Speculative attacks and investor attention

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ABSTRACT

This paper presents the first evidence that retail investors play a central role in a speculative attack. Investigating the attacks that affected several emerging economies in the second semester of 2018, I document a strong influence of investor attention on the price and risk of the currency under attack, and this influence monotonically rises with the increase of the attacks' severity. Moreover, this association is absent outside of the attacks or for those emerging currencies that did not experience an attack in the sample period. These findings are robust to several alternative explanations and provide further support for the importance of retail investors to asset pricing.

Keywords: Speculative Attacks; Investor attention, Exchange rate; Google Trends.

JEL Classification: F31, F37, G12, G15

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1. Introduction

In financial markets a representative speculator is usually associated with hedge funds or major investors such as George Soros. Due to their unique economic power, these agents are commonly behind some famous speculative trades like Soros'shorting British pounds in 1992, or hedge funds' shorting subprime mortgages in 2007. Consequently, there seems to be no room left for more modest speculators, usually represented by noise traders, to shake the markets under these circumstances. On the other hand, there is a growing empirical literature documenting that retail investors can play a central role in moving securities prices (Da et al., 2011; Joseph et al., 2011; Vozlyublennaia, 2014; Bijl et al., 2016; Dimpfl and Jank, 2016) and also in taking efficient short positions (Kelley and Tetlock, 2017). Even in the Forex, one of the most liquid markets dominated by institutional agents, recent papers have found that retail investors directly affect currency prices (Han et al., 2018; Wu et al., 2019) and risk (Goddard et al., 2015).The centrality of less informed investors in asset pricing is also present in several economic models predicting that these agents can also influence securities returns (De Long et al., 1990; Shleifer and Summers, 1990; Barber et al., 2009) and risk (Andrei and Hasler, 2015) during more turbulent periods (Barberis and Huang, 2008). Grounded on this new bulk of studies, one could plausibly speculate on the role (if any) of such "marginal" investors in speculative attacks. During events of this nature, in which major investors and Central Banks dominate the stage, could noise traders affect currency prices and risk? On such occasions, would retail investors be able to intensify the outcome of an attack? Based on the evidence presented in this paper, my answer to both questions is a resounding yes.

In this article, I analyze the series of speculative attacks that affected some emerging economies during the second half of 2018. On that occasion, the assaults on Turkey, due to its fragile economic fundamentals, provoked a decrease around 40% on the lira during the first two weeks of August, and rapidly spread to other emerging economies such as Argentina, South Africa and Russia, whose currencies faced major devaluations of around 30%, 16% and 12% respectively in the following weeks. The findings of the paper demonstrate that retail investors were attracted by these events and directly affected the price and risk of the currencies under attack, intensifying the effect of the assaults.

To investigate this relationship, my sample is composed of the daily returns of currency prices (to USD) from June 2018 to December 2018 of the four aforementioned emerging economies (Argentina, Turkey, South Africa and Russia), which suffered attacks of different magnitudes in this period, together with two other emerging countries (Brazil and Mexico) that did not experience strong attacks and, consequently, serve as control groups for the analysis. The choice of these two countries as control groups is particularly pertinent based on the fact that both held general elections during the sampled period, driving the attention of investors' toward these events more than to the attacks on the peer countries. The data actually demonstrate that investors' attention to Brazilian reais and Mexican pesos reached its maximum on the day following the election results, with modest attention during the attacks.

To assess the influence of retail investors on the exchange rate of these countries I use the volume of online searches on Google. In their seminal paper, Da et al (2011) demonstrate that the Google Search Volume (GSV) is a direct measure of retail investors' predisposition to trade the asset under research. Recently, GSV has been widely used in the finance literature to assess noise traders' attention to different classes of assets like stocks (Da et al., 2011; Joseph et al., 2011; Vozlyublennaia, 2014; Bijl et al., 2016; Dimpfl and Jank, 2016), currencies (Goddard et al., 2015; Han et al., 2018; Wu et al., 2019), cryptocurrencies (Dastgir et al, 2019; Eom et al., 2019), REITs (Yung and Nafar, 2017) precious metals (Baur and Dimpfl, 2016), commodities (Yao et al., 2017) and others. In the present paper, following previous studies, I capture investor attention by downloading the GSV for the currencies' names (e.g.: "Argentine Pesos") from the Google Trends platform.

