Do Jumps and Co-jumps Improve Volatility Forecasting of Oil and Currency Markets?

Fredj Jawadi,[a] *Waël Louhichi,*[b]* *Hachmi Ben Ameur,*[c] *and Zied Ftiti*[d]

ABSTRACT

This paper aims at modeling and forecasting volatility in both oil and USD exchange rate markets using high frequency data. We test whether extreme co-movements (co-jumps) between these markets, as well as intraday unexpected news, help to improve volatility forecasting or not. Accordingly, we propose different extensions of Corsi (2009)'s model by including co-jumps and news. Our analysis provides two interesting findings. First, we find that both markets exhibit significant co-jumps driven by unexpected macroeconomic news. Second, we show that our model outperforms Corsi (2009)'s model and provides more accurate forecasts. In particular, while co-jumps constitute a key variable in forecasting oil price volatility, the unexpected news is relevant to forecasts of USD exchange rate volatility.

Keywords: Volatility, Oil price, U.S. dollar exchange rate, Co-jumps, Forecasts

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I. INTRODUCTION

Since the eighties, the seminal paper of Hamilton (1983) has highlighted the important effect of an oil price shock on the economy. Hamilton (1983) has been the origin of serval studies (Reboredo, 2012) showing that an oil price shock might induce both increases in inflation, unemployment, and trade deficits and a decrease in investment, yielding thus rising uncertainty and triggering an economic recession. Furthermore, as the international oil market trade is conducted in the U.S. dollar, the first channel showing the transmission of oil price shocks on the real economy is the U.S. exchange rate. Accordingly, the linkage between oil price and the U.S. dollar exchange rate is obvious and does matter for investors, hedgers, and policymakers. Indeed, a depreciation of the U.S. dollar raises the purchasing power for oil importing countries and decreases it for oil exporting countries. However, an appreciation of the U.S. currency might induce an oil price increase for oil importing countries, yielding a further oil demand shock that might affect the economies of the oil exporting countries as has occurred since the slowdown of the Chinese economy (the top oil consumer in the world) since the aftermath of the recent global financial crisis.

Interestingly, during the last two decades, the evolution of oil prices and U.S. currency has been characterized by extreme movements. Indeed, from 2001 to 2008 the U.S. dollar fell against main currencies, such as 63.3% against the Euro, and showed similar behavior against most currencies defining the DXY index. However, since 2008, this trend has been reversed, as the U.S. dollar

a University of Lille, France.
b ESSCA School of Management, France.
c INSEEC School of Business & Economics, INSEEC U, France.
d EDC Paris Business School, France.
* Corresponding author. ESSCA School of Management, 55 quai Alphonse Le Gallo 92513 Boulogne-Billancourt, France. Tel.: +33 (0)1 41 86 20 10. Fax: +33 (0)1 41 86 04 86. E-mail: wael.louhichi@essca.fr.

has gained more than 20% of its value in 2018 compared to 2008. In the same time, oil prices have exhibited great volatility, jumping from USD 27 in 2001 to 142 USD in 2008 before falling to 49 USD in 2009, then rising again and exceeding 120 USD in 2011, before another fall to 40 USD in 2018.

To understand better these oil and USD changes and their bilateral effects, it would be interesting to investigate how oil exchange rate volatilities are related. This question appears relevant for investors in identifying investment and speculation opportunities, for hedgers regarding currency hedging, and for policymakers in terms of pricing and currency risk management. Accordingly, we study in this paper the relationship between oil and exchange rate volatilities while focusing on these extreme movements of oil price and the USD and testing whether these extreme movements might be useful in forecasting the volatilities of both markets. More specifically, we aim to analyze whether these extreme movements occur simultaneously in both markets, thereby yielding co-jumps, and also whether these jumps and co-jumps provide helpful information in improving forecasting volatilities of both oil prices and the U.S. dollar.

From a theoretical point of view, five main channels can explain the oil–U.S. dollar relationship. First, through the oil demand and supply channel, when the U.S. dollar appreciates, oil becomes more expensive for countries whose currencies are not pegged to the U.S. dollar. This yields a cut in the real income of these oil-consuming countries, dampening their oil demand, and thereby decreasing oil prices. Thus, a negative relationship is expected between oil prices and the U.S. dollar, and the causality runs from the U.S. dollar to oil prices. The second channel is related to petrodollar recycling, which was earlier documented by Golub (1983) and Krugman (1983a, 1983b), suggesting reverse causality (from oil to the U.S. dollar). Indeed, as noted by Coudert and Mignon (2016), most members of the Organization of the Petroleum Exporting Countries (OPEC) hold their wealth from oil production in U.S. dollars. Thus, an oil price increase implies a further increase in demand for U.S. dollar assets, as these petrodollars boost the USD exchange rate. Third, similar to the second channel and with reference to the literature on the long-run real exchange rate (Clark and McDonald, 1998), oil might affect U.S. currency because changes in oil prices might drive important variations in trade through the Balassa–Samuelson effect.[1] A fourth channel has been observed through the recent financialization of commodities and, in particular, the development of commodity futures since mid-2005, which has yielded an on-going arbitrage between financial assets, foreign exchange (forex) currencies, and commodity contracts (Domanski and Heath, 2007; Greely and Currie, 2008).[2] All things being equal, a fall in U.S. financial asset prices would push investors to prefer commodities, yielding an oil price increase and therefore, this financialization channel also illustrates a negative oil–dollar relationship from the dollar to oil prices. Finally, a fifth indirect channel through U.S. monetary policy might explain the oil–dollar relationship. For example, when the Fed increases the U.S. interest rate, it might lead to lower investment, a higher dollar (through the uncovered interest parity theory), yielding a slowdown in the world economy with lower oil demand, which implies a lower oil price and also supports a negative relationship between oil prices and the U.S. dollar.

From an empirical viewpoint, the related literature does not provide a unanimous conclusion regarding this oil–dollar relationship. Indeed, Hamilton (1983) showed that oil prices affect U.S. macroeconomic variables. Amano and Van Norden (1995) also found oil prices as the main driving factor for the long-term evolution of U.S., German, and Japanese exchange rates. Sadorsky

1. The Balassa–Samuelson effect refers to the difference in relative productivity between tradable and non-tradable sectors.

2. Indeed, investors use commodity futures to hedge and diversify their portfolios in bear markets, as oil is considered a form of hedge against losses in U.S. financial assets (Kat and Oomen, 2007), while oil futures constitute a form of alternative investments, according to Geman and Kharoubi (2008).

(2000), Zhang et al. (2008), Reboredo et al. (2014), and Coudert and Mignon (2016) found a negative relationship between oil and the dollar, while De Truchis and Keddad (2016) found no significant relationship between the dollar and oil in the long run. Huang and Guo (2007) found a weak relationship between the U.S. dollar and oil prices, while Golub (1983), Krugman (1983a), and Bloomberg and Harris (1995) found a positive relationship. Ding and Vo (2012) found a bi-directional transmission between oil and the U.S. currency markets, while more recently, Ferraro et al. (2015) showed that a significant relationship between oil prices and the U.S. dollar is more pronounced in the very short-term. Overall, there is no empirical consensus on the co-evolution of oil prices and the U.S. dollar exchange rate and this heterogeneous result can be explained in many different ways: i. an unstable correlation between oil prices and the U.S. dollar since the 2000s, with this relationship alternating between positive (1975–1979, 1986–1989, and 1996–2002) and negative (1976, 1980–1981, 1991–1993, and 2007–2008); ii. the difference between oil–U.S. dollar relationship in the short and the long terms; and, iii. the presence of jumps and co-jumps in both markets implying more complexity.[3]

Further, in the related literature, this relationship has always been investigated using low-frequency data, without distinguishing between continuous and discontinuous price changes, while the availability of high-frequency data for both markets might help to improve characterization of this relationship and improve forecasting of oil and the U.S. dollar volatility, through taking their abrupt movements into account.[4] This is particularly interesting, as the West Texas Intermediate spot price moved from USD25/barrel in 2000 to USD145 in July 2008 and USD43 in June 2017, with various jumps over the last period. The U.S. dollar exchange rate has also fluctuated significantly over the last years, yielding further evidence of jumps and co-jumps in the oil and U.S. exchange rate markets.

More particularly, the issue of jumps in the oil market was not extensively discussed in the literature except in some recent studies (Askari and Krichene, 2008; Chevallier and Lepo, 2013; Sévi, 2015; Da Fonseca and Ignatieva, 2019). Moreover, these studies focused mostly on the factors impacting oil price jumps. As for jumps in the U.S. dollar market, we also noted only a few studies (El Ouadghiri and Uctum, 2016; Kilic, 2017). Regarding the relationship between jumps across oil and the U.S. dollar markets, Jawadi et al. (2016) investigated the relationships between jumps in the oil price and in the Euro/U.S. dollar and they found further evidence of volatility spillover effect through jumps from the exchange rate to oil price. Li et al. (2017) investigated the conditional spillover effect between oil price jumps and exchange rate on a weekly basis. However, these studies do not allow an analysis of the co-jumps between these two markets, which correspond to a simultaneous occurrence of jumps in both markets.

Unlike the few above studies, we focus on jumps, co-jumps, and even multiple jumps between oil and the U.S. dollar exchange rate markets. *Co-jumps* are simultaneous jumps or abrupt price changes that occur for different assets that simultaneously react to common news. Further, co-jumps might be associated with common information on economic fundamentals (Das and Uppal, 2004; Bollerslev et al., 2008).

3. Jumps are always associated with abrupt price changes induced by the arrival of unexpected news (Maheu and Mccurdy, 2004; Andersen et al., 2007a; Evans, 2011).

4. The use of intraday data has resulted in highly significant progress in modeling volatility through the use of realized volatility, which incorporates a jump component. In fact, the availability of high frequency data has made a real improvement in the modeling and forecasting of volatility based on intraday information. Accordingly, Andersen et al. (2003) assume that multi-variate ARCH and stochastic volatility models suffer from a curse-of-dimensionality problem that constrains their practical application; the authors thus recommend the use of observable realized volatility, which is unbiased and easily computed from intraday returns. Realized volatility is also useful for non-parametric tests based on high-frequency data to detect the discontinuity in prices (jumps).

