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Understanding exchange rate shocks during COVID-19

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ABSTRACT

Using a dynamic VAR model fitted to hourly data, we evaluate the evolution of spillover shocks from exchange rates returns of EURO, Yen, CAD and GBP. We find that over the COVID-19 sample: (a) total exchange rate shock spillovers explain around 37.7% of the forecast error variance in the exchange rate market compared to only 26.1% in the pre-COVID-19 period; and (b) exchange rate own shocks explain between 56% to 75% of own exchange rate movements. These results hold in multiple robustness tests. The implication is that exchange rates predict most of their own changes. We confirm this through an economic significance test where we show that the shock spillovers predict exchange rate returns and these predicted exchange rates can be useful in extracting buy and sell trading signals.

1. Introduction

When [Meese and Rogoff \(1983a,b\)](#) claimed that no economic model predicts exchange rates better than a random walk, this proposition became a puzzle. It not only garnered a voluminous literature, but the search for successful predictors—both statistical and economic—continues. Thirty years post the Meese-Rogoff claim, [Rossi \(2013\)](#) re-ignited the puzzle by claiming that the random walk was the toughest benchmark. This saw further growth in interest on exchange rate predictability. The current COVID-19 pandemic by disrupting financial markets, including influencing exchange rates, has brought into question the relevance of exchange rate predictability.

Our hypothesis is that if the random walk model of exchange rate is active then exchange rate shocks should explain more of its own rate as well as rates of others. Faced with an unprecedented crisis in the form of the COVID-19 pandemic, exchange rate fundamentals may become stronger or weaker given that the pandemic shock dominates. If this is so, we should expect a weaker or a stronger prevalence of exchange rate shocks in explaining themselves. Our argument is that the COVID-19 shock has persisted beginning in February/March, 2020 when countries began closing international borders and implementing other preventive measures, such as lockdowns. As a result, exchange rates have been impacted by the pandemic for over six months giving them a level of resilience to the pandemic. In other words, exchange rates have absorbed the pandemic shock. Supporting this line of thought is a recent study by [Narayan et al. \(2020\)](#), who show that the information content in exchange rates has improved in the COVID-19 period such that the Yen predicted stock market returns by 71% of average Japanese stock returns. A subset of this COVID-19 literature examines the effect and behavior of exchange rates. Specifically, there is now evidence to suggest that: (a) exchange rates are characterized by bubbles and the intensity of bubble activity increased during the COVID-19 period (see [Narayan, 2020a](#)); (b) exchange rates became more resistant to shocks during the COVID-19 period (see [Narayan, 2020b](#)); (c) exchange rate depreciation improves stock returns (see [Narayan et al. 2020](#)); and (d) exchange rates have become inefficient during the COVID-19 pandemic (see [Ali et al., 2020](#)). Other studies on stock return predictability show that the information content in predictor variables has increased during the COVID-19 period allowing for

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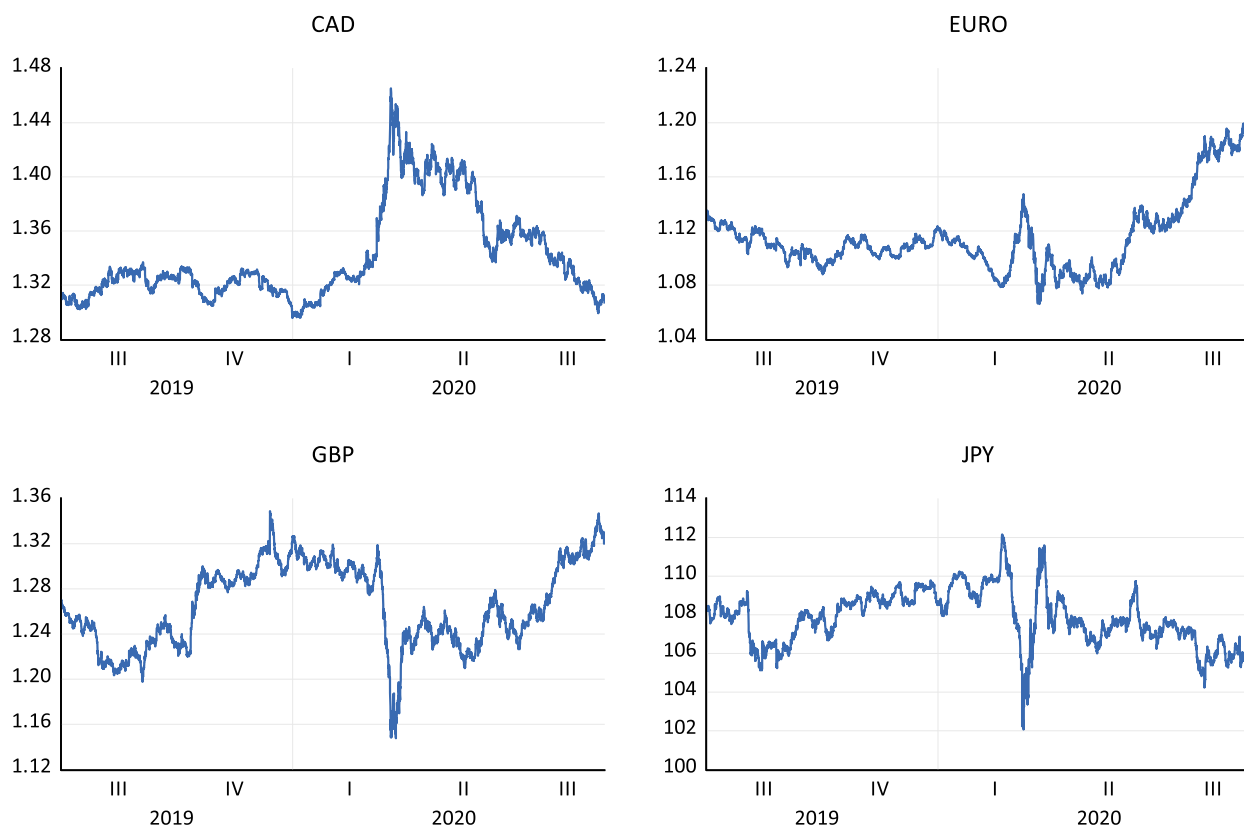