My main findings are as follows. There is a positive influence of attention on returns for all currencies under attack. This influence rises monotonically as the attacks become more severe, and is especially strong in the case of Argentine pesos and Turkish lira, which suffered particularly severe attacks. This relationship is also economically significant since, during the assaults, a one standard deviation of attention causes a contemporaneous daily change in prices of 2.15% and of 2.34% for these currencies, respectively. However, virtually no relationship is found out of the attacks for the affected currencies, or for the control groups throughout the period in question. The reverse relationship (returns causing attention) is only found during attacks and for the most exposed currencies (Argentine pesos and Turkish lira), indicating a feedback process in which a sudden change in price grabs the attention of retail investors who attempt to speculate on the currency, leading to further changes in prices. Since these currencies suffered the most intense attacks, this pattern indicates that retail investors play a central role in the strength of the assault.

Similar behavior is observed for the variance-attention relationship. During the attacks, the VAR analysis demonstrates that the change in volatility in these events attracts the attention of naïve traders, and that this change in attention proportionally affects currencies' risk. Once more, this association is only found during the attacks and is absent for the control group subsample (Brazilian reais and Russian rubles). Similar to the pattern observed for the return analysis, during the attacks, investor attention is crucial to explain the contemporaneous and future changes in variance of the exposed currencies. In concrete terms, in the case of Argentine peso and Turkish lira, investor attention has higher explanatory power on future variance than the lagged variance, which is quite remarkable since it is well established that an asset's variance is efficiently captured by auto-regressive models.

The results documented here are robust regarding a series of alternative explanations. First, I conduct an out-of-sample test to avoid a possible bias from my sample period choice. In this respect, I focus on the Russian ruble crisis of December 2014 to run the same analysis, and find very consistent results: a strong association between return (variance) and attention that is only present during the attack. Second, since the Google Search Volume is sensitive to the terminology used as a proxy to capture investors' attention, I employ different terms used in other studies (Goddard et al., 2015; Han et al., 2018; Wu et al., 2019). I then download five different term-series and use a Principal Component Analysis to extract the common factor among them. Overall, I find very similar results that, in some cases, are even stronger in terms of return (variance) and attention relation. Third, I employ an alternative length for the speculative attack window and, once again, find exactly the same pattern.

Overall, the findings of this work contribute to the literature in at least four ways. First, to my knowledge, this is the first paper to document the centrality of retail investors in the intensity of a speculative attack, contributing to a growing literature documenting that noise traders are central to asset pricing, as expected by seminal articles on the subject (De Long et al., 1990; Shleifer and Summers, 1990). Second, linked to this finding, several works have associated the severity of speculative attacks with structural idiosyncratic features like economic fundamentals (Eichengreen et al., 1995) monetary authorities' policy (Erler et al., 2014) interest rates (Angeletos et al., 2006), and Central Banks' reputations (Huang, 2017), among others. However, little attention has been paid to behavioral explanations like the noise trader approach. Nevertheless, the main findings registered here indicate that these are relevant aspects to take into account in order to explain the intensity of a speculative attack. Third, in their models, Shefrin and Statman (2000), Barberis and Huang (2008) and Barberis and Xiong (2012), advocate that retail investors are attracted by skewness in a preference for lottery-like securities. This paper provides empirical evidence in this regard, since I find a strong causation of variance on attention under very volatile circumstances (i.e., speculative attacks) that is not observable during calmer periods. Finally, Andrei and Haslaer (2015) propose a model in which security return and risk are affected by attention and uncertainty.

This hypothesis is supported by the results, as I document a strong influence of attention on both risk and return predominantly during speculative attacks (higher uncertainty environment).

