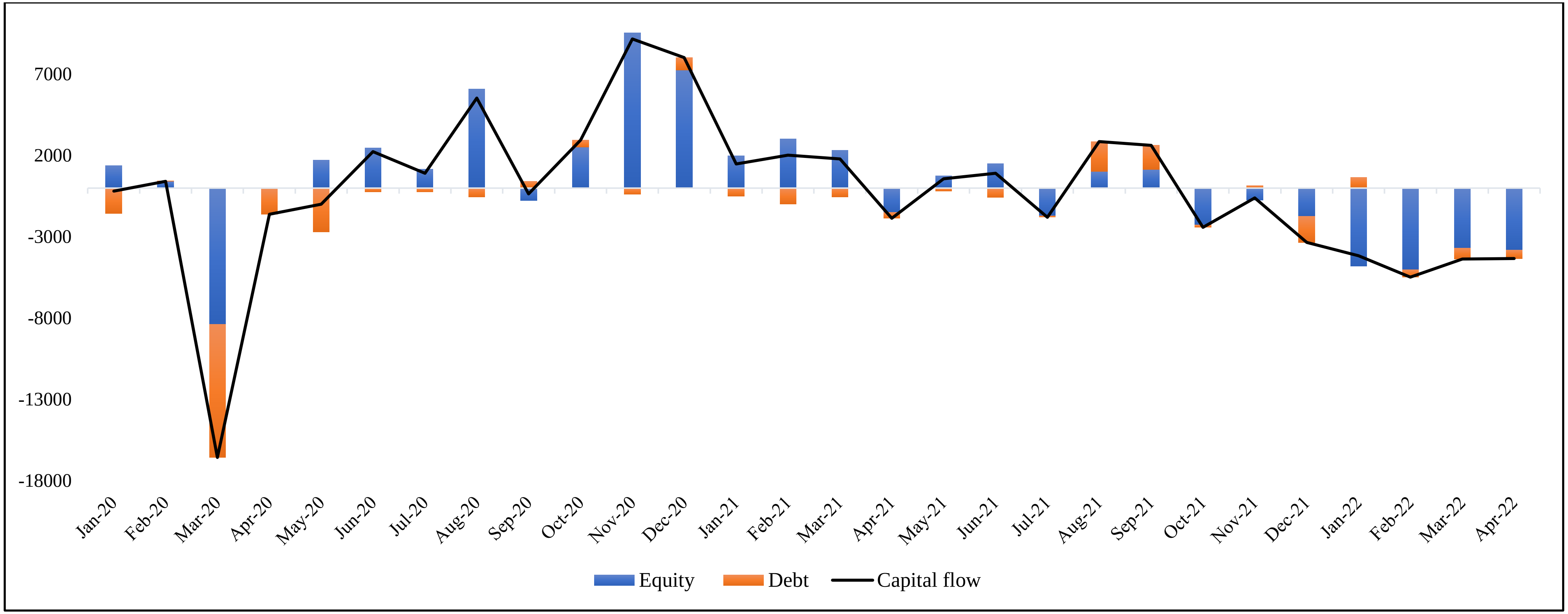
Note: (1). Shaded region highlights the four nation-wide lockdowns that India observed in an attempt to contain the spread of coronavirus.

Figure 2: Co-movement of exchange rate and world infections (percentage change)