Fig. 1. A plot of exchange rate, 01/07/2019 to 04/09/2020

This figure plots the four exchange rates, namely the Canadian dollar (CAD), the EURO, the Great British Pound (GBP), and Japanese Yen (JPY). The data are intraday from 01/07/2019 to 04/09/2020 of hours from 01:00am to 05:00pm (17 hours per day). To interpret these, an increase in values of Yen and CAD implies a depreciation while an increase in EURO and GBP implies an appreciation of these two currencies.

more success in both out-of-sample and in-sample predictability; see [Salisu and Adediran \(2020\)](#); [Salisu et al. \(2020a,b\)](#). Based on this evidence, we would expect exchange rate shocks to be more important for exchange rates. Whether this is the way exchange rates have behaved in the COVID-19 period is unknown and is an empirical issue which is the subject of our paper.

We test our hypothesis using a high frequency hourly dataset that contains four exchange rates, namely the EURO, the YEN, the Canadian dollar (CAD), and the British Pound Sterling (GBP). Section II discusses data in detail. We apply a vector autoregressive model, proposed by [Diebold and Yilmaz \(2012\)](#) that identifies the role of each exchange rate return shock in explaining the forecast error variance of other exchange rate returns. Our results show that the total spillover of shocks from the four exchange rates improved from 23% in the pre-COVID-19 period to over 37% in the COVID-19 period, which, in robustness tests based on higher forecasting horizons, higher order VARs and bigger rolling window, improves to 40%. The importance of own shocks remains strong: in the COVID-19 sample, they are in the 56.4% (EURO) to 74.5% (Yen) range. Total contribution of exchange rate shocks to other exchange rates improves from 92.3% in the pre-COVID-19 period to 149.2% in the COVID-19 period. We test the economic significance of the spillover shocks by using it as a predictor of exchange rate returns. We show that buy and sell trading signals generated from spillover index-based exchange rate forecasts lead to profits.

Our work connects to the literature on forecasting exchange rates. We find that between 56% to 75% of the forecast error variance of exchange rate returns can be explained by exchange rate shocks themselves. The remaining (at least 1/3) variations in exchange rates can be attributed to other factors shown to predict exchange rates. [Salisu et al. \(2019\)](#), for instance, show the importance of commodity prices. The random walk model of exchange rates has occupied significant interest of researchers, such that, over half a century, concerted research has been devoted to finding exchange rate predictors that can beat the random walk model; for recent research, see [Pincheira-Brown and Neumann \(2019\)](#). Our results demonstrate that the bulk of the variation in exchange rates is due to exchange rate shocks.

Overall, from our work, results support the [Meese-Rogoff \(1983b\)](#) claim that exchange rates are best predictors of themselves. We show that even a global shock as unprecedented as the COVID-19 has not contributed to dissipating the exchange rate predictability puzzle that has gripped the attention of financial economists for over half a decade.

