Investor Sentiment and Volatility Prediction of Currencies and Commodities During the COVID-19 Pandemic

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In this note, we examine whether the volatility predictive power of investor sentiment for currencies and commodities is sensitive to the COVID-19 pandemic. The Credit Suisse Fear Barometer (CSFB) and the VIX are used to measure investor sentiment. The volatility of seven major currencies, gold, and oil is investigated. Using daily data from 2005 to 2020, we show that VIX is a better predictor than CSFB. However, they have no predictive power during the COVID-19 pandemic period. This may be attributed to the different nature of fear sentiment during the crisis.

I. Introduction

The objective of this study is to examine how investor sentiment can predict the volatility of currencies and commodity returns (Smith, 2012). Indeed, during the COVID-19 pandemic, we observe a sense of fear from both investors and individuals alike (Samuel et al., 2020). Since the onset of COVID-19, investor sentiment has been dented, and it is well known that investor sentiment plays an important role in asset pricing (Bouteska, 2019; Cagli et al., 2020; Smales, 2014). Sharma (2020) shows how Asian market volatility has been dynamic and sensitive to the pandemic. This leads us to question whether investor sentiment during the COVID-19 pandemic can predict financial markets. We focus on the predictability of currencies and commodities because during the COVID-19 pandemic, international trade has been strongly impacted due to the state/province/country lockdown policies (Narayan, 2020a; see Phan & Narayan, 2020; Sha & Sharma, 2020; Sharma & Sha, 2020; Vidya & Prabheesh, 2020). On the other hand, commodities were also heavily impacted, with oil prices decreasing strongly to a negative value on 20 April 2020 at -37.63 USD (see Bajaj, 2020; Narayan et al., 2020). By comparison, gold prices continue to increase, assuming its hedge and safe haven roles (Baur & Lucey, 2010; Corbet et al., 2019). These developments inspire an investigation of whether investor sentiment can really help predict the volatility of currencies and commodities during the COVID-19 crisis. This is what we seek to understand in this research letter. Subsequently, this is what we contribute to the literature. To-date, when analysing the behaviour of asset prices during the COVID-19 pandemic, studies have shown that: (a) exchange rates (Yen) became more resistance to shocks during the pandemic (Narayan, 2020a); (b) oil prices do not predict the Japanese Yen (Devpura, 2020); bubble activity in exchange rate markets increases significantly during the pandemic (Narayan, 2020b); and the depreciation of Yen had a significant positive effect on returns in the Japanese stock market during the pandemic (Narayan et al., 2020). We contribute to this literature by showing that investor sentiment was in-

active in predicting currency and commodity markets.

To achieve the goal of this paper, we use daily data for seven major currency exchange rates (AUD, CAD, CHF, EUR, GBP, JPY, and NZD) against the USD, as well as gold (London) and oil prices (West Texas Intermediate, WTI) over the 01/2005-05/2020 period. We then use a GARCH (1,1) model to test if investor sentiment (proxied by the Credit Suisse Fear Barometer (*CSFB*) and the *VIX* (more details in Section III)), predicted currency and commodity markets. Our empirical results show that *VIX* is a better predictor than the *CSFB* in the whole period and in the global financial crisis (GFC) period. However, they have no predictive power during the COVID-19 pandemic. This result suggests that the COVID-19 pandemic is fundamentally different from the GFC, pointing also to the fact that the nature of investor fear is different during the pandemic compared to the financial crisis.

II. Data and Methodology

A. Data

The *CSFB* measures the protection against a market crash. It is calculated by selling a 10% out-of-the-money (OTM) call on the S&P 500 and using that premium to purchase a downside protection. The level of the index indicates the 0% OTM strike of the put that makes the strategy net zero cost. A high *CSFB* signals a high cost of protection relative to upside calls. Therefore, the *CSFB* measures the option premium which changes in response to the supply and demand for that option. Indeed, buying call options indicates that a trader thinks the market is going higher. Thus, the options being bought and sold indicate that investors are fearful of the potential future risks. So, the higher the *CSFB*, the higher is the fear sentiment of the market.