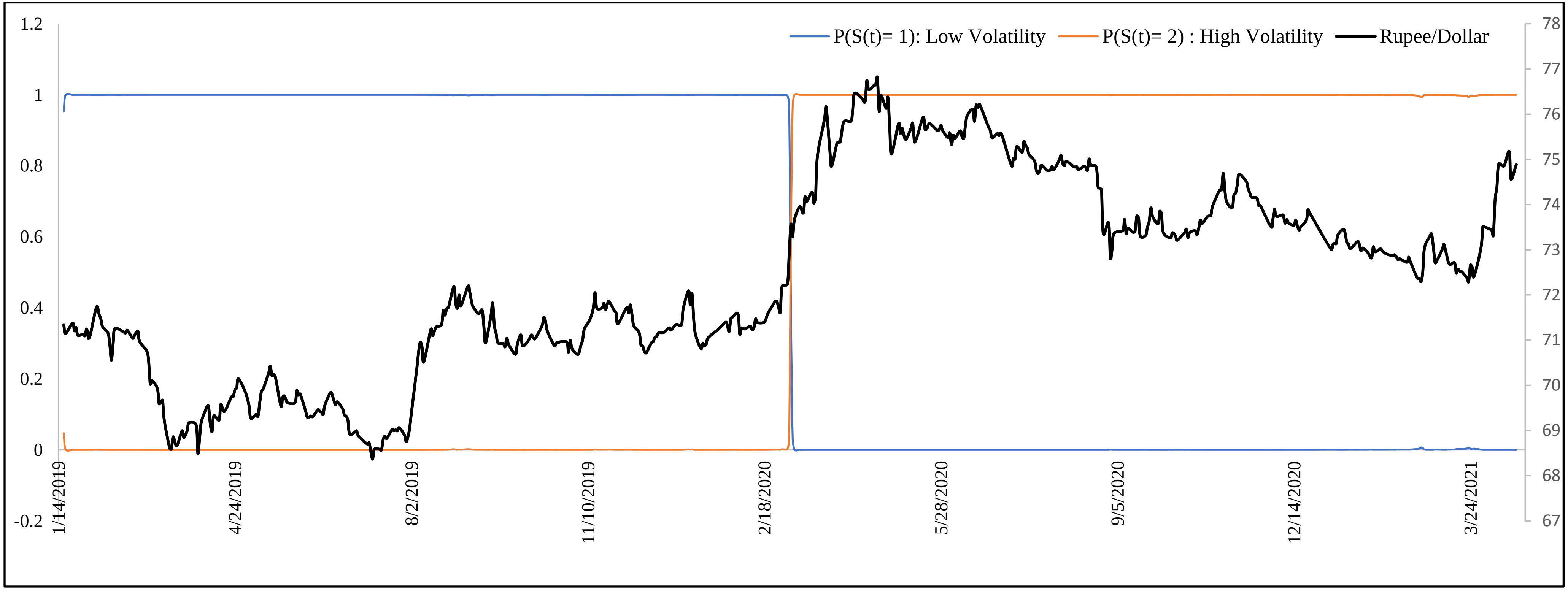
Source: Authors construction

Figure 3: India's Net Capital Outflow (Debt + Equity)



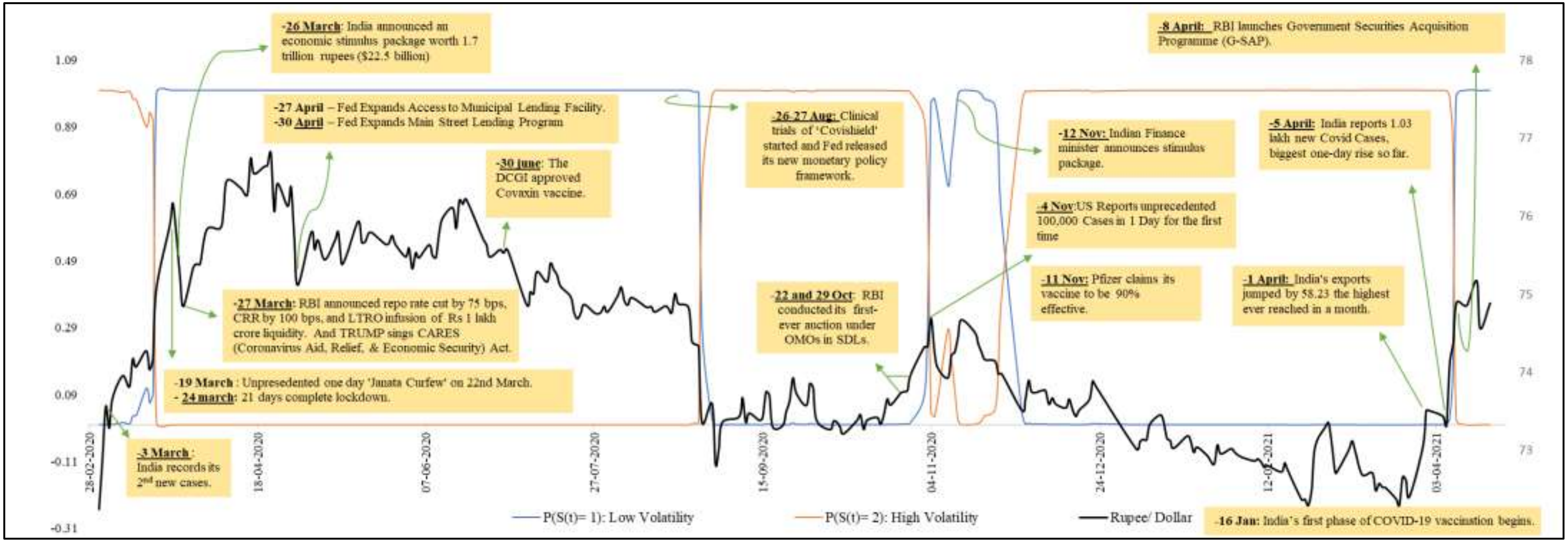
Source: Institute of International Finance Capital Flow Tracker (undated)