Lastly, our work contributes to an evolving COVID-19—financial systems literature. Various themes have been covered by this literature, including oil market reactions and performance ([Gil-Alana and Monge, 2020](#)), stock market reactions and volatility

Table 1

Selected descriptive statistics of exchange rate returns

This table reports selected descriptive statistics (mean, standard deviation (SD), maximum, minimum, skewness, kurtosis, the NP unit root test, and the first order autoregressive coefficient and the null hypothesis that the slope coefficient is zero—the *t*-statistic is reported in parenthesis) for four exchange rate returns, namely Canadian dollar (RET_CAD), EURO (RET_EURO), the Great British Pound (RET_GBP), and Japanese Yen (RET_JPY). The statistics are generated for two sub-samples: the pre-COVID-19 sample (7/01/2019, 2:00am to 12/31/2019, 5:00pm) in Panel A, and the COVID-19 sample (1/01/2020, 1:00 am to 9/04/2020, 5:00pm) in Panel B. To interpret these, an increase in returns of Yen and CAD implies a depreciation while an increase in EURO and GBP implies an appreciation of these two currencies. The critical values for the Narayan and Popp test are -4.67, -4.08, and -3.77 at the 1%, 5%, and 10% levels, respectively. The structural break unit root models require a data trimming factor, which following Narayan and Popp (2013), we set to 10%. Controlling serial correlation is also important in this test. The optimum lag length is chosen using the Narayan information criterion starting with a maximum of 8 lags. The NP first and second breaks are denoted Break1 and Break2, respectively. Finally, * (**) *** denote statistical significance at the 10% (5%) 1% levels.

	RET_CAD	RET_EURO	RET_GBP	RET_JPY
Panel A: Pre-COVID-19 sample (2227 observations)				
Mean	-0.004	-0.0005	0.0019	0.0002
SD	0.0723	0.0758	0.1385	0.0845
Maximum	0.5829	0.8190	2.8800	1.2658
Minimum	-0.4831	-0.7844	-0.8945	-0.6721
Skewness	0.2711	0.4579	4.4855	1.0003
Kurtosis	12.2008	20.2468	92.1171	33.4552
AR(1)	-0.0330 (-1.563)	-0.0308 (-1.459)	-0.0587*** (-2.784)	0.0324 (1.536)
NP test	-0.7269 (-13.50)	-0.7253 (-13.48)	-0.7242 (-13.47)	-0.7253 (-13.48)
Break1	11/20/2019, 9am	11/27/2019, 9am	11/27/2019, 9am	11/13/2019, 9am
Break2	11/27/2019, 9am	12/11/2019, 9am	12/11/2019, 9am	11/20/2019, 9am
Panel B: Pre-COVID-19 sample (3043 observations)				
Mean	0.0002	0.0018	0.000048	-0.0007
SD	0.1387	0.1279	0.1702	0.1356
Maximum	2.0955	1.0822	1.0109	1.0904
Minimum	-0.9377	-0.8841	-1.8363	-3.1107
Skewness	0.9084	0.1785	-0.4515	-4.0472
Kurtosis	26.5639	10.1629	13.7362	101.499
AR(1)	-0.0434** (-2.391)	0.0118 (0.648)	-0.0321* (1.768)	-0.0170 (-0.936)
NP test	-0.7685 (-15.78)	-0.7700 (-15.77)	-0.7744 (-15.88)	-0.7699 (-15.84)
Break1	8/5/2020, 2am	7/29/2020, 3pm	7/15/2020, 2pm	8/5/2020, 2am
Break2	8/12/200, 2am	8/5/2020, 2am	7/29/2020, 3pm	8/12/200, 2am

(Akhtaruzzaman et al. 2020; Al-Awadhi et al. 2020; Zhang et al. 2020; Sharma (2020); Zaremba et al. 2020; Haroon and Rizvi, 2020a, b); firm performance (Gu et al. 2020); air quality (Ming et al. 2020); household decision making and labor force participation (Yu et al. 2020); and gold and cryptocurrencies (Corbet et al. 2020; Conlon and McGee, 2020). We add to this literature an analysis of the importance of exchange rate shocks during the COVID-19 period.

The rest of the paper proceeds as follows. Data and results are discussed in Section 2. Section 3 complements Section 2 with a range of robustness tests. The final section summarizes the key contribution of the paper.