On the other hand, the *VIX* is an indicator of the volatility of the US financial market. It is calculated daily by the Chicago Board Option Exchange (CBOE). It is the average of annual volatilities of call and put options on the S&P 500. It, thus, measures the fear of investors that is included in the premium of the options on the S&P 500. The higher the

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VIX, the higher is the investor fear.

In addition to the investors' sentiment proxies, our data sample also includes seven major currency exchange rates against the USD, as well as gold prices from the afternoon fixing of the London market, and oil prices (the WTI). Daily data are from 03/01/2005 to 08/05/2020 and are collected from the Bloomberg terminal.

To make the comparison between the GFC and the COVID-19 crisis periods, we consider three different sample periods. The first one includes the whole period (03/01/2005-08/05/2020). The second one is related to the GFC period (01/04/2007-05/08/2011), and the third one covers the COVID-19 pandemic period (24/01/2020-08/05/2020). [Table 1] presents descriptive statistics of the considered currencies and commodities over the three sub-samples of data.

From [Table 1], we can see that only the CAD/USD, JPY/USD, gold, and oil prices have a positive rate of return over the study period. We also note that the average value is much lower during the COVID-19 pandemic than during the GFC for all the variables. This means that the COVID-19 pandemic has had a stronger effect on the economy than the GFC. As for investor sentiment measures, we note that the value of *VIX* is much higher than *CSFB*. Furthermore, their value is much higher during the COVID-19 pandemic than during the GFC. It shows that the COVID-19 pandemic has created a stronger fear sentiment than the GFC.

III. Methodology

We follow Smith (2012) and use a two-step estimation of the GARCH (1,1) model in which two lags of investor sentiment (1-day and 5 days) are included in the second step as potential predictors of the volatility of the currency and commodity returns. In the first step, we model daily log returns by the ARCH framework developed by Engle (1982) and Bollerslev (1986). In this model, the conditional variance of the returns is a function of past squared residuals of the return generating process. We consider $a_t = r_t - \mu_t$ as the return innovation on day t, with r_t the rate of return on day t, and μ_t the residual of the return generating process on day t. Then, we consider a_t which follows a GARCH (1,1) as follows:

$$a_t = \sqrt{h_t}\epsilon_t, \ h_t = \omega + \alpha a_{t-1}^2 + \beta h_{t-1} \qquad (1)$$

Where ϵ_t is a sequence of *iid* random variables with mean 0 and variance 1, $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\alpha + \beta < 1$. The latter condition implies that the unconditional variance of a_t is finite, whereas its conditional variance, h_t, evolves over time. We estimate the above equation via the method of maximum likelihood with normally distributed errors.

In step 2, we seek to know whether investor sentiment can be a predictor of the volatility of the sampled currencies and commodities. For that, we consider the GARCH (1,1) model defined as follows:

$$ln(\alpha_t^2) = \alpha + \beta h_t + k_1 ln(CSFB_{t-1})$$
$$+ k_2 \frac{1}{5} \sum_{i=1}^{5} ln(CSFB_{t-i}) + z_t \qquad (2a)$$

$$ln\left(\alpha_t^2\right) = \alpha + \beta h_t + k_3 ln(VIX_{t-1})$$
$$+ k_4 \frac{1}{5} \sum_{i=1}^{5} ln(VIX_{t-i}) + z_t \qquad (2b)$$

Where $ln(\alpha_t^2)$ are the squared residuals of the mean equation, $r_t - \mu_t$. h_t is the conditional variance of the returns of the sampled currencies and commodities, as defined in Equation (1). In Equation (2a), $ln(CSFB_{t-1})$ is the short-term predictor representing the *CSFB* data a day ahead (*t-1*), and $\frac{1}{5}\sum_{i=1}^{5} ln(CSFB_{t-i})$ is the medium-term predictor representing the 5-days moving average of the *CSFB*. The same definition is applied in Equation (2b) for $ln(VIX_{t-1})$ and $\frac{1}{5}\sum_{i=1}^{5} ln(VIX_{t-i})$; z_t is a mean zero disturbance term; α is the intercept term; and β, k_1, and k_2 (as well as k_3 and k_4) are parameter estimates for the marginal effects of different factors on the log volatility of the sampled currencies and commodities, $ln(\alpha_t^2)$:

- GARCH(1,1) conditional variance with the coefficient β;
- The predictive power of *CSFB* is captured by the coefficients k_1 and k_2;
- The predictive power the *VIX* is captured by the coefficients k_3 and k_4.