The remainder of the paper is structured as follows. Section 2 describes the data and event-window definition. Section 3 presents and discusses the results. Section 4 presents the robustness tests, while the work is concluded in Section 5

2. Data

The primary data of this study is composed of the daily returns from June 2018 to December 2018 calculated based on the prices to USD[1] of six currencies from emerging countries: Argentine pesos (ARS), Turkish lira (TRY), South African rand (ZAR), Russian rubles (RUB), Brazilian Reais (BRL) and Mexican Pesos (MXN), obtained from Investing.com. The reason for this sample choice is that due to the deterioration of Turkish economic fundamentals, in the first half of August/2018 speculators attacked the Turkish lira provoking a decline of 20% in its price. This assault rapidly spread across other emerging countries such as Argentina, Russia and South Africa. In the case of the former, the attacks were particularly intense, causing a devaluation of 30% on the peso during the two weeks following the attacks on Turkey. Therefore, to achieve the main objective of this paper, investigating the price-attention relationship for these currencies during the speculative contagion that took place in the second semester of 2018 would be a natural step.

I include Brazil and Mexico in the sample to work as control groups, aiming to avoid sample period biases. There are two good reasons for this choice. First, both countries are emerging economies, and, consequently, share very similar characteristics with the other countries in the sample, which is a desirable feature for a control group. Second, these two nations held presidential elections during this period (July 1st in the case of Mexico, and October 28thin Brazil). These events presumably exerted an important influence on investor attention, attenuating the effects of speculative attacks on investors' concerns regarding these economies. Figure 1 indicates that this was indeed the case, since there is a clear spike in Google Search Volumes for both currencies on the very day of the corresponding elections' results (July 2nd for Mexico and October 29th for Brazil). To sum up, if investor attention and speculative attacks are indeed connected, this sample choice means that a more intense

[1]The preference to use the currency price to USD, and not the opposite, facilitates the comparison between the peaks in price and in online searches.

relationship should be expected for ARS and TRY, a modest relationship for RUB and ZAR and virtually no association for BRL and MXN.

The data for Google searches were collected from the Google Trends platform (www.google.com/trends) by using the name of the currency (e.g., Argentine pesos) as the search term, employing the filter for "currency" available on the platform when searching for a given term. The data in Google Trends are made available daily and in relative terms, where the period with the largest number of searches receives the amount of 100. To meet the attacks, the dataset starts on 2018.06.01 and ends on 2018.12.31. Since the Google Trends time-series are non-stationary, I use the change in Google Trends to examine the relations proposed in the paper[2], in keeping with several studies (e.g., Dastgir et al, 2018; Zhang et al, 2018).

Defining the starting point of a speculative attack is a very difficult and controversial task, given that there are no clear features of this phenomenon, which is usually very brief. However, a common pattern of these attacks is that they usually lead to a sharp increase in currencies' prices to USD, resulting in a sudden spike in their prices to USD. Relying on this characteristic, I define a speculative attack as the period comprising the 22 days before and after the peak of the currency price to USD during the entire dataset, totaling a 45-day window[3]. I am aware that a speculative attack is usually shorter in length. However, employing a longer window implies a less rigorous assumption that stands against the central hypothesis of the paper, which advocates that the return-attention relationship is predominantly observable during attacks. Finally, for comparative purposes, in the case of the Mexican peso, I reduced the window to assess the price peak to meet the attacks on emerging markets. If I employed the 2018's second semester window, its price peak would be in June/2018, which means before the advent of the attacks. In this specific case, I employ the peak observed between July/2018 and September/2018, as the "center" of the speculative attack window for this currency.

Figure 1 displays the price to USD of the six sampled currencies for the analysis window. On each chart, the price (black line) is presented on the left axis, whereas the information on Google Search Volume (gray line) is plotted on the right axis. The gray area indicates the attack window for each currency. The spike in price, indicating the epicenter of the attacks, is

[2]The time series of the Changes in Google Trends measured by the augmented Dickey-Fuller test are stationary at the 1% level for all currencies.