2. Data and results

2.1. Data

We have four spot exchange rates, namely the Japanese Yen (Yen per US dollar), the Canada dollar (CAD per US dollar), the EURO (US dollar per EURO), and the Great Britain Pound (GBP, US dollar per pound). To interpret these, an increase in returns of Yen and CAD implies a depreciation while an increase in EURO and GBP implies an appreciation of these two currencies. All data series are sampled at the hourly frequency, covering 17 hours per day, from 1:00am to 5:00pm for the period 01/07/2019: 2:00am (July 2019) to 04/09/2020: 5:00pm (September 2020). We downloaded the intraday data from REFINITIV, Datascope. We consider the 01/07/2019: 2:00am to 31/12/2019: 5:00pm as the pre-COVID-19 sample and the sample thereafter as the COVID-19 sample. These series are plotted in Fig. 1. There is clearly a pattern of return clustering in the COVID-19 sample period. The figure implies greater exchange rate volatility in the COVID-19 period. Table 1 confirms this. In the pre-COVID-19 period, we observe that CAD appreciated by 0.004% and in the COVID-19 sample it depreciated by 0.0002%. EURO (Yen) depreciated by 0.0005% (0.0002%) pre-COVID-19 and then appreciated by 0.0018% (0.0007%) in the COVID-19 period. GBP appreciated in both periods, but the appreciation was significantly milder in the COVID-19 sample (4.98E-06%) compared to the pre-COVID-19 period (0.0019%). Standard deviations suggest that volatility doubled in the COVID-19 period compared to the pre-COVID-19 period.

The first order autoregressive coefficient of exchange rate returns together with the *t*-test testing the null hypothesis that the slope coefficient is zero. There is mixed evidence in terms of statistical significance but the magnitude of the slope coefficient in absolute

Table 2

Exchange rate return spillover for four currencies

This table reports the spillover results for the VAR model containing four exchange rate returns, namely Canadian dollar (RET_CAD), EURO (RET_EURO), the Great British Pound (RET_GBP), and Japanese Yen (RET_JPY). The dynamic estimates are obtained using: a VAR lag of 4, a rolling window of 200 hours (approximately 12 days), and a forecast horizon, h , 10 hours. TO represents for the contribution to others; FROM represents contribution from others and OWN represents contributions from own shocks; NET represents the difference between gross return shocks transmitted to and gross return shocks received from all other markets. Finally, the TSI indicates the total spillover index. The results are provided for three sample periods: the full-sample (7/01/2019, 2:00am to 9/04/2020, 5:00pm) in Panel A, pre-COVID-19 sample (7/01/2019, 2:00am to 12/31/2019, 5:00pm) in Panel B, and the COVID-19 sample (1/01/2020, 1:00 am to 9/04/2020, 5:00pm) in Panel C.

	RET_CAD	RET_EURO	RET_GBP	RET_JPY	FROM
Panel A: Full Sample (VAR order 4 lags, h=10, 200 rolling window)					
RET_CAD	68.788	13.683	12.266	5.264	31.212
RET_EURO	11.813	60.644	18.689	8.854	39.356
RET_GBP	10.928	19.492	63.580	6.000	36.420
RET_JPY	5.510	11.136	6.793	76.562	23.438
Contribution TO others	28.251	44.310	37.748	20.118	130.427
Contribution including own	97.038	104.954	101.328	96.679	
Net spillovers	-2.962	4.954	1.328	-3.321	TSI=32.607
Panel B: Pre-COVID-19 (VAR order 4 lags, h=10, 200 rolling window)					
RET_CAD	77.764	10.466	7.103	4.667	22.236
RET_EURO	9.213	65.779	16.247	8.761	34.221
RET_GBP	6.461	17.165	71.018	5.356	28.982
RET_JPY	4.688	9.921	4.447	80.944	19.056
Contribution TO others	20.362	37.552	27.797	18.784	104.495
Contribution including own	98.125	103.331	98.816	99.727	TCI
Net spillovers	-1.875	3.331	-1.184	-0.273	26.124
Panel C: COVID-19 (VAR order 4 lags, h=10, 200 rolling window)					
RET_CAD	61.847	16.006	16.301	5.846	38.153
RET_EURO	13.773	56.651	20.568	9.008	43.349
RET_GBP	14.470	21.116	57.713	6.701	42.287
RET_JPY	6.182	12.151	8.748	72.920	27.080
Contribution TO others	34.425	49.273	45.616	21.555	150.869
Contribution including own	96.272	105.925	103.329	94.475	TCI
Net spillovers	-3.728	5.925	3.329	-5.525	37.717

values implies that except for CAD other rates of return have smaller coefficients. This means that persistency of shocks in the COVID-19 period has declined meaning that any shock has had a short life. The Narayan and Popp (2010) structural break unit root test confirms this.