Figure 4: Regime Probabilities for Entire Period



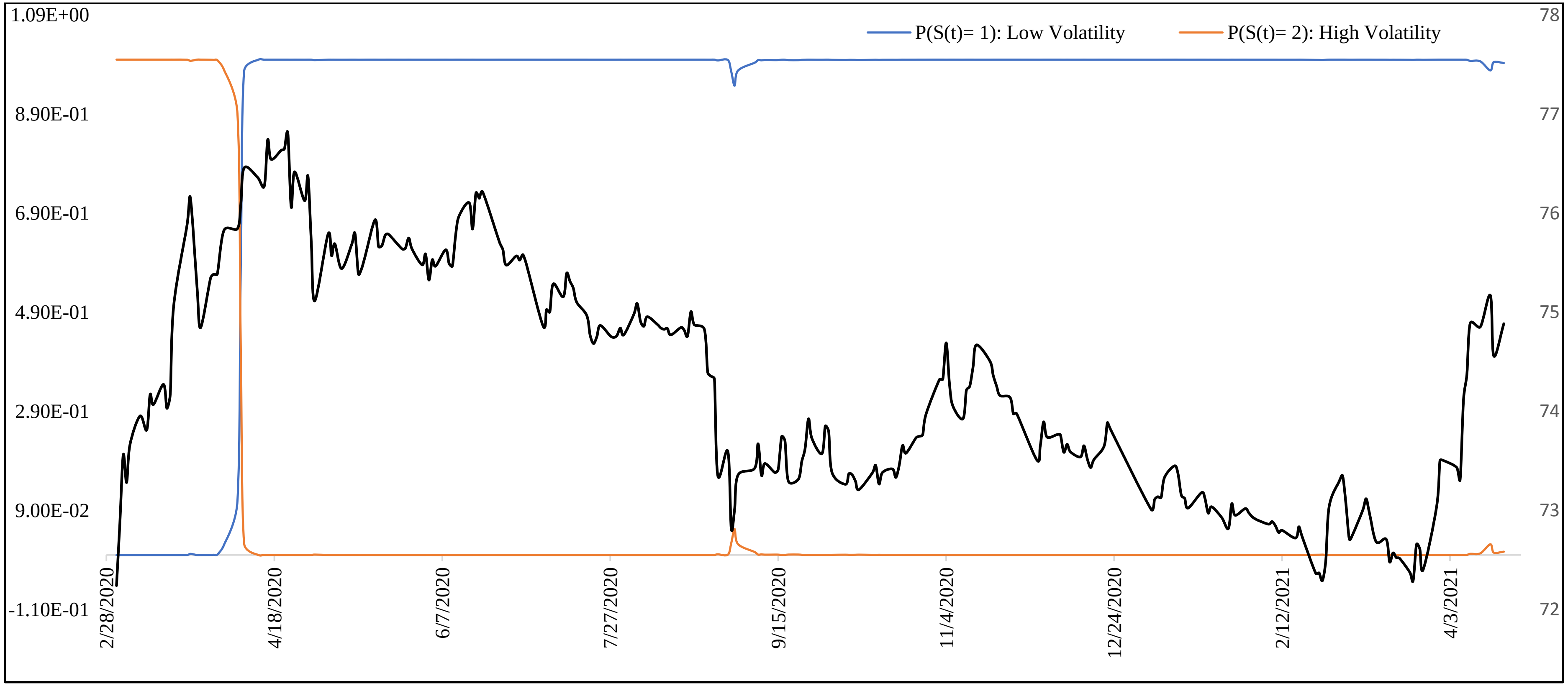
Source: Authors construction

Figure 5: Regime Probabilities for During Pandemic without News



Source: Authors construction