Accordingly, using intraday data for the West Texas Intermediate (WTI) oil index, the U.S. dollar effective exchange rate, and its main components—the Euro (EUR), Japanese Yen (JPY), British Pound (GBP), Canadian Dollar (CAD), Swiss Franc (CHF), and Swedish Krona (SEK), our paper provides an original intraday study of the oil–U.S. dollar relationship over the period September 1, 2014 to April 30, 2018.[5] Thus, we conduct an original empirical investigation of the instantaneous intraday linkage between oil prices and the U.S. exchange rates that makes several contributions to the related literature. First, we compute intraday jumps for both markets using intraday jump tests proposed by Andersen et al. (2007a) and Lee and Mykland (2008), which enable us to instantaneously identify extreme movement in oil prices and the U.S. exchange rate. Second, we test for instantaneous co-movements between oil prices and the U.S. currency exchange rates by identifying bilateral and multivariate co-jumps,[6] and, in line with the mixture distribution hypothesis (MDH), we test whether considering unanticipated U.S. macroeconomic news headlines recorded by the Bloomberg database as a latent mixed variable could explain the simultaneous co-jumps in the oil and U.S. forex markets. Third, we extend the Corsi (2009) HAR (heterogeneous autoregressive) model by considering jumps and co-jumps to improve the forecasting of oil and USD exchange rate realized volatility (RV).

Our results show that while jumps and co-jumps appear to contribute significantly to improving the forecast of oil price volatility, the unexpected U.S. macroeconomic news is relevant for improving the forecast of U.S. exchange rate volatility. Further, our augmented HAR model outperforms Corsi's (2009) model and provides more accurate volatility forecasts. This finding suggests an active relationship from the exchange rate to the oil market in line with the first channel noted earlier, in which the exchange rate drives the oil market, suggesting that investors should keep a close watch on own U.S. dollar exchange rate jumps, co-jumps, and on unexpected U.S. macroeconomic news to improve forecasting of oil and U.S. dollar volatilities. Accordingly, our paper completes the new strand of literature (Jawadi et al., 2016 and Li et al., 2017) both while analyzing the relationship between oil and the U.S. dollar exchange rate through their bivariate and multivariate jumps and while using this information to propose a new empirical specification to improve forecasting of their respective volatilities.

The remainder of this paper is organized onto five sections. Section 2 is centered on the measurement and analysis of intraday jumps in oil and currency markets. Section 3 tests bivariate and multivariate co-jumps and explains their sources through unexpected news in both markets. Forecasting oil and currency volatilities using news, jumps, and co-jump information is the focus of section 4. Section 5 concludes.

II. MEASURING JUMPS IN THE OIL AND EXCHANGE RATE MARKETS

A. The Data

Our data include two main variables: the WTI (West Texas Intermediate) oil price[7] and the effective U.S. dollar exchange rate (noted hereafter as the DXY[8] index). The DXY index measures

5. While the selection of the sample is constrained by data availability, the use of both aggregated (effective exchange rate) and disaggregated (individual exchange rate) data for the U.S. dollar over this recent period enables us to better investigate the properties of the oil–U.S. dollar exchange rate relationship.

6. To our knowledge, this is the first study that focuses on multivariate co-jumps for the oil and the U.S. currency markets.

7. It is possible to use other proxies for oil prices (i.e., Brent), but we prefer to use the WTI as it a common benchmark when considering the oil price and the U.S. economy relationship.

8. The fact that the oil is quoted in the U.S. dollar for the international trading leads to the investigation of the intraday relationship between the oil market and the DXY index as a global indicator of the exchange of the U.S. dollar against the

the U.S. dollar exchange rate against a panel of currencies. In particular, the DXY index provides the value of the U.S. dollar relative to a basket of foreign currencies chosen based on trade partnerships. The DXY is computed based on the weighted geometric mean of the dollar's value relative to the six following selected currencies: the Euro (EUR), Japanese Yen (JPY), Pound Sterling (GBP), Canadian Dollar (CAD), Swedish Krona (SEK), and Swiss Franc (CHF), weighted at 57.6%, 13.6%, 11.9%, 9.1%, 4.2%, and 3.6%, respectively. The DXY index, which began in 1973 with a value of 100, has the advantage of being quoted intradaily and commonly disseminated in the media to comment on the dynamic fluctuations of the U.S. dollar. The use of the aggregated DXY index allows us to check whether there is a general trend that may be identified with reference to all the foreign exchange markets included in this index, which remains highly commented upon by the media toward investors. However, the DXY refers to an aggregate measure of the U.S. exchange rate, which might be a source of bias when investigating the oil-exchange rate relationship. To limit this bias, and be consistent with Barnett (1980, 2012), we also consider a sample of disaggregated data while considering the individual exchange currency market data, and in particular, the DXY index's six exchange rate series. This is particularly interesting as Bollerslev et al. (2008) suggest that the presence of jumps is more pronounced when considering individual exchange currency market data (disaggregated data). The intraday data under consideration are obtained from the Bloomberg database and cover the period from September 1, 2014 to April 30, 2018. This sample has the advantage of including the most recent data and covering the most recent changes in oil prices. Using this data, we compute the 5-minute logarithmic price difference for each series to compute the intraday returns series.

B. Intraday Univariate Jump Tests

In the related financial literature, jumps might be identified in terms of daily frequency with daily jump tests (Barndorff-Nielsen et al., 2006; Aït-Sahalia and Jacod, 2009; Jiang and Oomen, 2008), or by accounting for the number of jumps per day with an intraday jump test (Andersen et al., 2007b). Our approach in this paper identifies intraday jumps rather than detects trading days that contain jumps via daily jump tests. Accordingly, we use an intraday jump test that detects the number and exact timing of jumps within the trading day and allows us to capture more information about the intraday movements across oil prices and U.S. exchange rates. Hence, we rely hereafter on the intraday jump tests of Andersen et al. (2007b) and Lee and Mykland (2008) in testing for and identifying intraday jumps. These tests are recommended by Hanousek et al. (2012) because they minimize the false negative probability in the Monte-Carlo simulation among fourteen price-jump indicators. Both tests examine the null hypothesis of continuity across the price dynamics against the alternative hypothesis of intraday jumps. An *intraday variation* is defined as a jump based on the statistic $\mathcal{L}(\mathrm{i})$ defined in equation (1) in appendix A. In the first step of the test, we estimate $\mathcal{L}(\mathrm{i})$, which is the log returns standardized by the realized bipower variation over a given window size. The second step consists in determining the critical value based on the Gumbel distribution. Then, in the last step, we compare the statistic $\mathcal{L}(\mathrm{i})$ standardized as max $(\mathcal{L}(\mathrm{i}))$ with the critical value based on the Gumbel distribution. Finally, the intensity of a significant intraday jump is determined according to the corresponding 5-minute returns.

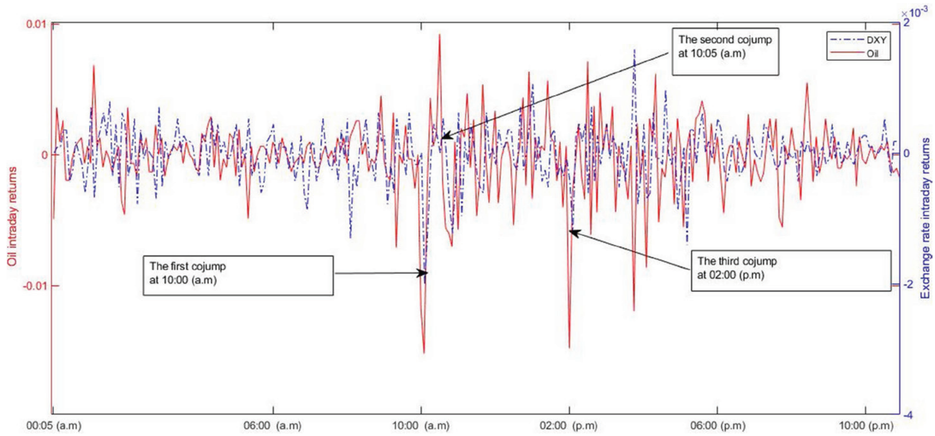
These tests are applied to check for the presence of intraday jumps in the currency and oil markets. Interestingly, intraday jumps always characterize and appear simultaneously in both markets, yielding further evidence of co-jumps. To illustrate better the potential co-jumps between

main currencies.

the oil and U.S. exchange rate markets, in Figure 1, we plot jumps for both markets for February 16, 2016.[9] Figure 1 and our intraday jump tests confirm the detection of three jumps occurring simultaneously in the oil and exchange rate markets at 10:00 a.m., 10:15 a.m., and 2:00 p.m. This preliminary result suggests significant co-movement between oil and U.S. exchange rates and supports the hypothesis of oil–U.S. dollar exchange rate spillovers discussed earlier through different channels (the oil demand and supply channel, the commodity financialization channel, petrodollar recycling, and trade effect).

Next, we apply the intraday tests and compute intraday jumps in both markets. To provide an overview of the data, Table 1 summarizes the main descriptive statistics for 5-minute intraday jumps computed using the Lee and Mykland (2008) test[10] and shows several interesting results.

Figure 1: The intraday oil and DXY exchange rate returns on February 16th, 2016



First, both the oil price and U.S. exchange rate series show an important number of intraday jumps, suggesting further evidence of extreme volatility in these markets. The DXY index exhibits the lowest number of jumps, which might be explained by the use of aggregated data (Aghababa and Barnett, 2016). This result is not unexpected, as jumps for the DXY are detected only when many of its individual components jump simultaneously (Bollerslev et al., 2008; Aït-Sahalia and Jacod, 2012). Second, when considering disaggregated data, the number of jumps and their intensities are more relevant but vary with the U.S. exchange rate series. Indeed, the USD/EUR, USD/CAD, and USD/CHF exchange rates show the highest numbers of jumps, while the USD/JPY has the lowest number of jumps but exhibits the highest value in terms of average jump intensity. Third, the oil market (WTI) shows the highest number of jumps and, on average, the highest intensity compared to U.S. currency rates, which is in line with the recent evolution of oil prices.