2.2. Results

We begin an appraisal of results in Table 2. These results are based on a generalized spillover approach proposed by Diebold and Yilmaz (2012) that is based on a V -variable (which in our case is a 4-variable model) VAR model. The main attraction of this model is that the results are insensitive to the ordering of the VAR, and the approach offers multiple ways to interpret the role of shocks, such as the total spillover effect (how much of the markets' forecast error variance is explained by total spillovers), directional spillovers (allowing one to gauge the role of specific variable shocks on other variables in the system), net spillovers (allowing one to compute whether a variable shock is a net contributor of shocks to others or a net taker of shocks from others in the system), and own shock spillovers (allowing one to estimate how much of own shocks explain its future). We provide a brief account of this method next. Consider a V -variable VAR(q) model: $y_t = \sum_{i=1}^q \Psi_i y_{t-i} + \mu_t$, $\mu_t \sim (0, \Sigma)$ is a vector of iid disturbances. The key part of the model is that y_t is a moving average (MA), such that $\sum_{i=0}^{\infty} B_i \mu_{t-i}$, where the $V \times V$ coefficient matrices $B_i = \Psi_1 B_{i-1} + \Psi_2 B_{i-2} + \dots + \Psi_q B_{i-q}$. The MA coefficients capture system dynamics. The method draws on the variance decompositions (VDs), as proposed in the work of Koop et al. (1996) and Pesaran and Shin (1998), allowing one to extract the forecast error variance (FEV) of each variable. The VDs tell us the percentage of the h -step-ahead error variance in forecasting y_i that is due to shocks in y_j , where i and j are different markets, given that $\forall_j \neq i$ for each i .¹ To see how own variance shares—that is the FEV of y_i that is due to y_i , denote the h -step-ahead FEVDs by $\lambda_{ij}(h)$ to obtain:

$$\lambda_{ij}(h) = \frac{SD_{ij}^{-1} \sum_{l=0}^{h-1} (\mu'_i B_l \Sigma \mu_j)^2}{\sum_{l=0}^{h-1} (\mu'_i B_l \sum B'_l \mu_j)} \tag{1}$$

Where Σ is the variance matrix for the error vector μ , SD_{ij} represents the standard deviation of the j^{th} equation's error term and μ_i is the

¹ Interested readers are referred to Diebold and Yilmaz (2012) for original details and for applications see Antonakakis (2012), Antonakakis et al. (2018a,b).

selection vector with one as the i^{th} element and zeros otherwise. The spillover index is given by: $\hat{\lambda}_{ij}(h) = \lambda_{ij}(h) / \sum_{j=1}^V \lambda_{ij}(h)$ and the total spillover index (TSI) at h -step-ahead becomes:

$$TSI(h) = \frac{\sum_{i,j=1}^V \hat{\lambda}_{ij}(h)}{V} \times 100, \text{ where } V = \sum_{i,j=1}^V \hat{\lambda}_{ij}(h) \quad (2)$$

The directional spillovers to market i from all other markets, j , ($DS_{i \rightarrow j}$), is:

$$DS_{i \rightarrow j}(h) = \frac{\sum_{i,j=1}^V \hat{\lambda}_{ij}(h)}{V} \times 100 \quad (3)$$

And, the directional spillovers from market i to all markets, j , ($DS_{j \rightarrow i}$), is:

$$DS_{j \rightarrow i}(h) = \frac{\sum_{i,j=1}^V \hat{\lambda}_{ji}(h)}{V} \times 100 \quad (4)$$

Our first VAR model setup has 4 lags, a forecasting horizon, h , of 10 hours and a rolling window consisting of 200 hours (roughly 12 days).

The total spillover index is 32.6%, suggesting that 32.6% of exchange rate shocks matter to exchange rates. When we observe the importance of own shocks, we see that Yen shocks explain 76.6% of Yen while the other exchange rate shocks explain between 60.6% to 68.8% of their own currencies forecast error variance. This represents a strong role of exchange rate shocks in explaining their own exchange rate movements. We then compare the pre-COVID-19 and COVID-19 periods in more details. These results are presented in Panels B and C. Several points of importance are observable relating to our hypothesis. First, notice that the total importance of exchange rate spillovers rises from 26.1% to 37.7%. This implies that exchange rate spillovers became 44% more important in the COVID-19 period. Second, own shocks explain between 65.8% to 80.9% of their own exchange rates in the pre-COVID-19 period which declined to between 56.7% and 72.9% in the COVID-19 period. This still means that over half to three quarters of movements in exchange rates in the COVID-19 period was explained by exchange rate shocks themselves, leaving aside a smaller contribution to non-exchange rate factors. Third, we see that the total contribution of exchange rates to other exchange rates increased from 104.5% (pre-COVID-19) to 150.9% (COVID-19), with the role of EURO and GBP becoming stronger in the COVID-19 period.