[3]The attack windows are as follows: ARS: 2018.08.14 to 2018.10.15; TRY: 2018.07.12 to 2018.09.12; RUB 2018.08.02 to 2018.10.03; ZAR: 2018.08.06 to 2018.10.05; BRL: 2018.08.14 to 2018.10.15; MXN: 2018.08.09 to 2018.10.10.

particularly pronounced for ARS and TRY, which coincides with the intuition that these currencies suffered particularly pronounced assaults. For example, on 2018.08.13, the Turkish Lira reached its peak, being traded at 6.8834 TRY to USD, which represents an increase of 40% in only 9 working days. In the case of the Argentine Peso, the sudden increase in price in the second half of August/2018, just after the attack on the Lira, represented a high of 31% in only 11 working days (from 2018.08.20 to 2018.09.04), indicating a speculative spillover effect. It should be noted that the spikes in price coincide with the spikes on Google Searches, which suggests that both variables are related.

(Figure 1)

This connected movement is also observable, but in a less pronounced way, for the currencies that suffered more modest attacks. In the case of the South African Rand, the two spikes in online searches during the attack window coincide with two sudden increases in prices, which is similar to the pattern observed for the Russian Ruble. For these currencies, the price increase was 16% (from 2018.08.07 to 2018.09.05) and 12% (from 2018.08.01 to 2018.09.10), respectively, during the first part of the attack window. Consistently, the spikes of investor attention for these currencies are also less acute than those of the ARS and TRY. Finally, for the control groups (Brazilian Reais and Mexican Pesos), even though prices and online searches also seem to be in tandem, it is clear that the spike in attention occurs out of the attack windows, both being related to the corresponding election outcomes (2018.10.29 for Brazil and 2018.07.02 in the case of Mexico), which is exactly the desired behavior for the currencies serving here as control groups to examine the relationship between investor attention and speculative attacks.

To better illustrate some features of the main variables, Table 1 shows the summary statistics for the currencies' returns (Panel A) and changes in Google Search Volumes (Panel B) throughout the sampled period. The mean return decreases almost monotonically with the decrease in severity of the attacks. This pattern is virtually the same as the one observed for the changes in searches. As expected, the currencies under more severe attacks (ARS and TRY) has the highest Standard Deviation and considerable Skewness and Kurtosis in their returns as well as for online searches.

(Table 1)

It is also interesting to observe that the Russian Ruble shows lower Standard Deviation and Skewness in comparison with the control group currencies (BRL and MXN), which might be surprising at first glance if the major escalation in price faced by RUB in August 2018 is taken into account, as previously presented. This feature, however, can be explained by the fact that the local Central Bank is more active regarding its monetary policy vis-à-vis the other countries, leaving less room for a major evaluation in prices. In this respect, it should be noted that the online searches on RUB shares the same characteristics (lower Standard Deviation and Skewness), providing further indications that retail investor attention and currency prices are related. Overall, the statistics presented in Table 1 suggest that the attention-return relationship is somehow influenced by speculative attacks. The next section includes a more in-depth examination of this hypothesis.

3. Results

This section provides considerable evidence concerning the relationship between investor attention and currency price and volatility during speculative attacks. In this regard, Section 3.1 examines the statistical causation between attention and currency returns by employing Granger causality and VAR models. Section 3.2 investigates the influence of online searches on currency prices. Section 3.3 explores the causality between attention and currency volatility, while section 3.4 looks at the influence of online searches on currency volatility.