C. Modeling the relationship between intraday jumps in oil and U.S. exchange rate markets

To specify a potential contemporaneous relationship between jumps in the oil and U.S. exchange rate markets, and to test whether the occurrence of a jump at time (t) in one market is

9. This date corresponds to the announcement of an agreement between Saudi Arabia and Russia to maintain stable oil production.

10. Using the two intraday jump tests, we obtain similar results. To save space, we report only the results based on Lee and Mykland's (2008) test. The results of Andersen et al.'s (2007b) test are available upon request.

Table 1: Main descriptive statistics for 5-minute intraday jump intensity

	DXY	USD/EUR	USD/GBP	USD/JPY	USD/CAD	USD/CHF	USD/SEK	WTI
Mean	0.0014	0.0016	0.0016	0.0017	0.0015	0.0015	0.0018	0.0059
Min	0.0004	0.0004	0.0004	0.0003	0.0004	0.0005	0.0006	0.0016
Max	0.0084	0.0129	0.0427	0.0292	0.0086	0.0085	0.0118	0.0363
STD	0.0009	0.0011	0.0013	0.0014	0.0009	0.0008	0.0010	0.0031
N	1318	2010	1926	1868	1992	1988	1927	2601
Prop (%)	0.854	1.303	1.248	1.211	1.291	1.289	1.249	1.686

Note: Min, Max, and STD denote the minimum, maximum, and standard deviation values, respectively. *N* denotes the number of 5-minute intraday jumps. Prop (%) is the proportion of jumps compared to the total number of observations.

related to a jump in another market, we run a Tobit estimation (Equation (1)). In fact, as jump is a discontinuous variable that takes the value of the intensity if a jump is detected and zero otherwise, we use a Tobit specification, which is suitable when the time series is composed of positive values, with a pileup at the value zero.[11] We also augment this regression with the oil trading volume on the right-hand side of the equation, in line with the MDH as in Giot et al. (2010), to capture the trading/news effect on jumps.

$$J_{o,t} = \alpha_1 + \alpha_2 J_{i,t} + \alpha_3 Log\left(vol_{o,t}\right) + \varepsilon_t \tag{1}$$

where $J_{o,t}$ (resp. $J_{i,t}$) denotes the jump intensity of oil (resp. U.S. exchange rate i) during the 5-minute interval t for $i=$DXY, USD/EUR, USD/GBP, USD/JPY, USD/CAD, USD/CHF, and USD/SEK. $Log(vol_{o,t})$ denotes the 5-minute logarithm of oil trading volume.

We estimate model (9) and report the main results in Table 2. Overall, our results show a positive contemporaneous relationship between oil price and the U.S. exchange rate intraday jumps; the highest effect is with the USD/CAD exchange rate.[12] These findings point to further bilateral interactions between oil prices and the U.S. dollar, which is not unexpected, as global oil prices are expressed in U.S. dollars and an oil price change might *a priori* affect U.S. currency and vice versa through different channels. Next, we explicitly check these findings using co-jump tests and investigate the potential drivers of these co-jumps.

Table 2: Results of intraday jump Tobit model (Eq. 1)

	DXY	USD/EUR	USD/JPY	USD/GBP	USD/CAD	USD/CHF	USD/SEK
Constant	-0.063^{***}	-0.069^{***}	-0.0682^{***}	-0.068^{***}	-0.059^{***}	-0.062^{***}	-0.062^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)
$j_{i,t}$	3.608^{***}	2.314^{***}	2.105^{***}	1.720^{***}	6.507^{***}	3.117^{***}	2.681^{***}
	(0.000)	(0.010)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
$Logvol_{o,t}$	0.004^{***}	0.006^{***}	0.005^{***}	0.005^{***}	0.004^{***}	0.004^{***}	0.003^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	667.433	822.85	818.64	935.95	776.83	974.04	974.66

Note: Values in (.) denote p-values of t-ratios with standard errors robust for autocorrelation and heteroscedasticity through Newey and West's approach. *** denotes statistical significance at the 1% level.

11. We also test the robustness of our results by using a Poisson regression. The results reported in appendix C confirm the robustness of our findings. We thank an anonymous referee for this suggestion.

12. We also regressed intraday jumps of U.S. exchange rates on oil jumps and found evidence of a contemporaneous relationship. To save space, we do not report these results, but they are available upon request.

III. DOES INTRADAY INFORMATION FLOW GENERATE OIL AND U.S. EXCHANGE RATE CO-JUMPS?

A. Bivariate and Multivariate Co-jump Tests

While the above tests examine univariate intraday jumps (taking into account only univariate jumps occurring independently in each market), we extend our analysis while testing whether the interaction between the U.S. exchange markets and the oil market varies simultaneously from one currency market to another one (yielding a bivariate analysis of jumps between each currency market and oil), or whether this interaction is common to all currency markets (a multivariate analysis of jumps is then carried out). From an empirical point of view, on the one hand, we identify the co-jumps between each currency market and the oil market (bivariate jumps), and on the other hand, we test for the occurrence of co-jumps between the oil market and all currencies included in the DXY (multi-jumps).[13] We test in this way for simultaneous jumps with the well-known Bollerslev et al.'s (2008) co-jump test. Furthermore, we check the robustness of our results using the recent test proposed by Caporin et al. (2017). First, Bollerslev et al. (2008) compute the mean cross product of the prices log returns (equation 9 in appendix B) for the intraday returns. Then, the intraday co-jumps are identified by comparing the studentized statistic previously estimated to the appropriate critical value determined from the standard normal distribution.

We run Bollerslev et al.'s (2008) co-jump test to check for the presence of common intraday jumps across the oil and U.S. exchange rate markets. We then report the main related results and co-jump statistics in Table 3, with two interesting results.[14] First, the co-jump hypothesis between oil and U.S. exchange rates is statistically relevant. In particular, while the USD/JPY on average shows the lowest co-jump intensity, the highest mean co-jump intensity is found for the oil and USD/SEK exchange markets. This result might be explained by the fact that although Sweden has a high level of trading in refined petroleum with the US, this relationship is expected to be affected by the on-going Swedish national program to make Sweden an oil-free society. For the USD/EUR and USD/GBP market, the lowest number of co-jumps might be explained by the fact that trade between the U.S. and Europe is not primarily based on oil products. The oil market jumps 228 times simultaneously with all six exchange rate markets. Second, Table 4 presents the ratios of currency market jumps for bivariate and multivariate jumps. The ratios of bivariate jumps, which are computed as the number of co-jumps divided by the number of jumps, indicate that 36.2% of U.S. DXY jumps occurred at the same time as those in the WTI oil index. In addition, on average, 26% of jumps that occurred in U.S. dollar exchange rates coincide with jumps detected in the oil market. The ratios of multi-jumps, which are computed as the number of multivariate co-jumps (occurring simultaneously in the six exchange markets) divided by the number of bivariate co-jumps, show that almost 50% of co-jumps occur in all currency markets at the same time.

The finding of common co-jumps is of great interest in particular for both policymakers and investors who might expect further jumps in the U.S. dollar exchange rates while keeping a close watch on the evolution of oil price. At the same time, oil demand and supply might be adjusted when considering further changes in U.S. currency purchasing parity, which is affected by changes in oil prices. After identifying these jumps and co-jumps across oil and U.S. currency markets, a crucial next step is to explain the drivers of the co-jumps.

13. To our knowledge, this is the first study that provides a multivariate analysis of co-jumps between the oil and currency markets.

14. The results of Caporin et al.'s (2017) test provide similar results. They are not included to save space but are available upon request.

Table 3: Main descriptive statistics of intraday 5-minute co-jumps

	Co-jumps Oil– DXY	Co-jumps Oil–USD/ EUR	Co-jumps Oil–USD/ GBP	Co-jumps Oil–USD/ JPY	Co-jumps Oil–USD/ CAD	Co-jumps Oil–USD/ CHF	Co-jumps Oil–USD/ SEK	Co-jumps Oil– All markets
Mean (10^{-6})	0.556	0.542	0.583	0.5390	0.828	0.737	1.236	0.588
Min (10^{-8})	0.428	0.866	2.190	0.420	1.160	1.420	0.534	0.987
Max (10^{-5})	1.517	1.450	2.230	1.290	2.370	2.070	6.840	2.314
STD (10^{-6})	1.587	1.334	1.662	1.332	1.961	1.970	4.412	1.884
Numbers	477	447	432	493	570	496	616	228
Prop (%)	0.309	0.290	0.280	0.320	0.369	0.322	0.399	0.1478

Note: Min, Max, and STD denote THE minimum, maximum, and standard deviation values, respectively. *N* represents the number of five-minute intraday co-jumps. Prop (%) is the proportion of Co-jumps compared to the total number of observations.

Table 4: Frequency of co-jumps

	DXY	*USD/EUR*	*USD/GBP*	*USD/JPY*	*USD/CAD*	*USD/CHF*	*USD/SEK*
Numbers of jumps	1318	2010	1926	1868	1992	1988	1927
Numbers of co-jumps	477	447	432	493	570	496	616
$\boldsymbol{Frequency\left(\frac{cojumps}{jumps}\right)}$	0.362	0.222	0.224	0.264	0.286	0.250	0.320
Number of multi-jumps	—			228			
$\boldsymbol{Frequency\left(\frac{multijumps}{cojumps}\right)}$	—	0.510	0.527	0.462	0.400	0.460	0.370

B. Modeling the Relationship between Co-jumps and News Arrival

Given that both oil and the U.S. dollar might affect the real economy as whole, a rational assumption is that news might affect both oil price and the U.S. currency market, thereby yielding common jumps for these two markets. We empirically test this assumption by investigating a further connection between information flow arrival and co-jumps that occurred simultaneously in these two markets. A focus on the news may better explain the sources of co-jumps.