These findings that own shocks are important in explaining exchange rate changes regardless of the pandemic is consistent with the literature that favors the random walk model of exchange rates (see Rossi, 2013). In addition, recent studies on COVID-19 and exchange rates find that exchange rates have become less prone to shocks—in other words, they have been shock-resistant (see Narayan, 2020b). This implies that the information content of exchange rate is not diluted by shocks—at least not in the COVID-19 period. Therefore, exchange rates ability to influence other exchange rates is less surprising.²

2.3. Economic significance test

Recent studies evaluating the exchange rate market have considered devising buy-sell signal-based trading strategies (see). show that buying when there is a depreciation and selling when there is an appreciation leads to profits from exchange rate trading. We follow their profitability analysis framework and extract buy and sell signals from a forecast of exchange rates, where the predictor variable is the time-varying spillover index. The objective is to test whether spillover index-based exchange rate forecasts generate successful buy and sell signals. To general forecasts, we use the () time-series predictability model fitted to 50% of the sampled data (7/01/2019, 1:00 to 1/31/2020 17:00) to forecast recursively the remaining 50% of the sample (2/03/2020 1:00 to 9/04/2020 1:00). The buy and sell signals are extracted from these forecasted exchange rates. By estimating profits from these forecasts tells us of the economic significance of the exchange rate spillover index. We find the annualized profits from each exchange rate market to be statistically significant, valued at 1.38% (Euro), 7.02% (GBP), 20.99% (Yen), and 61.9% (CAD).

3. Robustness tests

We mount several additional lines of inquiry to check any evidence of sensitivity that overturns our conclusions on the hypothesis that the bulk of the movements in exchange rates in the COVID-19 period were explained by exchange rate shocks themselves and the

² We also attempted to understand what was happening to the exchange rate markets during the COVID-19 period. In other words, was COVID-19 influencing the market. We run regressions of exchange rate returns on specific government policies (like travel bans, lockdowns and stimulus packages) using dummy variables for each market. We do not find any statistically significant results, suggesting that these events were not instrumental in influencing exchange rates. We also run regressions of exchange rate returns on a COVID-19 dummy variable that took a value of one from 1 January 2020 to 4 September 2020 and a value of zero otherwise. We again find that in each of the four markets the slope coefficient was statistically zero. This is reflected in our spillover results. For example, we find that in both the pre-COVID-19 and COVID-19 periods the importance of own exchange rates shocks is high. We note that the effect of own shocks did not die out due to COVID-19.

Table 3

Exchange rate return spillover with higher order VAR

This table reports the spillover results for the VAR model containing four exchange rate returns, namely Canadian dollar (RET_CAD), EURO (RET_EURO), the Great British Pound (RET_GBP), and Japanese Yen (RET_JPY). The dynamic estimates are obtained using: a VAR lag of 8, a rolling window of 200 hours (approximately 12 days), and a forecast horizon, h , 10 hours. TO represents for the contribution to others; FROM represents contribution from others and OWN represents contributions from own shocks; NET represents the difference between gross return shocks transmitted to and gross return shocks received from all other markets. Finally, the TSI indicates the total spillover index. The results are provided for three sample periods: the full-sample (7/01/2019, 2:00am to 9/04/2020, 5:00pm) in Panel A, pre-COVID-19 sample (7/01/2019, 2:00am to 12/31/2019, 5:00pm) in Panel B, and the COVID-19 sample (1/01/2020, 1:00 am to 9/04/2020, 5:00pm) in Panel C.

	RET_CAD	RET_EURO	RET_GBP	RET_JPY	FROM
Panel A: Full Sample (VAR order 8 lags, h=10, 200 rolling window)					
RET_CAD	66.030	14.441	13.192	6.337	33.970
RET_EURO	12.547	58.769	18.964	9.720	41.231
RET_GBP	11.836	19.672	61.207	7.285	38.793
RET_JPY	7.114	12.280	8.206	72.400	27.600
Contribution TO others	31.498	46.393	40.362	23.341	141.594
Contribution including own	97.528	105.162	101.570	95.741	TCI
Net spillovers	-2.472	5.162	1.570	-4.259	35.399
Panel B: Pre-COVID-19 (VAR order 8 lags, h=10, 200 rolling window)					
RET_CAD	74.706	11.041	8.342	5.911	25.294
RET_EURO	9.827	64.027	16.657	9.490	35.973
RET_GBP	7.315	17.313	68.781	6.592	31.219
RET_JPY	6.379	11.434	5.914	76.273	23.727
Contribution TO others	23.520	39.787	30.912	21.993	116.213
Contribution including own	98.226	103.814	99.694	98.266	TCI
Net spillovers	-1.774	3.814	-0.306	-1.734	29.053
Panel C: COVID-19 (VAR order 8 lags, h=10, 200 rolling window)					
RET_CAD	59.418	16.848	16.950	6.784	40.582
RET_EURO	14.519	54.833	20.745	9.903	45.167
RET_GBP	15.375	21.345	55.235	8.045	44.765
RET_JPY	7.752	12.816	10.127	69.304	30.696
Contribution TO others	37.645	51.010	47.823	24.732	161.209
Contribution including own	97.063	105.843	103.058	94.036	TCI
Net spillovers	-2.937	5.843	3.058	-5.964	40.302