3.1 Causation between return and attention in and out of speculative attacks

To examine the relationship between currency return and investor attention, I employ Granger causality tests. Even though many recent studies document that changes in investor attention influence the price of securities (Joseph et al., 2011; Vozlyublennaia, 2014), as well as in the case of Forex market (Han et al., 2018), it is pertinent to examine the contrary relationship (changes in price affecting attention), especially in the case of speculative attacks, which usually draw the concern of media coverage, presumably impacting the attention of less informed investors. To address this, the Granger causality between daily currency return (R) and corresponding changes in Google searches (S) is tested in the following model specification:

$$R_{t,i} = \delta_0 + \delta_1 R_{t-1,i} + \cdots + \delta_n R_{t-n,i} + \gamma_1 S_{t-1,i} + \cdots + \gamma_n S_{t-n,i} + \varepsilon_t \quad (1)$$

$$S_{t,i} = \delta_0 + \delta_1 R_{t-1,i} + \cdots + \delta_n R_{t-n,i} + \gamma_1 S_{t-1,i} + \cdots + \gamma_n S_{t-n,i} + \varepsilon_t \quad (2)$$

I run the test for each currency return and the corresponding volume of online searches. To distinguish the mutual causation during and out of the speculative attacks, I create a pair of series for investor attention[4] defined as $S_{i,t}^{IN} = S_{i,t}D_{i,t}$ and $S_{i,t}^{OUT} = S_{i,t}(1 - D_{i,t})$, where $D_{i,t}$ is a dummy that equals 1 if the search volume of the currency i belongs to the corresponding speculative attack window, and 0 otherwise. I consider two lags specifications according to the AIC[5].

In Table 2, Panel A reports the p-values for pairwise Granger causality between return and attention. The first line displays the p-values for the null hypothesis that return does not cause changes in attention, while the second shows the p-values for the null hypothesis that online searches do not cause changes in currency prices. The results for the entire sample, during and out of speculative attack windows, are given in the first, second and third column, respectively. Taken together, the results indicate that investor attention causes price changes during speculative attacks, but not out of these circumstances. Furthermore, this influence is statistically stronger for currencies that suffered major attacks in the period examined (ARS and TRY) than for currencies that experienced mild attacks (ZAR and RUB). The reverse direction, however, is only observable in the case of severe speculative assault (e.g., ARS and TRY), indicating a feedback process in which a change in price leads to an increase in attention, which leads to another change in price. Finally, it is worth mentioning that no causation is found in the case of BRL and MXN, which did not experience attacks in the period in question.

(Table 2)

To enrich the analysis, I run VAR models to explore the sign and timing of the documented relationship. The results are shown in Panel B in two parts: the first with the coefficients of the regression using investor attention as the dependent variable, and the

[4]This process is very similar to the one employed in the seminal paper of Kristoufek (2013) to investigate the return-attention relationship of Bitcoin after positive and negative weekly returns.
[5]Evidently, the AIC is not unanimous for all currencies, ranging from 1 to 3 depending on the case. For comparison purposes, however, I decide to maintain lag 2, since this was the most common result. It is worth mentioning that this procedure does not weaken the findings.

second using return as the dependent variable. For brevity, Panel B only reports the coefficients for the alternative lagged variable (i.e.: returns in the case of searches and vice-versa). The results indicate that investor attention move in tandem with recent currency prices (lag 1) in the case of ARS, TRY, ZAR and RUB, and that this co-movement is more pronounced during speculative attacks. The relationship in the opposite direction (attention causing returns) is observed during speculative attacks and is especially intense for those currencies that experienced a strong attack (i.e., ARS and TRY). It is also interesting to observe that investor attention is not always positively correlated with returns, which differs from the previous literature on stocks (Da et al., 2011; Joseph et al., 2011) but is consistent with related findings on the Forex market (Han et al., 2018). Finally, there is virtually no return-attention relationship for BRL and MXN during the attacks.