From a theoretical view, the news effect is supported by the information efficiency theory and the mixture distribution hypothesis (MDH). From an empirical view, the relationship between news announcements and price volatility is supported by Ederington and Lee (1993), Berry and Howe (1994), Kalev et al. (2004), and Bauwens et al. (2005), among others, while Das (2002), Johannes (2004), Huang and Tauchen (2005), Andersen et al. (2007a), and Evans (2011) validate the linkage between public information and the jump part of volatility. Unlike these studies, we measure the co-jump probability for the oil and U.S. currency markets and specify the co-jump drivers.

In practice, and in line with Ederington and Lee (1993), Bauwens et al. (2005), and Rosa (2011), we define the information arrival proxy using U.S. macroeconomic news headlines (items) that are recorded by the Bloomberg database[15] and we test how far this news drives co-jumps on the oil and U.S. exchange rate markets. In particular, as in Brooks et al. (2003) and Christie-David et

15. The U.S. macroeconomic news released through the Bloomberg screens include the Employment Report, estimates and revisions to Gross Domestic Product (GDP), the Producer Price Index (PPI), Whole Sales, Current account deficit, Leading Indicators, etc.

al. (2003), we focus only on the unpredictable part of announcements and measure the information flow by the number of unanticipated U.S. macroeconomic news items. To separate the anticipated and the unanticipated portions of news announcements, we compare the realized and the expected content before news is released. We retain only macroeconomic news that contains a "surprise" effect—i.e., news for which the realization is different from the expectation.[16] Finally, we note that a large amount of U.S. macroeconomic news is generally released at 13:30 GMT and 15:00 GMT.

Econometrically, we regress co-jumps on the number of unexpected macroeconomic news items recorded through Bloomberg terminals. We conduct a logistic analysis and we estimate the following logit model to test whether information flow increases co-jump probability:

$$Coj_{t,j} = \beta_0 + \beta_1 News + \varepsilon_t \tag{2}$$

where the variable *coj* takes the value 1 if there is a co-jump between both markets and 0 otherwise.

From Equation (2), if the coefficient β_1 is statistically significant, we conclude that co-jumps between the oil market and exchange rate market are led by information flow arrival, especially unexpected macroeconomic news.

We also regress the intensity of the co-jump (*mcp* from Eq. 9 in the appendix B) between both markets on the number of news items as:

$$|mcp_{t,j}| = \theta_0 + \theta_1 News + \zeta_t \tag{3}$$

Because multiple channels of dependency exist, the relationship between oil and currency markets is quite complex, and there is no consensus on whether the direction of this relationship is positive or negative. For this reason, we consider the absolute value of co-jumps in order to consider co-jumps with opposite directions of returns.[17] We report the main results of the estimation of Eq. (2) and Eq. (3) in Tables 5 and 6 and point to a positive relationship between the number of unexpected macroeconomic news items and co-jump probability. Further, from Table 6, the news releases enter with a positive and statistically significant effect on co-jump intensity, suggesting that unexpected information might affect both markets via, for example, the demand and supply channel discussed earlier. This result also indicates that co-jumps appear to be subordinated to similar news, which is in line with the MDH hypothesis.

Table 5: Estimate results of the logit model (co-jump probability and unexpected macroeconomic news)

	Coj_OIL-DXY	Coj_OIL-USD/EUR	Coj_OIL-USD/GBP	Coj_OIL-USD/JPY	Coj_OIL-USD/CAD	Coj_OIL-USD/CHF	Coj_OIL-USD/SEK	Coj_OIL- All markets
β_0	0.861***	0.1171	0.174	0.364***	0.712***	0.109	0.959***	1.266***
Khi2 Wald	17.963	0.821	1.696	7.529	20.094	0.530	31.104	55.982
Pr>Khi2	(0.000)	(0.364)	(0.192)	(0.006)	(0.000)	(0.466)	(0.000)	(0.000)
β_1	0.039*	0.033**	0.018**	0.034**	0.036**	0.061***	0.048**	0.037**
Khi2 Wald	3.103	4.702	5.133	4.773	3.888	11.808	5.372	4.140
Pr>Khi2	(0.078)	(0.030)	(0.023)	(0.028)	(0.048)	(0.000)	(0.020)	(0.042)

Note: Values in (.) provide p-values of the Khi2 Wald test. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

16. The expected values are available on the Bloomberg database.

17. To test the robustness of our results, we considered only positive co-jumps (with same direction of returns) and we found similar results. To save space, we do not report these results in the paper, but they are available upon request.

Table 6: Estimate results of the OLS model (co-jump intensity and unexpected macroeconomic news)

	Coj_OIL-DXY	Coj_OIL-USD/EUR	Coj_OIL-USD/GBP	Coj_OIL-USD/JPY	Coj_OIL-USD/CAD	Coj_OIL-USD/CHF	Coj_OIL-USD/SEK	Coj_OIL-All markets
θ_0 **(10^{-7})**	1.699	0.968	1.223	2.118***	4.424***	2.603**	4.773*	0.216***
	(0.152)	(0.146)	(0.153)	(0.002)	(0.000)	(0.020)	(0.083)	(0.000)
θ_0 **(10^{-7})**	0.308***	0.317***	0.294***	0.190***	0.214*	0.278**	0.668**	0.743**
	(0.010)	(0.000)	(0.002)	(0.010)	(0.098)	(0.022)	(0.025)	(0.041)
F	6.690	17.350	9.310	6.700	2.740	5.270	5.02	4.19
	(0.010)	(0.000)	(0.002)	(0.010)	(0.098)	(0.022)	(0.025)	(0.041)
R^2	0.12	0.20	0.11	0.07	0.04	0.09	0.08	0.05

Note: Values in (.) provide p-values of the t-ratio test with Newey–West corrected standard errors. F denotes the Fisher global significance test and R^2 the adjusted R-squared. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

In the following section, we propose to check for the contribution of our intraday indicators (news releases, jumps and co-jumps) to improve the volatility forecasts of oil prices and USD exchange rates.

IV. MODELING AND FORECASTING ENERGY FUTURES VOLATILITY WITH JUMPS, CO-JUMPS, AND NEWS

A. The Econometric Specification

While specifying the volatility dynamics, we test whether univariate, bivariate, and multivariate jumps and co-jumps might improve volatility modeling and forecasting. We do not follow studies in the related literature that rely on conventional time-series approaches, such as generalized autoregressive conditional heteroscedasticity models (Ding et al., 1993; Baillie et al., 1996; Ding and Granger, 1996; Andersen and Bollerslev, 1997). Instead, we use the realized volatility measure, as it represents observed market volatility, includes more information, and thus, implies fewer measurement errors, (Andersen and Bollerslev, 1998; Corsi, 2009; Maheu and McCurdy, 2011; Ftiti et al., 2016).[18] In particular, we rely on the heterogeneous autoregressive model of Corsi (2009) to forecast realized volatility, hereafter HAR-RV. This framework is particularly appropriate as it relaxes the strong hypothesis of homogenous investors in favor of heterogeneous investors, enabling us to consider high frequency trading information.

Our exercise in forecasting volatility is based on the intraday sum of square returns. This realized measure of volatility has the advantage of considering all information concerning intraday price variations. Following the approach of Corsi (2009), we propose to forecast price changes in the medium and long horizons by using this realized volatility as a basis. As investors are heterogeneous and have different investment horizons (short, medium, and long), it is interesting to test the predictability of price variations from intraday timescale to months. The obtained results have several implications, especially in terms of market efficiency. If investors react immediately to news, the market is efficient, and it is not possible to predict long-term price changes from the intraday

18. Conventional time-series models are always criticized because they assume the hypothesis of homogenous investors, while financial markets include distinct traders (chartists, fundamentalists, noise traders). Further, these models cannot reproduce some stylized facts of financial volatility (Teräsvirta and Zhao, 2011).

data. However, under the hypothesis of the heterogeneity of investors, information flow might be a source of differential interpretations among investors. In this case, judgments might sometimes persist solely to be integrated into prices. Also, the price reaction to an event can both draw media attention and provoke further news announcements and changes in investors' sentiment on many different horizons, thereby creating a "ripple effect." For these reasons, we propose hereafter to investigate the predictability of long-term returns from intraday data and to test the market efficiency hypothesis for different timescales.

Formally, the original HAR-RV model proposed by Corsi (2009) is characterized by an autoregressive structure in realized volatility for which daily $\left(RV_t^{(d)}\right)$, weekly $\left(RV_t^{(w)}\right)$, and monthly $\left(RV_t^{(m)}\right)$ enter as regressors as:

$$RV^{(d)}{}_{t+1d} = \varphi_0 + \varphi^{(d)} RV_t^{(d)} + \varphi^{(w)} RV_t^{(w)} + \varphi^{(m)} RV_t^{(m)} + \varepsilon_{t+1d} \tag{4}$$

where $RV^{(d)}{}_{t+1d}$ is the ex post volatility estimate. The notations d, w, and m indicate the cascade daily, weekly, and monthly horizons, respectively. $RV_t^{(d)}$, $RV_t^{(w)}$, and $RV_t^{(m)}$ denote daily, weekly, and monthly RV at time t. ε_{t+1d} is an error term.

The HAR-RV can be rewritten as:

$$RV_{i,t+1,t+h} = \varphi_{i,\,0} + \varphi_{i,1} RV_{i,t} + \varphi_{i,5} RV_{i,t-1,t-4} + \varphi_{i,22} RV_{i,t-5,t-21} + \varepsilon_{i,t+1} \tag{5}$$

where i = DXY, USD/EUR, USD/JPY, USD/GPB, USD/CAD, USD/CHF, USD/SEK, and WTI. $[t+1, t+h]$ denotes the period of analysis and h denotes the forecasting horizon, while $\varepsilon_{i,t+1}$ denotes the forecasting error term for market (i) at time $(t+1)$.