Table 4

Exchange rate return spillover for four currencies-higher order VAR and rolling window

This table reports the spillover results for the VAR model containing four exchange rate returns, namely Canadian dollar (RET_CAD), EURO (RET_EURO), the Great British Pound (RET_GBP), and Japanese Yen (RET_JPY). The dynamic estimates are obtained using: a VAR lag of 8, a rolling window of 408 hours (approximately 24 days), and a forecast horizon, h , 10 hours. TO represents for the contribution to others; FROM represents contribution from others and OWN represents contributions from own shocks; NET represents the difference between gross return shocks transmitted to and gross return shocks received from all other markets. Finally, the TSI indicates the total spillover index. The results are provided for three sample periods: the full-sample (7/01/2019, 2:00am to 9/04/2020, 5:00pm) in Panel A, pre-COVID-19 sample (7/01/2019, 2:00am to 12/31/2019, 5:00pm) in Panel B, and the COVID-19 sample (1/01/2020, 1:00 am to 9/04/2020, 5:00pm) in Panel C.

	RET_CAD	RET_EURO	RET_GBP	RET_JPY	FROM
Panel A: Full Sample (VAR order 8 lags, h=10, 408 rolling window)					
RET_CAD	71.093	12.929	12.204	3.774	28.907
RET_EURO	11.101	61.844	18.730	8.325	38.156
RET_GBP	11.109	19.614	64.225	5.051	35.775
RET_JPY	4.217	10.363	5.476	79.945	20.055
Contribution TO others	26.427	42.906	36.409	17.151	122.892
Contribution including own	97.520	104.750	100.634	97.096	TCI
Net spillovers	-2.480	4.750	0.634	-2.904	30.723
Panel B: Pre-COVID-19 (VAR order 8 lags, h=10, 408 rolling window)					
RET_CAD	81.398	8.890	6.965	2.746	18.602
RET_EURO	7.875	68.506	16.230	7.389	31.494
RET_GBP	6.482	17.314	72.839	3.365	27.161
RET_JPY	3.133	8.635	2.870	85.361	14.639
Contribution TO others	17.491	34.839	26.066	13.501	91.896
Contribution including own	98.889	103.344	98.905	98.862	TCI
Net spillovers	-1.111	3.344	-1.095	-1.138	22.974
Panel C: COVID-19 (VAR order 8 lags, h=10, 408 rolling window)					
RET_CAD	62.882	15.741	16.583	4.795	37.118
RET_EURO	13.366	56.456	20.682	9.495	43.544
RET_GBP	15.044	21.202	57.260	6.494	42.740
RET_JPY	5.212	12.193	7.928	74.667	25.333
Contribution TO others	33.622	49.136	45.193	20.784	148.735
Contribution including own	96.504	105.592	102.453	95.451	TCI
Net spillovers	-3.496	5.592	2.453	-4.549	37.184

Table 5

Exchange rate return spillover for four currencies-higher order VAR, forecasting horizon and rolling window

This table reports the spillover results for the VAR model containing four exchange rate returns, namely Canadian dollar (RET_CAD), EURO (RET_EURO), the Great British Pound (RET_GBP), and Japanese Yen (RET_JPY). The dynamic estimates are obtained using: a VAR lag of 8, a rolling window of 408 hours (approximately 24 days), and a forecast horizon, h , 30 hours. TO represents for the contribution to others; FROM represents contribution from others and OWN represents contributions from own shocks; NET represents the difference between gross return shocks transmitted to and gross return shocks received from all other markets. Finally, the TSI indicates the total spillover index. The results are provided for three sample periods: the full-sample (7/01/2019, 2:00am to 9/04/2020, 5:00pm) in Panel A, pre-COVID-19 sample (7/01/2019, 2:00am to 12/31/2019, 5:00pm) in Panel B, and the COVID-19 sample (1/01/2020, 1:00 am to 9/04/2020, 5:00pm) in Panel C.