White (1980) standard errors are calculated for the usual tests of significance. Equations (2a) and (2b) are estimated via the maximum likelihood method.

IV. Results

In [Table 2], the results for Equations (2a) and (2b)[1] for the three considered periods (whole period, GFC period, and the COVID-19 pandemic period) allow us to draw the following observations. First, the β coefficient is significant in all cases. This means that the conditional variance of the returns is a good predictor for the volatility of the considered currencies and commodities. Second, the *CSFB* is not a good predictor of the volatility of the considered currencies and commodities. Indeed, coefficients k_1 and k_2 are insignificant in almost all cases (except for *EUR* and *NZD* in the whole period, and for *AUD, CAD,* and *CHF* in the GFC period; and *CAD* in the COVID-19 pandemic period). Third, the *VIX* is a good predictor for the volatility of the sampled currencies and commodities, mostly in the medium term, with a lag of five days (except for *CHF, EUR, GBP,* and *oil* in the GFC period). In the short term, with a lag of one day, the predictive power of the *VIX* is less efficient, except for *CHF* and *oil* in the whole period, and for *AUD, CAD* and *oil* in the GFC period. Fourth, in the COVID-19 period, both the *CSFB* and *VIX* lose the predictive power in explaining the volatility of the sampled currencies and commodities, except for *CAD* in the medium term. This result clearly shows that there is a structural change in the currency and commodity markets during the COVID-19 pandemic.

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[1] To save space, the results of Equation (1) based on the ARCH model are not presented here but are available upon request. In the text, we would like to focus on the main results related to Equations (2a) and (2b).

Table 1: Descriptive statistics

	AUD	CAD	CHF	EUR	GBP	JPY	NZD	GOLD	OIL	CSFB	VIX
Whole period (03/01/2002-08/05/2020)											
Mean	-1.75E-05	1.39E-05	-1.85E-05	-2.34E-05	-4.46E-05	3.75E-06	-1.50E-05	0.000149	7.55E-06	4.55E-05	5.56E-05
Std. Dev.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.03
Skewness	-0.38	0.12	-4.96	0.09	-0.91	-0.03	-0.32	-0.35	0.23	0.15	1.04
Bai &Ng test	1.86	3.29	1.06	4.63	1.27	3.09	2.40	3.66	2.01	2.74	2.34
	(0.03)	(0.00)	(0.14)	(0.00)	(0.10)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)
Ljung- Box test	(0.66)	(0.87)	(0.39)	(0.89)	(0.96)	(0.80)	(0.53)	(0.88)	(0.00)	(0.01)	(0.00)
Jarque-Bera	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GFC period (01/04/2007-05/08/2011)											
Mean	8.44E-05	-5.77E-05	-0.000182	2.26E-05	-7.36E-05	-0.000159	4.93E-05	0.000361	8.02E-05	-0.000107	0.000457
Std. Dev.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.03
Skewness	-0.42	0.18	-0.28	0.08	-0.41	0.12	-0.39	-0.15	0.11	0.32	0.64
Bai &Ng test	1.93	2.75	1.92	3.00	3.17	1.86	1.84	2.89	3.34	3.62	3.07
	(0.02)	(0.00)	(0.02)	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
Ljung-Box test	(0.72)	(0.87)	(0.94)	(0.54)	(0.66)	(0.49)	(0.86)	(0.58)	(0.04)	(0.01)	(0.02)
Jarque-Bera	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
COVID-19 crisis period (24/01/2020-08/05/2020)											
Mean	-0.000438	0.000322	-7.36E-05	-0.000102	-0.000183	-8.92E-05	-0.000497	0.000695	-0.006318	-0.001210	0.005768
Std. Dev.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.03	0.05
Skewness	-1.21	0.71	0.23	-0.34	-0.67	0.66	-1.10	-0.39	-0.53	-0.32	1.15
Bai &Ng test	1.71	1.75	1.93	2.40	3.57	1.86	1.21	2.08	3.31	3.64	3.01
	(0.02)	(0.00)	(0.02)	(0.00)	(0.01)	(0.03)	(0.03)	(0.00)	(0.01)	(0.00)	(0.01)
Ljung-Box test	(0.62)	(0.78)	(0.84)	(0.43)	(0.53)	(0.51)	(0.86)	(0.41)	(0.04)	(0.01)	(0.02)
Jarque-Bera	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: Std. Dev. denotes standard deviation. (.) shows probability values. Bai & Ng (2005) test is used to test excess kurtosis. The null hypothesis is no excess kurtosis. The Ljung-box test is used to test serial correlation: the null hypothesis is no serial correlation. The Jarque-Bera is a test for normality: the null hypothesis is that the distribution is normal. *AUD, CAD, CHF, EUR, GBP, JPY, NZD* are currencies of Australia, Canada, Switzerland, Europe, the UK, Japan, and New Zealand, respectively. *GOLD* represents gold prices (London), *OIL* denotes the WTI oil prices, *CSFB* is Credit Suisse Fear Barometer, and *VIX* is the financial market volatility.