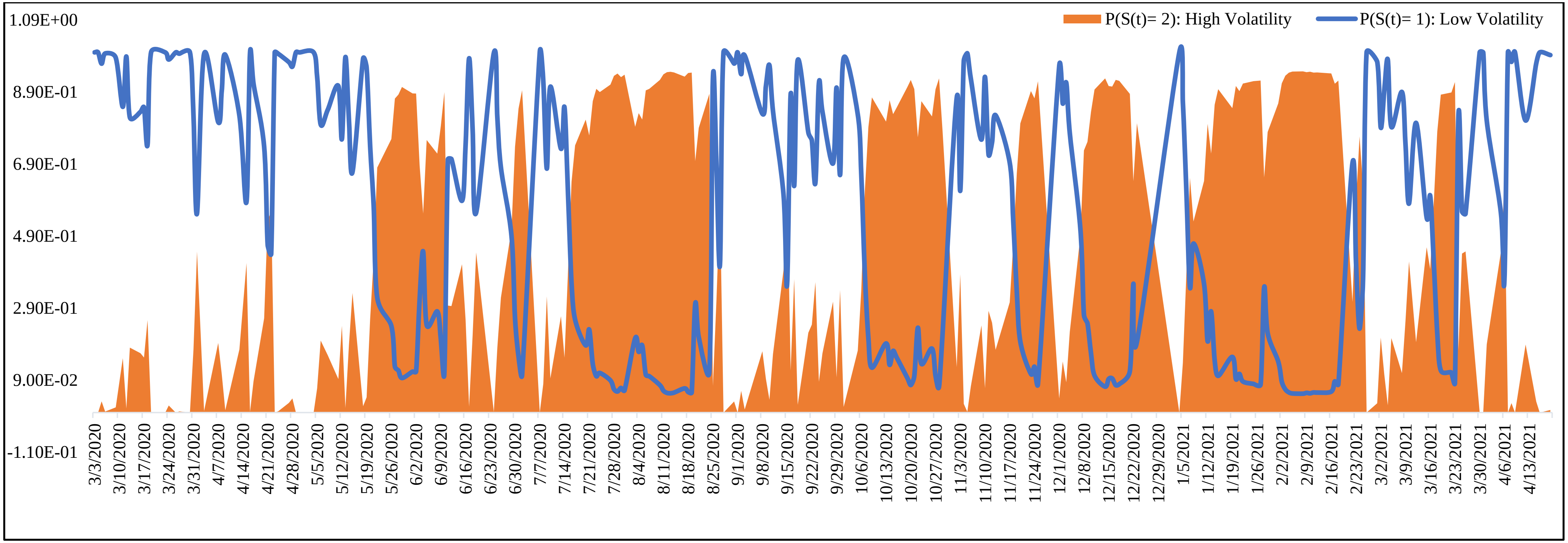
Figure 6: Regime Probabilities During Pandemic with News Controls



Source: Authors construction

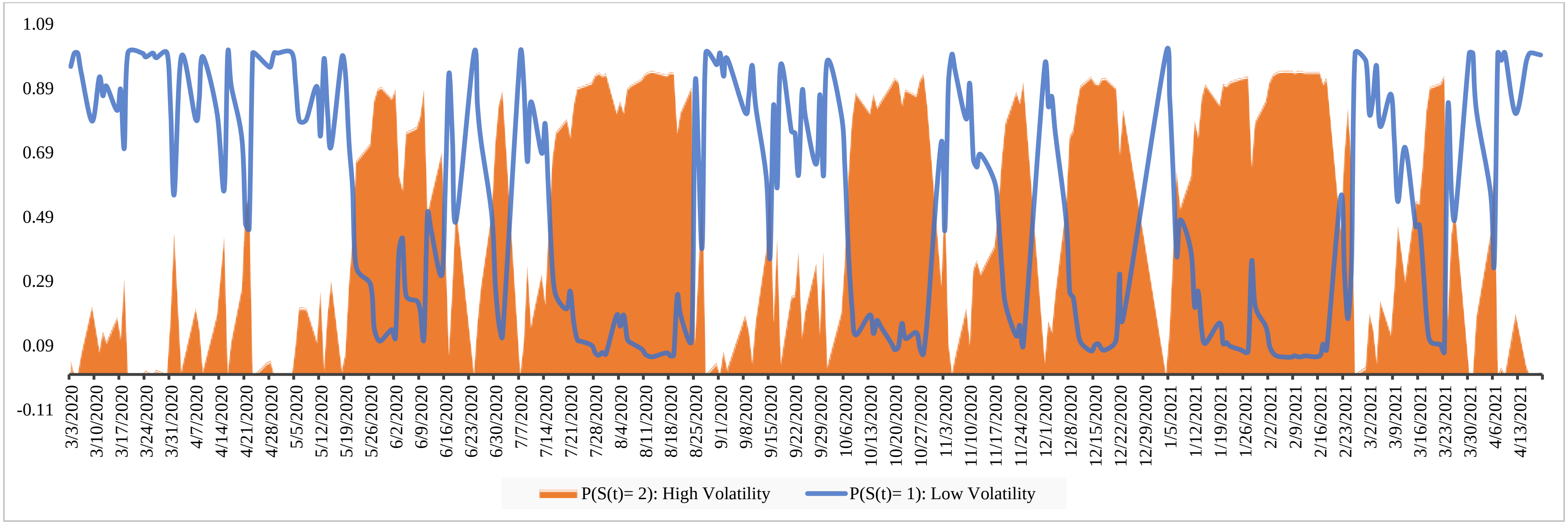
Note: (1) Relevant events can be traced from figure 5.