Next, we propose four alternative extensions of Corsi's (2009) model. The first extension augments Corsi's (2009) model with jumps, yielding the following HAR-RV-J model:

$$RV_{i,t+1,t+h} = \varphi_{i,\,0} + \varphi_{i,1} RV_{i,t} + \varphi_{i,5} RV_{i,t-1,t-4} + \varphi_{i,22} RV_{i,t-5,t-21} + \beta_{i,NJ}\, NJ_{i,t} + \varepsilon_{i,t+1} \tag{6}$$

where $NJ_{i,t}$ is the number of intraday jumps that occurred in market i on day t and is computed as the sum of the intraday jumps that occurred on day t.

The second extension model considers bivariate co-jumps between oil and exchange markets, and provides the following HAR-RV-BJ model:

$$RV_{i,t+1,t+h} = \varphi_{i,\,0} + \varphi_{i,1} RV_{i,t} + \varphi_{i,5} RV_{i,t-1,t-4} + \varphi_{i,22} RV_{i,t-5,t-21} + \beta_{i,BJ}\, BJ_{i^*,t} + \varepsilon_{i,t+1} \tag{7}$$

Where $i^* = DXY, USD/EUR, USD/JPY, USD/GPB, USD/CAD, USD/CHF, USD/SEK$. $BJ_{i^*,t}$ is the bivariate jump between exchange rate (i^*) and the oil market, computed as the number of intraday co-jumps that occurred between U.S. currency markets on day t. For the oil market, the bivariate jump is computed with the DXY index.

In the third extension, we consider multivariate co-jumps and define the following HAR-RV-MJ model:

$$RV_{i,t+1,t+h} = \varphi_{i,\,0} + \varphi_{i,1} RV_{i,t} + \varphi_{i,5} RV_{i,t-1,t-4} + \varphi_{i,22} RV_{i,t-5,t-21} + \beta_{i,MJ}\, MJ_t + \varepsilon_{i,t+1} \tag{8}$$

where $MJ_{i,t}$ is the number of intraday jumps that occurred simultaneously in the oil market and the six currency markets (multivariate co-jumps).

Finally, we consider the fourth specification where we consider the effect of unexpected intraday U.S. macroeconomic news:

$$RV_{i,t+1,t+h} = \varphi_{i,\,0} + \varphi_{i,1} RV_t + \varphi_{i,5} RV_{i,t-1,t-4} + \varphi_{i,22} RV_{i,t-5,t-21} + \beta_{i,N}\, N_t + \varepsilon_{i,t+1} \tag{9}$$

where N_t denotes the number of unexpected intraday U.S. macroeconomic news items.

B. Estimating RV Dynamics with Intraday Information

We estimate and compare the original HAR-RV model and our four extensions. The estimation is realized through a weighted linear squares regression with a fitted value of an OLS regression, after correcting standard errors from further heteroscedasticity in the data using the Eicker–White approach. We report the main results in Table 7. We note two interesting results in Table 7. On the one hand, the oil and U.S. currency markets exhibit different volatility dynamics. In fact, for the oil market, the coefficients for univariate jumps, bivariate jumps, and multivariate jumps are positive and significant for models 2, 3, and 4, respectively, while model 3 (HAR-RV-BJ), which includes bivariate co-jumps between the oil market and the U.S. exchange rate market, shows the highest explanatory power with an adjusted R squared reaching 71.67%. This finding suggests that bivariate co-jumps constitute a significant driver of oil volatility.

This finding is interesting, as we confirm that oil volatility reacts instantaneously to the extreme co-movement between the oil and U.S. currency markets. In other words, the common information driving the extreme movement in both markets is reflected in the dynamic of the oil volatility. This finding is useful for investors and policymakers. For investors, this result has an interesting implication for investors' portfolio allocation and their strategy of portfolio diversification, whereas for policymakers, this finding is useful in better regulating the pricing in these markets.

On the other hand, unlike the oil market, the USD exchange rates appear more sensitive to news. The information flow variable has a significant effect at the 1% level for all currency markets, suggesting that the U.S. exchange rate markets react more to the arrival of unexpected U.S. macroeconomic news than the oil market. In other words, unexpected U.S. macroeconomic news is reflected instantaneously in the USD exchange rates. However, the adjusted squared R support the model that accounts for the jump, suggesting that the information driving the jump in U.S. currency rate is more informative and instantaneously transmitted to the U.S. currency market.

Overall, our findings suggest that while co-jumps should be considered when modeling oil volatility, unexpected news should play a key role when modeling U.S. exchange rate volatility[19]. Thus, in relation to the channels discussed earlier regarding the oil–USD relationship, it appears that, at least in the sample, co-jumps between oil and the USD drive the oil RV. We check this assumption on out of sample data through a forecasting analysis.

C. Forecasting Realized Volatility Based on Intraday Information

One of the main goals of the paper is to test the predictability of price variations from intraday data. Accordingly, we proposed the construction of some indicators (e.g., news releases, jumps, co-jumps) to help investors to forecast future price variations and act ahead of other traders. Our forecasting results might help investors to balance and optimize their investment strategies.

To identify which information drives future oil and U.S. dollar exchange rate volatilities, we compute out-of-sample forecasts using the five abovementioned volatility models and compare

19. This result is interesting and might be justified by the fact that we consider only U.S. macro news, which is likely to be very important for the USD. Further, given that the U.S. has lesser need to import oil, perhaps it is not surprising that oil volatility is less sensitive to the U.S. macroeconomy in this sample. This might also help explain the lack of importance of co-jumps for USD volatility. The lower sensitivity of the U.S. economy to oil would suggest that USD volatility is less affected by co-jumps with oil, whereas oil volatility would be influenced by co-jumps with the USD.

Table 7: Estimates of the RV-HAR model and its extensions (Eqs. 5–9)

	DXY					Oil				
Model	**HAR-RV**	**HAR-RV-J**	**HAR-RV-BJ**	**HAR-RV-J-MJ**	**HAR-RV-N**	**HAR-RV**	**HAR-RV-J**	**HAR-RV-BJ**	**HAR-RV-J-MJ**	**HAR-RV-N**
$\varphi_0 * 10^{-4}$	0.1305***	-0.0026	0.01174***	1.2134***	0.0084**	0.3706	-1.2558***	0.0808	0.2598	0.5281
	(3.8991)	(-0.6605)	(3.5388)	(3.9474)	(2.3946)	(1.1194)	(-3.4460)	(0.2414)	(0.7670)	(1.5115)
φ_1	0.4010**	0.3920***	0.3988**	0.3964**	0.3999**	0.6553***	0.6665***	0.6549***	0.6536***	0.6557***
	(2.0350)	(2.6085)	(2.0187)	(1.9861)	(2.0272)	(5.3000)	(5.5045)	(5.2977)	(5.3125)	(5.2963)
φ_5	-0.0005	0.0447*	-0.0004	-0.0003	-0.0008	0.1860**	0.1901**	0.1863**	0.1865**	0.1870**
	(-0.1736)	(1.7823)	(-0.1549)	(-0.1208)	(-0.2876)	(2.0632)	(2.1419)	(2.0700)	(2.0786)	(2.0725)
φ_{22}	0.0123	0.0001	0.0116	0.0131	0.0139	0.0825*	0.0780*	0.0824*	0.08169*	0.0810*
	(0.6154)	(0.0587)	(0.5714)	(0.6426)	(0.6829)	(1.9550)	(1.8367)	(1.9346)	(1.9185)	(1.9396)
$\beta_{NJ} * (10^{-6})$		0.7163***					42.3580***			
		(5.1408)					(7.2971)			
$\beta_{BJ} * 10^{-4}$			0.0018					0.3883***		
			(0.9446)					(2.7977)		
$\beta_{MJ} * (10^{-5})$				0.3641					4.6013**	
				(1.4151)					(2.3802)	
$\beta_{NJ} * (10^{-5})$					0.5547***					1.9058
					(4.3203)					(0.7986)
Adjusted R^2	0.1566	0.4346	0.1562	0.1590	0.1684	0.6952	0.7097	0.7167	0.6956	0.6950
	USD/CAD					**USD/CHF**				
$\varphi_0 * 10^{-4}$	0.1066***	-0.0157	0.0955***			0.1942***	0.0781	0.1738***	0.1877***	0.15381***
	(5.4311)	(-0.6259)	(4.9051)			(9.6964)	(0.1777)	(8.7242)	(10.5009)	(6.4526)
φ_1	0.3184***	0.3735***	0.3120***			0.2442***	0.3092***	0.2483***	0.2343***	0.2471***
	(4.9393)	(5.9050)	(4.8757)			(3.2239)	(3.6551)	(3.2981)	(3.0798)	(3.3063)
φ_5	0.2180***	0.2025***	0.2149***			0.0651**	0.0772***	0.0679**	0.0649**	0.0557*
	(3.4896)	(3.9019)	(3.4692)			(2.0367)	(2.8143)	(2.2291)	(2.1235)	(1.8399)
φ_{22}	0.1046***	0.1124***	0.1038***			0.02075	0.0316	0.1088	0.0197	0.0218
	(2.6853)	(3.2511)	(2.7102)			(0.6821)	(1.0250)	(0.6038)	(0.6454)	(0.7049)
$\beta_{NJ} * (10^{-6})$		4.3247***					6.8721***			
		(6.9672)					(4.2854)			
$\beta_{BJ} * 10^{-4}$			0.0196					0.3993*		
			(1.4363)					(1.8764)		
$\beta_{MJ} * (10^{-5})$				0.5651					0.5674*	
				(0.3209)					(1.8830)	
$\beta_{NJ} * (10^{-5})$					0.3810***					0.6384***
					(3.2006)					(4.2285)
Adjusted R^2	0.2140	0.3863	0.2147	0.2176	0.2242	0.0647	0.3019	0.06762	0.0705	0.07816

(continued)

Table 7: Estimates of the RV-HAR model and its extensions (Eqs. 5–9) *(continued)*