Table 2: Results on the predictability of the volatility of currencies and commodities

Whole period	Parameter estimate						t-statistics						
	α	β	k_1	k_2	k_3	k_4	α	β	k_1	k_2	k_3	k_4	Adj. R^2
AUD	-1.20**	1.01***	1.78	-5.98	0.74	9.42***	-1.97	19.42	0.86	-1.14	0.64	3.23	0.08
CAD	0.01	1.11***	0.65	2.44	1.57	12.13***	0.02	19.80	0.31	0.45	1.34	4.10	0.09
CHF	-2.74***	0.91***	-0.22	-6.63	-2.47**	9.41***	-4.10	16.15	-0.10	-1.22	-2.04	3.07	0.06
EUR	-0.40	1.08***	0.00	-16.75***	0.88	9.97***	-0.53	17.12	0.00	-2.93	0.70	3.14	0.07
GBP	-1.68**	0.98***	1.37	-4.23	0.41	6.03**	-2.17	15.28	0.68	0.80	0.35	2.06	005
JPY	0.79	1.06***	-5.06**	-4.49	-0.39	19.73***	1.07	16.31	-2.37	-0.06	-0.33	6.54	0.07
NZD	-0.32	1.09***	2.67	-10.03**	0.31	11.65***	-0.45	17.53	-1.31	-1.93	0.27	4.03	0.07
Gold	-3.07***	0.88***	2.82	9.08	-0.38	13.58***	-4.62	14.82	1.19	1.50	-0.29	4.06	0.05
Oil	-1.87***	0.97***	-3.46	0.87	-3.21**	12.35***	-3.84	18.77	-1.50	0.14	-2.49	3.97	0.08