Figure 7: Regime Probabilities (First Difference) During Pandemic without News



Source: Authors construction

Figure 8: Regime Probabilities (First Difference) During Pandemic with News



Source: Authors construction

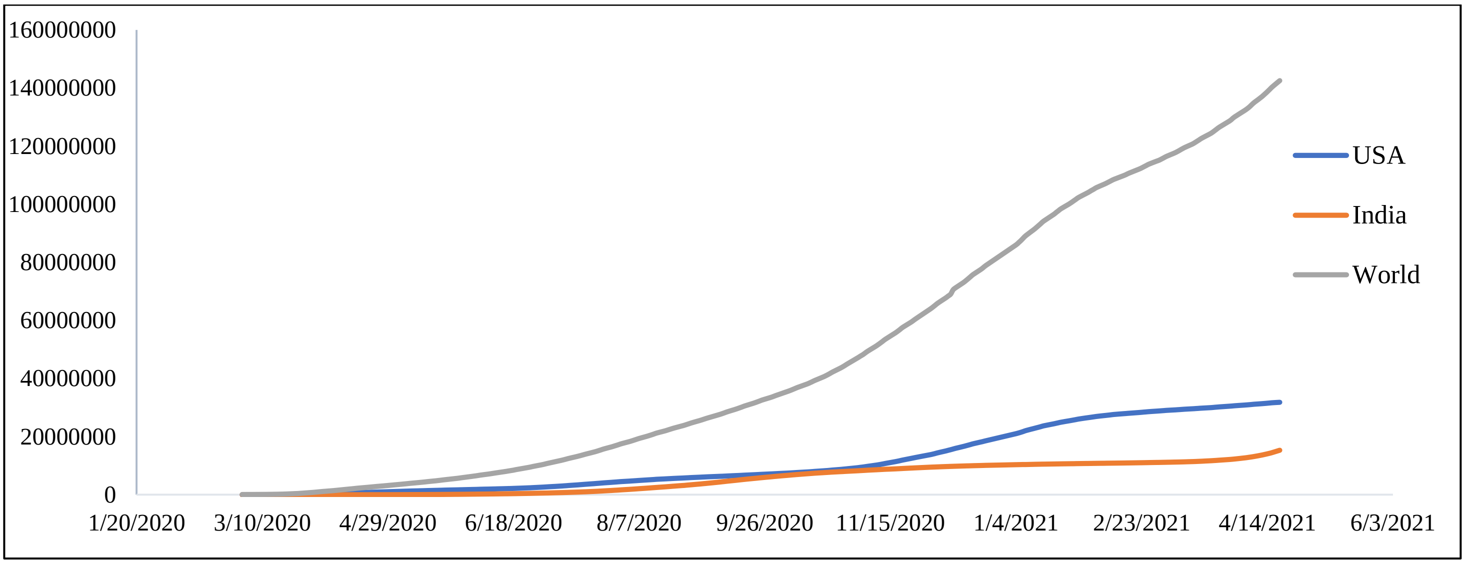
Appendix

Table A1: Unit root test

Variable	Level	1st difference	2nd difference	3rd difference	Result.
EX	-4.094693 (0.0073) *	-			~I (0)
Inf^{WLD}	-0.997233 (0.9414)	-4.209380 (0.0050) *			~I (1)
Inf^{IND}	-0.299294 (0.9903)	1.827872 (1.0000)	1.828636 (1.0000)	-8.491715 (0.0000) *	~I (3)
Inf^{USA}	-1.670983 (0.7613)	-3.154219 (0.0963) **	-17.06785 (0.0000) *	-	~I (2)
$Death^{WLD}$	-17.13 (0.0000) *	-			~I (0)
$Death^{IND}$	-3.042113 (0.1230)	-0.679693 (0.9728)	-18.61107 (0.0000) *	-	~I (2)
$Death^{USA}$	-1.460820 (0.8404)	-3.006619 (0.1325)	-15.38863 (0.0000) *	-	~I (2)
$rate\_differential$[5]	-3.310885 (0.0669)	-5.663554 (0.0000) *			~I (1)
FPI	-10.42506 (0.0000) *	-	-	-	~I (0)

Note: (1). Augmented Dickey Fuller test statistics are reported. (2). $p-\ value$ in parenthesis. (3). '*' depicts statistical significance at 5% level of significance.

Figure A1: Total number of coronavirus cases



Source: Authors construction.

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