	USD/EURO					USD/GBP				
$\varphi_0 * 10^{-4}$	0.2231***	-0.0018	0.2053***	0.2096***	0.1621***	0.3586***	0.2499***	0.2969***	0.3575***	0.2848***
	(11.1148)	(-0.3974)	(11.5802)	(10.9194)	(7.4891)	(8.3465)	(6.5401)	(4.7472)	(6.6460)	(3.0950)
φ_1	0.1795***	0.2376***	0.1752***	0.1735***	0.1832***	0.0429***	0.0481***	0.0435***	0.0427***	0.0458***
	(2.9440)	(3.3154)	(2.9423)	(2.8821)	(3.0524)	(3.0657)	(2.9789)	(2.8693)	(3.2765)	(3.0954)
φ_5	0.0668*	0.0897**	0.0667*	0.0681*	0.0579	0.0432	0.4650	0.0410	0.0433	0.0381
	(1.6783)	(2.3501)	(1.7148)	(1.7458)	(1.5796)	(1.4305)	(1.3539)	(1.1279)	(1.0398)	(1.1996)
φ_{22}	-0.00001	0.0179	-3.2090	-0.0001	0.0014	0.0004	0.00007	-0.0001	0.0003	0.0039
	(-0.0054)	(0.8145)	(-0.1275)	(-0.0632)	(0.0574)	(0.0500)	(0.0830)	(-0.1273)	(0.0411)	(0.4890)
$\beta_{NJ} * (10^{-6})$		0.0082***					4.1147***			
		(4.7641)					(6.2217)			
$\beta_{BJ} * 10^{-4}$			0.0354					0.1070*		
			(1.2690)					(1.7162)		
$\beta_{MJ} * (10^{-5})$				0.5742*					0.4405	
				(1.7146)					(0.0821)	
$\beta_{NJ} * (10^{-5})$					0.8477***					1.0030***
					(4.7796)					(3.4161)
Adjusted R^2	0.0352	0.2555	0.3582	0.0381	0.0476	0.1542	0.1609	0.1596	0.1542	0.1570
	USD/JPY					**USD/SEK**				
$\varphi_0 * 10^{-4}$	0.3445***	0.00697	0.2728***	0.3174***	0.2597***	0.315***	0.0870	0.2930***	0.3143***	0.27674***
	(9.4488)	(0.7918)	(4.6522)	(4.7725)	(4.8917)	(11.2400)	(1.0523)	(8.3009)	(8.1265)	(8.8726)
φ_1	0.1046*	0.1359*	0.1007*	0.1020*	0.1040*	0.1908**	0.2227**	0.1882**	0.1851**	0.1913**
	(1.6752)	(1.6547)	(1.6549)	(1.6849)	(1.6201)	(2.1983)	(2.3349)	(2.1989)	(2.1898)	(2.2359)
φ_5	0.0252	0.0403	0.0278	0.0262	0.0229	0.0354	0.0554*	0.0369	0.0355	0.0317
	(0.9668)	(1.4997)	(1.1059)	(1.0163)	(0.9255)	(1.1244)	(1.6872)	(1.2396)	(1.1891)	(1.0760)
φ_{22}	0.0094	-0.0007	0.0078	0.0106	0.0071	-0.0218	0.0012	-0.0241	-0.0226	-0.0216
	(0.8173)	(-0.3832)	(0.6625)	(0.8976)	(0.6001)	(-1.1356)	(0.0832)	(-1.2026)	(-1.1653)	(-1.1356)
$\beta_{NJ} * (10^{-6})$		10. 8440***					0.0888***			
		(2.5846)					(3.0998)			
$\beta_{BJ} * 10^{-4}$			0.1194**					0.0514*		
			(2.3015)					(1.6994)		
$\beta_{MJ} * (10^{-5})$				1.0227					0.0749*	
				(1.5760)					(1.9272	
$\beta_{NJ} * (10^{-5})$					1.1882***					0.7566***
					(3.5327)					(3.9404)
Adjusted R^2	0.1998	0.2669	0.2032	0.2022	0.2045	0.0350	0.1939	0.03578	0.0387	0.0420

Note: The estimation is realized through a weighted linear squares regression with a fitted value of an OLS regression. The Newey–West (1987) adjusted t-statistics are given in parentheses. NJ, BJ, MJ, and N refer to the number of intraday jumps per day (t), Bivariate intraday jumps per day (t), the number of multivariate jumps per day (t), and the number of the intraday news items per day (t), respectively. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

their forecasting performance. We estimate all candidate models for the period[20] $\left(N_i - h\right)$, and then forecast volatility for horizon h. The h-step dynamic forecasts are calculated for $t = k_i,\ldots,T_i$, where k_i is the forecasting starting date and T_i is the end date of the studied series for market i, where i = DXY, USD/EUR, USD/JPY, USD/GPB, USD/CAD, USD/CHF, USD/SEK, and WTI. Further, as for the HAR-RV model of Corsi (2009), we adopt three forecasting horizons: daily ($h = 1$), weekly (5 days), and monthly (22 days).

The forecasts of the five models are computed for the oil market, the U.S. DXY index, and its six components. To measure the performance of our forecasts, we choose the strand of the tests comparing a large set of competitors instead of those based on the pairwise comparison, as this later might suffer from a data snooping bias (White, 2000). White (2000) highlighted that the selected model based on the pairwise method comparison might be the result of chance (Lehman and Wohlrabe, 2013). In his seminal paper, he challenged the forecasting evaluation issue through highlighting the bias arising from data snooping (data mining) through discussing the negative connotations of data mining; moreover, he highlights the fragility of model selection from masses of data. To overcome this limit, White (2000) proposes a new test known as Reality Check (RC) that allows for a rigorous method of testing the null hypothesis that the best model encountered during specification research has no predictive superior over a benchmark model. This method has the advantage of considering the data snooping that gives a non-biased result, but it suffers from the inclusion of poor and irrelevant candidate models, as highlighted by Hansen (2005). Hansen (2005) proposes rather a modified test of RC, the Superior Predictive Ability (SPA) test, that is stable against irrelevant and poor candidate models. The (SPA) test allows for a simultaneous comparison of M series of forecasts to check whether differences among these forecasting error measures are statistically significant. In particular, the SPA test aims to compare the relative performance of a benchmark model with the performances of its competitors based on a pre-specified loss function. (In this study, we choose the Mean Absolute Errors (noted the MAE) and the Mean Squared Errors (noted the MSE)). The null hypothesis is that the benchmark model is not outperformed by any of the other candidate models, and is defined as:

$$\mathrm{H_0} : \max_{\mathrm{i=1,\ldots,K}} \mathrm{E}\left[\mathrm{d_t}\right] \tag{10}$$

where $\mathrm{d_t} = \left(\mathrm{d_{i,t}}, \ldots, \mathrm{d_{K,t}}\right)'$ is a vector of relative performances. For example, $\mathrm{d_{i,t}} = \mathrm{L_{t,h}^{(BM)}} - \mathrm{L_{t,h}^{(i)}}$

Where $\mathrm{L_{t,h}^{(BM)}}$ and $\mathrm{L_{t,h}^{(i)}}$ denote the loss functions, at time (t) for the horizon of forecasting (h) for the benchmark model $\left(\mathrm{BM}\right)$ and the competitors' model (i), respectively.

The SPA test statistic corresponds to:

$$\mathrm{SPA} = \max_{\mathrm{i=1,\ldots,K}} \frac{\sqrt{\mathrm{n}}\ \overline{\mathrm{d_i}}}{\sqrt{\lim_{\mathrm{n}\to\infty} \mathrm{Var}(\sqrt{\mathrm{n}}\ \overline{\mathrm{d_i}})}} \tag{11}$$

where $\overline{\mathrm{d}} = \sqrt{\mathrm{n}}\ \sum \mathrm{d_t}$.

Hansen (2005) employs a stationary bootstrap procedure to obtain the p-values of the SPA.[21] However, the SPA test cannot discriminate between the selected best models based on some specific confidence. To overcome this limit, we employ the Model Confidence Set (MCS) method of Hansen et al. (2011), which allows such conclusion to be drawn. In particular, the MCS method permits discrimination between competitor models when the data is not informative enough, as

20. is the number of observations for market , while h denotes the forecasting horizon.

21. See Hansen (2005) for more details on the SPA test.

not only one model is shown to be the most accurate among others. The MCS method allows us to obtain a smaller set of models, called the *model confidence set*, containing the best forecasting competitors at a given level of confidence. It is shown that this set of competitors model provide equal predictive ability. The MCS method contains the best forecasts for a given level of confidence that do not differ significantly in terms of their forecast performance. [22] Table 8 reports the main results of the SPA test and MCS procedure.

From Table 8, we note two different interesting results. First, for the short horizon (1 day), model 2 (HAR-RV-J) outperforms the oil volatility forecasting according to the SPA test as well as the MSC procedure. This result highlights the important role of oil jumps in improving the out of sample forecasting of oil volatility for the short horizon (one day). In other words, for short-term investment (trading in the course of one day) the oil market might be predicted based on its own jumps; in this case, the U.S. currency market does not improve the oil volatility forecasting. This finding is useful for investors in terms of the strategy of asset allocation and the strategy of diversification. For a horizon of one week, a set of models (all except the HAR-RV-CJ) perform the oil volatility forecasting model, but the model 2 (HAR-RV-J) has the highest confidence level. For the longer horizon (one month) only two models are the best: the HAR-RV-J and HAR-RV-CJ. These findings have important policy implications for investors and policymakers in terms of portfolio diversification, risk management, asset allocation, and price regulation, among other actors.

Second, the results also have interesting implications for the U.S. exchange rate market. Indeed, for all currency under consideration, the HAR-RV-MJ model is the best fitted model for short and medium horizons (1 day and 1 week, respectively). This result highlights the fact that the common information simultaneously driving the extreme movement in both markets should be considered when forecasting U.S. dollar volatility. For the longer horizon (one month), the HAR-RV-J and HAR-RV-MJ are preferred. This result highlights the importance of considering both the information driving the U.S. currency market and those driving both oil and U.S. currency rates. These results show that volatility drivers might vary with the horizon and invite investors and policymakers to adjust their rules for asset management allocation, portfolio diversification, and price regulation differently with respect to the time horizon.