GFC period	Parameter estimate						t-statistics						
	α	β	k_1	k_2	k_3	k_4	α	β	k_1	k_2	k_3	k_4	Adj. R^2
AUD	-1.57	0.98***	9.50*	-21.13	4.29*	24.76***	-1.60	15.08	1.75	-1.45	1.67	3.37	0.10
CAD	-0.26	1.09***	14.48***	21.90	5.99**	24.81***	0.20	9.70	2.68	0.40	2.28	3.57	0.08
CHF	-1.53	0.99***	12.67**	7.42	4.06	1.21	-1.90	7.05	2.10	0.40	1.43	0.16	0.04
EUR	-1.55	0.98***	3.56	1.71	4.37	9.49	-1.18	8.77	0.60	1.07	1.56	1.28	0.06
GBP	-1.02	0.97***	3.43	-4.49	0.32	6.09	0.40	17.39	0.63	0.18	1.02	2.11	006
JPY	0.06	1.13***	9.57	19.32	1.86	23.34***	0.03	17.48	1.56	1.13	0.64	3.07	0.05
NZD	-0.01	1.12***	0.50	3.88	1.29	24.90***	0.01	9.45	0.09	0.26	0.87	3.57	0.07
Gold	-4.02***	0.77***	-1.53	-14.10	2.21	19.33**	-3.33	6.58	-1.40	-0.84	0.74	2.46	0.04
Oil	-1.38	1.00***	7.28	17.75	5.46**	10.99	-1.54	10.41	1.26	1.16	2.00	0.21	0.08

COVID-19 period	Parameter estimate						t-statistics						
	α	β	k_1	k_2	k_3	k_4	α	β	k_1	k_2	k_3	k_4	Adj. R^2
AUD	-1.22	0.99***	9.34	31.22	3.32	0.99	-1.34	13.08	0.12	0.28	0.76	0.37	0.13
CAD	-0.22	1.01***	9.30	66.60**	9.95	16.57	-0.10	19.30	1.38	1.96	2.21	1.17	0.22
CHF	-0.32	1.06***	12.49	30.88	4.98	-10.98	-0.08	3.60	1.37	0.61	0.69	-0.58	0.06
EUR	-4.96	0.70**	6.94	11.60	4.27	9.41	-1.23	1.98	1.88	0.07	1.26	1.27	0.06
GBP	-1.01	0.75***	3.13	-8.49	0.12	12.53	0.20	2.15	0.37	1.18	1.37	1.09	005
JPY	0.16	0.98***	2.27	12.31	2.84	13.34	1.03	7.42	1.16	1.03	0.23	1.27	0.13
NZD	-0.11	1.10***	1.51	3.18	1.19	4.90	-0.11	3.99	1.09	0.22	0.37	0.57	0.05
Gold	-4.01	0.97***	-1.52	4.10	2.11	19.97	-0.33	6.59	-1.39	0.84	0.14	2.16	0.14
Oil	-1.18	1.09*	7.82	7.51	5.62	0.92	-1.04	0.06	1.06	0.61	0.09	0.18	0.37

Notes: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. k_1= CSFB-1, k_2= CSFB-5, k_3=VIX-1, and k_4=VIX-5. *AUD, CAD, CHF, EUR, GBP, JPY, NZD* are currencies of Australia, Canada, Switzerland, Europe, UK, Japan, and New Zealand respectively. However, *GOLD* represents gold prices (London), *OIL* denotes oil prices of WTI, *CSFB* is Credit Suisse Fear Barometer, and *VIX* is the financial market volatility.

V. Conclusion

This research letter allows us to conclude that the COVID-19 crisis is of a different nature compared to the GFC, nature. Indeed, during the GFC, investor sentiment, proxied by the Credit Suisse Fear Barometer (*CSFB*) and the *VIX*, could help predict the volatility of the seven major currency exchange rates against the USD (*AUD, CAD, CHF, EUR, GBP, JPY, NZD*) and of the two major commodities (*gold* and *oil*). Furthermore, during the GFC period, the *VIX* showed a higher predictability power than the *CSFB*. However, both the *CSFB* and the *VIX* lose their predictability power during the COVID-19 crisis. This result suggests that the investor fear sentiment during the two crises is not of the same nature. During the GFC, the fear was mostly relat- ed to the financial loss. However during the COVID-19 cri- sis, the fear sentiment is strongly related to health issues, in addition to the fear of financial loss due to economic re- cession. This is why the *CSFB* and the *VIX*, proxies of in- vestor fear sentiment related to a financial loss, can help predict the volatility of currencies and commodities during the GFC, but not during the *Covid-19* crisis. This finding shows that it is necessary to construct more precise proxies for investor sentiment to be able to distinguish between dif- ferent natures of fear sentiment.

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