(Figure 2)

To provide information on the timing and direction of the relationship documented above, Figure 2 shows the impulse-response chart for the sampled currencies during and out of the speculative attacks. The charts on the left (right) present the attention (return) response to one standard deviation of the return (attention). For each currency, the first line of the two charts refers to the relationship during speculative attacks, which are followed below by the relationship out of the speculative attacks. The orthogonalized impulse response functions are displayed out to 8 periods after the one standard deviation shock. The significance of the shock is given by the confidence intervals that represent plus/minus two standard deviations. Hence, when the confidence bands do not cross the line zero, the impulse response is considered statistically different from zero at the 5% significance level. During the speculative attacks, when the impulse is currency return, the response of attention is only observable for ARS and TRY, with a different sign depending on the lag, and always of short duration (three lags). The reverse relationship (response of returns to attention shocks) is, however, more prevalent since this is observed for ARS, TRY, RUB and ZAR. The impact is always positive and ceases after two days, a short-lived effect consistent with some previous findings (Han et al., 2018). Nevertheless, out of speculative attacks there is no significant relationship between these variables in any direction for all sampled currencies. Finally, for the control groups (BRL and MXN), no significant relationship is documented in or out of the events.

3.2 Relationship between return and attention in and out of speculative attacks

The results so far suggest that the influence of retail investor attention on currency prices is observable only during speculative attacks, which could shed more light on prior studies that document a significant relationship between both variables (Han et al., 2018; Wu et al., 2019). To provide a more in-depth analysis of this influence, I run two OLS models specified as follows:

$$R_{t,i} = a_0 + \sum_{n=0}^{2} b_{i,n} S_{i,t-n} + \sum_{n=1}^{2} c_{i,n} R_{i,t-n} + \varepsilon_t \tag{3}$$

$$R_{t,i} = a_0 + \sum_{n=0}^{2} b_{i,n} D_{i,t-n} S_{i,t-n} + \sum_{n=0}^{2} c_{i,n} (1 - D_{i,t-n}) S_{i,t-n} + \sum_{n=1}^{2} d_{i,n} R_{i,t-n} + \varepsilon_t \tag{4}$$

The first equation analyzes the influence of contemporaneous and lagged attention on currency returns for the entire sample period aiming to investigate whether the relationship holds in the cross section of the currency prices. In Equation 4, I add a dummy variable that equals 1 during speculative attacks and 0 otherwise in order to capture the effect of attention in different circumstances regarding speculative attacks. Accordingly, the focus is on coefficients b's and c's, since significant b's and non-significant c's will lend support to the hypothesis that retail investors influence currency prices especially during speculative attacks.

In Table 3, Panel A presents the results for the entire sample (one regime), while Panel B reports the results during and out of speculative attacks (two regimes). The significant coefficients are in bold, followed by robust standard errors in parenthesis. The results of Panel A indicate a positive and strong influence of contemporaneous attention on a currency's return for all economies under speculative attacks (ARS, TRY, ZAR and RUB), whereas no relationship is found for Brazil and Mexico, which did not experience an attack during this period. In the case of ARS and TRY, which suffered a more severe attack, the lagged attention also exerts a significant impact on their price. These results are in keeping with previous findings (Han et al., 2018) that report a significant short-term relationship between investor attention and exchange rate returns but focusing on weekly data. It is also worth mentioning that the explanatory power of Equation 3 is particularly pronounced in the case of ARS and TRY (R2 of 0.43 and 0.44 respectively), monotonically decreasing with the reduction of the severity of the attacks, supporting the hypothesis of investor attention as a good predictor of a currency's price.

(Table 3)

The results in Panel B are indeed more interesting in this respect. First, the results indicate that investor attention only impacts exchange rate returns during speculative attacks, with virtually no influence outside of these circumstances. Second, this relationship is also economically significant, particularly for contemporaneous changes in attention. In this case, *coeteris paribus*, a one-standard deviation of search changes during speculative attacks causes a daily change in price of 2.15% and 2.34% for ARS and TRY, respectively. This influence continuously decreases with the waning of the strength of the attacks since the one-standard deviation of attention causes a change in price of 0.62% and 0.73% for RUB and ZAR, respectively. Third, the statistical significance of the relationship is also remarkable, since the t-stat for b_0 is 10.29 and 14.67 for ARS and TRY respectively. Fourth, this association is not observed for BRL and MXN, which serve here as control groups, as previously mentioned, in keeping with the assumption that investor attention affects currency prices in a more pronounced way during attacks. Overall, the results lend support for the Noise Trader Approach framework (Shleiffer and Summers, 1990; Barber et al., 2009; Han and Kumar, 2013) as they indicate that the attention of retail investors exerts an important influence on currency prices, especially during speculative attacks.