For the medium horizon, oil volatility forecasting is still performed based on model 2 (HAR-RV-J) in addition to model 4, which adds the multivariate co-jumps (HAR-RV-MJ). This result highlights that oil prices remain significantly tied to abrupt changes in the U.S. exchange rate market. However, for most currency markets, volatility forecasting is outperformed by models, including the co-jumps (model 3 (HAR-RV-BJ) and/or model 4 (HAR-RV-MJ)). This result suggests that for the medium horizon, investors should be more attentive to joint jumps between oil and currency markets to improve volatility forecasting.

For the long horizon (1 month), two models are preferred for forecasting oil volatility: the model that includes oil's own jump (HAR-RV-J) and the model including the bivariate co-jumps between oil and the exchange rate market (HAR-RV-BJ). Similar results are observed for all currency markets, except for JPY (which depends only on its own jumps), as the best suited models are those that include common jumps with the oil market (model 3 (HAR-RV-BJ) and model 4 (HAR-RV-MJ)).

Overall, our findings identify different drivers for volatility in both markets. Jumps and co-jumps appear to play a key role in improving the modeling and forecasting of oil volatility while

22. The MCS procedure is a model selection algorithm, filtering a set of competitors from a given large set of models. Contrary to the SPA test, we did not define any model as a Benchmark under the MCS method. We did not report the details of the MCS procedure to save space. For more details, see Hansen et al (2011).

Table 8: Results of forecasting evaluation tests (SPA and MCS tests)

	DXY			Oil		
Candidate models	1 month	1 week	1 day	1 month	1 week	1 day
Corsi's (2009) model	0.00000 (0.0000) [0.0000]	0.00000 (0.0000) [0.0000]	0.12430 (0.0000) [0.0000]	0.00060 (0.0000) [0.0041]	**0.21670** **(0.00001)** **[0.5138]**	0.00000 (0.00002) [0.0000]
Corsi with univariate jump	**0.11540** **(0.0000)** **[0.3659]**	**0.23650** **(0.0000)** **[0.5744]**	0.11000 (0.0000) [0.0000]	**0.66560** **(0.0000)** **[1.0000]**	**0. 64470** **(0.00001)** **[1.0000]**	**0.11790** **(0.00001)** **[1.0000]**
Corsi with bivariate co-jump	0.00000 (0.0000) [0.0008]	**0.35130** **(0.0000)** **[0.5744]**	0.00000 (0.0000) [0.0000]	**0.38540** **(0.0000)** **[0.7995]**	0.00230 (0.00001) [0.0000]	0.00000 (0.00002) [0.0000]
Corsi with multi co-jump	0.96740 **(0.0000)** **[1.0000]**	**0.81610** **(0.0000)** **[1.0000]**	**0.24220** **(0.0000)** **[1.0000]**	0.00150 (0.0000) [0.0043]	**0.45620** **(0.00001)** **[0.8337]**	0.00000 (0.00002) [0.0000]
Corsi with U.S. macro news	**0.40150** **(0.0000)** **[0.3659]**	0.03280 (0.0000) [0.0942]	0.0000 (0.0000) [0.0000]	0.00180 (0.0000) [0.0045]	**0.15340** **(0.00001)** **[0.2959]**	0.00000 (0.00002) [0.0000]
	USD/EUR			**USD/JPY**		
Corsi's (2009) model	0.00000 (0.0000) [0.0000]	0.00000 (0.0000) [0.000]	0.12430 (0.0000) [0.0000]	0.00000 (0.0000) [0.0000]	0.00000 (0.7999) [0.0000]	0.00000 (0.0000) [0.0000]
Corsi with univariate jump	**0.27410** **(0.0000)** **[0.5495]**	**0.36200** **(0.0000)** **[0.6812]**	0.11790 (0.0000) [0.0000]	**0.88820** **(0.0000)** **[1.0000]**	0.02590 (5.9999) [0.0386]	0.12430 (0.0000) [0.0000]
Corsi with bivariate co-jump	0.00010 (0.0000) [0.0031]	0.32040 (0.0000) [0.6812]	**0.24220** **(0.0000)** **[1.0000]**	**0.10500** **(0.0000)** **[0.1873]**	0.02590 (5.9999) [0.0386]	0.00000 (0.0000) [0.0000]
Corsi with multi co-jump	**0.75800** **(0.0000)** **[1.0000]**	**0.89570** **(0.0000)** **[1.0000]**	0.24220 (0.0000) [0.0000]	**0.11310** **(0.0000)** **[0.2134]**	**0.56770** **(0.0000)** **[1.0000]**	**0.11790** **(0.0000)** **[1.0000]**
Corsi with U.S. macro news	0.01650 (0.0000) [0.0433]	0.00440 (0.0000) [0.0752]	0.12430 (0.0000) [0.0000]	0.01530 (0.0000) [0.0390]	0.01920 (2.9999) [0.0386]	0.00000 (0.0000) [0.0000]
	USD/GBP			**USD/CAD**		
Corsi's (2009) model	**0.02380** **(0.0000)** **[0.1264]**	0.01550 (0.0000) [0.0000]	0.00000 (0.0000) [0.0000]	**0.06690** **(0.0000)** **[0.1528]**	0.02590 (5.9999) [0.0066]	**0.11790** **(0.0000)** **[1.000]**
Corsi with univariate jump	**0.14000** **(0.0000)** **[0.1688]**	**0.74040** **(0.0000)** **[1.000]**	0.11790 (0.0000) [0.0000]	**0.74610** **(0.0000)** **[1.0000]**	0.00000 (4.5999) [0.0066]	0.12430 (0.0000) [0.0000]
Corsi with bivariate co-jump	**0.91690** **(0.0000)** **[1.0000]**	**0.25970** **(0.0000)** **[0.6269]**	**0.12430** **(0.0000)** **[1.0000]**	**0.55570** **(0.0000)** **[0.5425]**	0.02590 (5.9999) [0.0066]	0.00000 (0.0000) [0.0000]
Corsi with multi co-jump	**0.03350** **(0.0000)** **[0.1245]**	0.01550 (0.0000) [0.0000]	0.24220 (0.0000) [0.0000]	**0.25070** **(0.0000)** **[0.4161]**	**0.44590** **(0.0000)** **[1.0000]**	0.11790 (0.0000) [0.0000]
Corsi with U.S. macro news	**0.08510** **(0.0000)** **[0.1562]**	0.00080 (0.0000) [0.0000]	0.11790 (0.0000) [0.0000]	0.01330 (0.0000) [0.0435]	0.02590 (5.9999) [0.0066]	0.00000 (0.0000) [0.0000]

(continued)

unexpected U.S. macroeconomic news is relevant for forecasting USD volatility. Further, through the analysis of volatility forecasting for different horizons, we show that multi-co-jumps (simulta-

Table 8: Results of forecasting evaluation tests (SPA and MCS tests) *(continued)*

	DXY			Oil		
Candidate models	1 month	1 week	1 day	1 month	1 week	1 day
	USD/SEK			USD/CHF		
Corsi's (2009) model	0.00000 (0.0000) [0.0007]	**0.02670** **(0.0000)** **[0.1456]**	0.11790 (0.0000) [0.0000]	0.00000 (0.0000) [0.0000]	0.00000 (0.0000) [0.0000]	0.00000 (0.0000) [0.0000]
Corsi with univariate jump	**0.46140** **(0.0000)** **[0.7826]**	**0.49630** **(0.0000)** **[1.0000]**	**0.12430** **(0.0000)** **[1.0000]**	**0.19770** **(0.00000)** **[0.3814]**	**0.32720** **(0.00000)** **[0.7160]**	0.11790 (0.0000) [0.0000]
Corsi with bivariate co-jump	0.00350 (0.00000) [0.0050]	**0.03888** **(0.00000)** **[0.1456]**	0.00000 (0.00000) [0.0000]	0.01020 (0.0000) [0.0325]	0.00000 (0.0000) [0.0000]	0.00000 (0.0000) [0.0000]
Corsi with multi co-jump	**0.62900** **(0.0000)** **[1.0000]**	**0.02280** **(0.0000)** **[0.1456]**	0.00000 (0.0000) [0.0000]	**0.85960** **(0.0000)** [1.0000]	**0.67540** **(0.0000)** [1.0000]	**0.12430** (0.0000) [1.0000]
Corsi with U.S. macro news	0.02760 (0.0000) [0.0936]	**0.05880** **(0.0000)** **[0.1456]**	0.24220 (0.0000) [0.0000]	0.00700 (0.0000) [0.0180]	0.00260 (0.0000) [0.0000]	0.00000 (0.0000) [0.0000]

Note: Numbers reported in this table denote the p-values of the SPA test of Hansen (2005) under the null hypothesis that a benchmark model cannot be outperformed by other candidate models. Values in (.) denote the value of the MSE loss function. Values in [.] denote the p-value of MCS test. The bold value indicates that the corresponding models are included on the MCS procedure. The underline models are the model having the highest confidence set based on the MCS methods. The p-values of the SPA test and MCS p-value are computed based on 10,000 bootstrap samples with mean squared errors as a loss function.* The confidence level for MCS is 90%. Mod 1, Mod 2, Mod 3, Mod 4, and Mod 5 refer to HAR-RV, HAR-RV-J, HAR-RV-BJ, HAR-RV-MJ, and HAR-RV-N, respectively.
* The results of the loss functions based on MAE are not presented to save place but are available upon request.

neous oil–U.S. dollar exchange rate co-movements) might drive and lead oil price volatility for all horizons (short, medium, and long), whereas the drivers of exchange rate volatility vary with the foreign currency considered (jumps, co-jumps, news), although news appears more determinant. These findings are relevant and might have different economic and policy implications. While investors might learn more about their portfolio investment and hedging when considering jumps and co-jumps, policymakers in the U.S. might be interested in looking at oil price jumps to control their monetary policy and USD power parity.