	RET_CAD	RET_EURO	RET_GBP	RET_JPY	FROM
Panel A: Full Sample (VAR order 8 lags, h=30, 408 rolling window)					
RET_CAD	70.982	12.968	12.233	3.817	29.018
RET_EURO	11.140	61.768	18.738	8.354	38.232
RET_GBP	11.141	19.629	64.135	5.094	35.865
RET_JPY	4.264	10.400	5.533	79.803	20.197
Contribution TO others	26.545	42.998	36.504	17.265	123.312
Contribution including own	97.528	104.766	100.639	97.067	TCI
Net spillovers	-2.472	4.766	0.639	-2.933	30.828
Panel B: Pre-COVID-19 (VAR order 8 lags, h=30, 408 rolling window)					
RET_CAD	81.293	8.930	6.996	2.781	18.707
RET_EURO	7.915	68.420	16.235	7.430	31.580
RET_GBP	6.517	17.325	72.749	3.410	27.251
RET_JPY	3.183	8.674	2.918	85.226	14.774
Contribution TO others	17.615	34.929	26.149	13.620	92.313
Contribution including own	98.907	103.349	98.897	98.846	TCI
Net spillovers	-1.093	3.349	-1.103	-1.154	23.078
Panel C: COVID-19 (VAR order 8 lags, h=30, 408 rolling window)					
RET_CAD	62.768	15.777	16.611	4.844	37.232
RET_EURO	13.410	56.380	20.695	9.515	43.620
RET_GBP	15.078	21.214	57.172	6.536	42.828
RET_JPY	5.261	12.230	7.989	74.520	25.480
Contribution TO others	33.749	49.221	45.296	20.894	149.160
Contribution including own	96.517	105.601	102.468	95.414	TCI
Net spillovers	-3.483	5.601	2.468	-4.586	37.290

overall strength of exchange rates in explaining their own movements strengthened in the COVID-19 period. The candidates for robustness tests are obvious when the theme is forecasting. They are the choice of lag length, the forecasting horizon, and the rolling window size. We tackle these three issues and report robustness test results in Tables 3–5.

We start with Table 3 and conclude that when we employ a higher order VAR—that is, when we double the VAR lag length from 4 to 8, the conclusion not only holds but becomes slightly stronger. The total spillover index increases from 29.1% (pre-COVID-19) to 40.3% (COVID-19). Own shocks in the COVID-19 sample explain between 54.8% (EURO) to 69.3% (Yen) of own exchange rate movements. Expanding the size of the estimation window provides equally consistent results (see Table 4). When we expand the size of the rolling window from 12 days to 24 days, the effects of own shocks post-COVID improve to between 56.5% (EURO) to 74.7% (Yen), and the total spillover index improves to 37.2% compared to 22.9% (pre-COVID-19).

The final robustness test is about increasing the forecasting horizon from 10 hours to 30 hours. When done, as results in Table 5 demonstrate, the total spillover index remains highest during COVID-19 (37.3%) compared to 23.1% in the pre-COVID-19 period. Importance of own shocks remains consistent as in previous models and in the COVID-19 sample the effect of shocks are in the 56.4% (EURO) to 74.5% (Yen) range. Total contribution of exchange rate shocks to other exchange rates improves from 92.3% in the pre-COVID-19 period to 149.2% in the COVID-19 period.

In summary, then, when we experiment with the shock spillover analysis and the importance of exchange rate shocks in explaining exchange rates forecast error variance by increasing the (a) VAR lag length, (b) expanding window size, and (c) the forecasting horizon, the importance of exchange rates only becomes stronger. We, therefore, conclude that our hypothesis that exchange rate shocks explain the bulk of the exchange rates over the COVID-19 sample remains insensitive to modeling choices. And, while the values of own shocks have declined they still cater for over half to three quarters of the exchange rate variation.

4. Concluding remarks

This paper is motivated by the need to understand the dynamics of exchange rates from their ability to forecast the future path of exchange rates. The fact that exchange rate shocks themselves are relevant in forecasting exchange rates more powerfully than non-exchange rate variables has become a central part of the debate in exchange rate economics. We contribute to this debate by showing that the importance of exchange rate shocks in explaining other exchange rates increased in the COVID-19 sample period compared to the pre-COVID-19 period. Our analysis shows that even own exchange rate shocks explained between 55% to 75% of their own exchange rates. It follows that COVID-19 pandemic did not dilute the effect of own exchange rate shocks in explaining exchange rate behavior.

With our findings there is scope for extensions. One area of future research is on studying possible trading strategies considering our findings that own shocks matter significantly to the evolution of exchange rates and that buy-sell signals can be generated when exchange rates are forecasted using the shock spillover index. Identifying successful trading strategies using other methods will be a useful extension.

Author statement

Paresh Kumar Narayan: Conceptualization; data analysis; Methodology; Original Draft; Writing—reviewing and editing

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