3.3 Causation between variance and attention in and out of speculative attacks

Several studies report a strong association between online searches and asset volatility for different types of securities (Joseph et al, 2011; Da et al, 2015; Baur and Dimpfl, 2016; Eom et al, 2019), which is also observable in the case of the Forex market (Smith, 2012; Goddard et al, 2015; Han, 2018). Even though a considerable number of works investigates the association in one direction (searches causing volatility) it is plausible to assume that the reverse relationship is also expected since there is considerable evidence in the recent finance literature that retail investors are attracted by high volatility and high skewness assets (Shefrin and Statman, 2000; Barberis and Huang, 2008; Kumar, 2009; Han and Kumar, 2013) as proposed in the theoretical framework of Andrei and Hasler (2015). Based on this literature and on the results documented above, I hypothesize that the mutual relationship of attention and variance is particularly pronounced during speculative attacks.

To investigate this, I generate a time series of the conditional variance by running a GARCH (1,1) model for each currency (Smith, 2012; Goddard et al., 2015) as a measure of volatility. To investigate the causality between volatility and attention, I follow the same structure of Equations 1 and 2 but, in this case, replacing a currency's return on a given date ($R_{t,i}$) by its corresponding conditional variance ($\sigma^2_{t,i}$). I also follow exactly the same process described on Section 3.1 to generate the series for attention during and out of speculative attacks. The results are shown in Table 4.

In Panel A, the p-values indicate a bi-directional relationship between attention and volatility for ARS and RUB. The most prevailing behavior, however, is the causation of volatility in online searches during speculative attacks, indicating that these circumstances are much more likely to attract the attention of retail investors. These findings are in keeping with the model proposed by Barberis and Huang (2008), based on Tversky and Kahneman's (1992) cumulative prospect theory, in which investors are attracted by skewed securities aiming to hold a lottery-like portfolio. Since currencies' variance only influences investor attention during speculative attacks, with no relationship between the variables outside of these more volatile conditions, a preference for skewness story seems to be a plausible explanation for these outcomes. Nevertheless, the results on the first part of Panel B seem to contradict this interpretation since most of the coefficients of the lagged variance are negative, indicating that an increase in volatility leads to a decrease in attention. My explanation for this puzzling finding is that the attention of retail investors is drawn to a given currency during speculative attacks in order to gamble in a more volatile environment. This is consistent with the peaks in online searches reported in Figure 1, and compatible with the models of Barberis and Huang (2008) and Barberis and Xiong (2012). However, in these situations, the investment decision is only made when volatility decreases[6].

(*Table 4*)

The results for the second part of Panel B indicate that, during speculative attacks, increases in investor attention are associated with higher volatility, in accordance with a number of studies (e.g., Smith, 2012; Andrei and Hasler, 2015; Goodard et al., 2015; Dimpfl and Jank, 2016), providing support for models in which retail investors'attention increases

[6] These results are somehow related to Dimpfl and Jank (2016). The authors also find negative coefficients in a VAR model relating attention and the volatility of the Dow Jones, when attention is the dependent variable. In their work, the coefficients are non-significant, as are my results outside of speculative attacks. Since they do not analyze speculative attacks, both results seem to be consistent.

securities risk (De Long et al., 1990; Andrei and Hasler, 2015). However, outside of these occasions, this relationship is much weaker, as it is only observable for 2 of the sampled currencies. The explanatory power of attention during the speculative attacks experienced by ARS and TRY is particularly remarkable, as the t-statistics for one-lag online searches are of 28.95 and 46.51, respectively.