V. CONCLUSION

This paper models and forecasts the volatility for oil and the USD exchange rates using high frequency data over the period 2014–2018. In particular, we investigate whether considering further abrupt intraday jumps, intraday co-jumps between oil and the USD exchange rate markets, as well as unexpected intraday news might help improve the modelling and forecasting of realized volatility. To this end, we carried out a concise analysis to identify the intraday jumps and co-jumps that characterize these two markets. Next, we proposed different empirical extensions of Corsi's (2009) HAR-RV model to model and forecast volatility dynamics, while augmenting the Corsi model with intraday jumps, co-jumps, and unexpected U.S. macroeconomic news.

Our findings point to different interesting results. First, we show the presence of several intraday jumps that characterize both markets, which might help us better understand the excess volatility that has characterized oil prices and the U.S. dollar over the last period. Second, our analysis shows the presence of significant bilateral and multi-co-jumps between oil and the USD exchange rate, suggesting significant co-movements between oil prices and the USD that work via intraday bilateral and multi-co-jumps. This result is particularly interesting as it points to a significant relationship between oil and the USD exchange rate that cannot be captured with low-frequency data. Third, our augmented HAR-RV model including jump and co-jump information outperforms the benchmark model and provides more accurate forecasts. In particular, while the inclusion of jumps and co-jumps yields more accurate volatility forecasts for the oil market, suggesting that co-jump information significantly drives oil volatility dynamics, volatility in the U.S. dollar appears to be driven more by unexpected U.S. macroeconomic news. Overall, the consideration of abrupt movements induced by short-term adjustments of supply and demand in oil and U.S. exchange rates improves oil and USD exchange rate volatility forecasts and thereby risk. These findings might have different policy implications as they invite both investors and policymakers to keep close eyes on bilateral and multi-intraday jumps to improve characterization of the oil-USD exchange rate relationship and improve their volatility forecasts. Finally, it is important to note that co-jumps could be also useful to forecast co-variance. This issue is not explicitly investigated in this paper and might be a further future extension of the current study.

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APPENDIX A: INTRADAY JUMP DETECTION

Formally, Lee and Mykland (2008) use the following statistic to test for the presence of a jump between price $P(t_i - 1)$ and price $P(t_i)$ where (t_i) denotes an intraday time t_i,:

$$\mathcal{L}(i) = \frac{\log\left(P(t_i) \middle/ P(t_{i-1}) \right) \Big/}{\hat{\sigma}(t_i)} \tag{1}$$

where $\hat{\sigma}(t_i)^2$ is the instantaneous volatility, computed as:

$$\hat{\sigma}(t_i)^2 = 1/(k-2) \sum_{j=i-k+2}^{i-1} \left|\log\left(P(t_i) \middle/ P(t_{i-1}) \right)\right| \left|\log\left(P(t_i) \middle/ P(t_{i-1}) \right)\right| \tag{2}$$

If there is no jump in the interval $[t_{i-1}, t_i]$, then $\Delta t \to 0$ and $\left(max\left|\mathcal{L}(i)\right| - C_n \right) / S_n) \to \zeta$ where ζ has a cumulative distribution function defined as F ($\zeta \le x$) = exp($-e^{-x}$). With:

$$C_n = \frac{(2logn)^{\frac{1}{2}}}{c} - \frac{log\pi + log(logn)}{2c(2logn)^{\frac{1}{2}}} \tag{3}$$

$$P_n = \frac{1}{c(2logn)^{\frac{1}{2}}} \tag{4}$$

where n defines the number of observations and k is the time window, which allows the effect of jumps on instantaneous volatility to disappear.

In practice, Lee and Mykland (2008) recommend an optimal time window of $k=270$ for 5-minute intraday data. Furthermore, for a 1% statistical significance level, the threshold $\beta^* = -log(-log(0.99))$=4.6001. Then, an intraday innovation is considered a jump if

$\left(max\left|\mathcal{L}(i)\right|-C_n\right)>4.6001$. The intensity of this intraday jump is equal to the corresponding 5-minute return.

To check the robustness of our results, we also use the intraday jump test of Andersen et al. (2007b). The authors check whether an intraday return is subject to a jump or not while defining the intraday return as:

$$r_{t+\delta.\Delta,\Delta}=\sum_{j=1}^{\frac{1}{\Delta}} r_{t+j.\Delta,\Delta} * \mathrm{I}(\delta=j) \tag{5}$$

where δ is an independently drawn index from the set $\left[1,2,\ldots,\frac{1}{\Delta}\right]$ and $r_{t+j.\Delta,\Delta}$ denotes an intraday sampled $\Delta-$ period return with conditional mean and variance given by $E\left(r_{t+j.\Delta,\Delta}\right)$ and $V\left(r_{t+j.\Delta,\Delta}\right)$, respectively.

In particular, Andersen et al. (2007b) test for the presence of an intraday jump by comparing the absolute value of the intraday return with the corresponding scaled-return realizations, which are distributed as:

$$\Delta^{-1/2} r_{t+\xi\Delta,\Delta} \rightarrow N\left(0,\Delta.BV_{t+1}(\Delta)\right) \tag{6}$$

where (BV) is the bipower variation, computed by Barndorff-Nielsen and Shephard (2004) as

$$BV_{t+1}(\Delta)=\mu_1^{-2}\sum_{j=2}^{\frac{1}{\Delta}}\left|r_{t+j.\Delta,\Delta}\right| * \left|r_{t+(j-1).\Delta,\Delta}\right|, \text{ with} \tag{7}$$

Next, Andersen et al. (2007b) check whether an intraday jump $k_s(\Delta)$ is statistically significant using this test:

$$k_s(\Delta)=r_{t+s.\Delta,\Delta} * \mathrm{I}\left|r_{t+j.\Delta,\Delta}\right|>\phi_{1-\frac{\beta}{2}}\sqrt{\Delta * BV_{t+1}(\Delta)}, \ \mathrm{s}=1,2,\ldots,\frac{1}{\Delta} \tag{8}$$

where $(1-\beta)$ is the corresponding confidence interval for intraday returns. $\beta=1-(1-\alpha)^{\Delta}, \phi_{1-\frac{\beta}{2}}$ corresponds to the appropriate critical value determined from the standard normal distribution with $\alpha=1\%$.

APPENDIX B: CO-JUMP TESTS

The Bollerslev et al.'s (2008) test statistic is based on the mean cross-product computed by the normalized sum of each individual high-frequency return for each intraday period and corresponds to:

$$mcp_{t,j}=\frac{2}{n(n-1)}\sum_{i=1}^{n-1}\sum_{l=i+1}^{n} r_{i,t,j} r_{l,t,j} \quad j=1,2.\ldots,M. \tag{9}$$

where $mcp_{t,j}$ denotes the mean cross-product of returns recorded over trading day t for a tick j, and measures how closely the n stocks ($i \neq l$) of equi-weighted portfolios move together.

Following Bollerslev et al. (2008), we might compute the mean cross-product using five-minute oil exchange rate returns and we studentize the abovementioned statistic as:

$$z_{mcp,t,j}=\frac{mcp_{t,j}-\overline{mcp_t}}{S_{mcp,t}}, j=1,2,\ldots,M \ . \tag{10}$$

where

$$\overline{mcp_t} = \frac{1}{M}\sum_{j=1}^{M} mcp_{t,j} \tag{11}$$

$$S_{mcp,t} = \sqrt{\frac{1}{M-1}\sum_{j=1}^{M}(mcp_{t,j} - \overline{mcp_t})^2} \tag{12}$$

Next, we test for significant co-jumps as:

$$mcp_{t,j}^{\;*} = mcp_{t,j} I(\left|z_{mcp,t,j}\right| > \Phi_{\alpha}^{-1}) \tag{13}$$

For $\alpha = 1\%$, we determine the appropriate critical value from the standard normal distribution (Φ_{α}^{-1}).

Next, to check the robustness of our results, we use also the simultaneous multivariate jump test of Caporin et al. (2017). This test is based on the comparison of two types of smoothed realized variance ($SRRV$) and ($\widetilde{SRV}$). The statistic to detect simultaneous jumps is defined as:

$$S_{n,N} = \frac{1}{V_n}\sum_{i=1}^{n}\frac{(SRRV(X^i) - SRV_2(X^i))^2}{SQ(X^i)} \tag{14}$$

where $V_n = \tau^2$, τ is the probability level.

$$\begin{cases} SRRV(X^i) = \sum_{j=1}^{n}\left|\Delta_j X^i\right|^2 K\left(\frac{\Delta_j X^i}{H^i_{j\Delta,n}}\right)\eta^i_j \; i = 1,\ldots,N \\ \widetilde{\mathrm{SRV}}(X^i) = \sum_{j=1}^{n}\left|\Delta_j X^i\right|^2 \left(K\left(\frac{\Delta_j X^i}{H^i_{j\Delta,n}}\right) + \prod_{k=1}^{N}\left(1 - K\left(\frac{\Delta_j X^K}{H^K_{j\Delta,n}}\right)\right)\right) \\ SQ(X^i) = \sum_{j=1}^{n}\left|\Delta_j X^i\right|^4 K^2\left(\frac{\Delta_j X}{H^i_{j\Delta,n}}\right), i = 1,\ldots,N \end{cases} \tag{15}$$

where X^i and H^i define the i^{th} component of the vector X and K. X, K, and H are respectively the returns, the kernel, and the bandwidth. η^i_j is the matrix of independent and identically distributed draws.

APPENDIX C

Robustness check results for intraday relationship between oil and exchange rate jumps: A Poisson regression

	DXY	USD/EUR	USD/JPY	USD/GBP	USD/CAD	USD/CHF	USD/SEK
Constant	-0.028^{***}	-0.040^{***}	-0.044^{***}	-0.043^{***}	-0.049^{***}	-0.040^{***}	-0.039^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)
$\boldsymbol{j_{i,t}}$	1.494^{***}	1.408^{***}	1.552^{***}	1.405^{***}	2.741^{***}	1.512^{***}	1.482^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	–855.32	–1383.88	–1382.27	–1275.73	–1021.71	–1058.45	–1058.90

Note: Values in (.) denote p-values of the Khi 2 statistic. *** denotes statistical significance at the 1% level.