Figure 3 exhibits the impulse-response graphs between variance and attention during and out of the speculative attacks. For the currencies that suffered a more severe attack (TRY and ARS) as well as for RUB, a one-standard deviation shock on variance (left charts) provokes a positive response in terms of retail investors' attention on the following day that reverts and eventually ceases, indicating that this relationship is short-lived. Such behavior is not observed out of the attacks for these currencies, nor in the case of the control group currencies (BRL and MXN). This pattern provides support for the findings commented on above, indicating indicate that the attacks attract the attention of less sophisticated investors, as hypothesized in some models of skewness preference (Barberis and Huang, 2008; Barberis and Xiong, 2012).

(Figure 3)

The response of currency volatility to one-standard deviation shocks on attention (right charts) during speculative attacks is also brief, and disappears on the second day after the impact. This behavior is observed for ARS, RUB and ZAR. On the other hand, out of these volatile circumstances, none of these currencies exhibit a significant impulse-response relationship between variance and attention, reinforcing the view that the increase of retail investor attention affects the variance of the asset (De Long et al., 1990; Smith, 2012; Andrei and Hasler, 2015; Baur and Dimpfl, 2016; Eom et al, 2019).

3.4 Relationship between variance and attention in and out of speculative attacks

Consistent with what was previously done with currency prices, I run two OLS regression models to investigate further the influence of attention on volatility as expressed in Models 5 and 6. The interaction term of the Dummy variable aims to capture the influence of online searches on a currency's variance during (D = 1) and out of speculative attacks (D = 0). The only structural difference between these models and the previous on returns is the lower number of lags, in accordance with AIC criteria[7].

$$\sigma^2{}_{t,i} = a_0 + \sum_{n=0}^{1} b_{i,n} \cdot S_{i,t-n} + c_{i,t} \cdot \sigma^2{}_{i,t-1} + \varepsilon_t \tag{5}$$

$$\sigma^2{}_{t,i} = a_0 + \sum_{n=0}^{1} b_{i,n} \cdot D_{i,t-n} \cdot S_{i,t-n} + \sum_{n=0}^{1} c_{i,n} \cdot (1 - D_{i,t-n}) \cdot S_{i,t-n} + d_{i,t} \cdot \sigma^2{}_{i,t-1} + \varepsilon_t \tag{6}$$

Once again, the focus is on coefficients b's for the first model, and on b's and c's for the second, in order to evaluate whether speculative attacks influence the relationship between attention and risk. The results are shown in Table 5.

The findings in Panel A indicate a positive influence of investors on volatility only for those currencies that underwent a speculative attack in the period in question (ARS, TRY, BRL and ZAR), with no relationship found for BRL and MXN. The sign of the relationship indicates that, in general, the increase of attention from retail investors causes an elevation of currencies' risk, in accordance with the seminal model of De Long et al. (1990) as well as with the most recent framework of Andrei and Hasler (2015), since the former predicts that the entrance of retail investors (or the increase of retail investor attention, in the case of the latter) increases the risk of the given security.

(Table 5)

Panel B shows the results for the two regimes (in and out of attacks) to analyze how the relationship documented above is affected by this phenomenon. For the currencies that experienced an attack (ARS, TRY, RUB and ZAR) the influence of attention on variance is always positive and observable out of the attacks too, albeit much more significant during such occasions, which indicates that the attacks play a central role in the attention-variance relationship. In this respect, it should be noted that for currencies that did not experience an attack (BRL and MXN) there is no significant relationship either during nor out of the speculative assaults. It is also important to observe that in the case of ARS and TRY, which

[7]Once more, the AIC is not unanimous for all currencies, ranging from 1 to 3 depending on the case. For comparison purposes, however, I decide to maintain lag 1 since this was the most common result. This procedure does not weaken the findings.

suffered severe attacks, the explanatory power of the lagged attention in these circumstances is even higher than the lagged variance: for ARS (TRY) the t-statistic for Lag 1 attention is 13.51 (14.44), while for Lag 1 variance is 6.92 (10.97). This finding is quite remarkable since it is well known that autoregressive models are very efficient in predicting the volatility of securities. Overall, the results indicate that the attention-variance relationship is driven by speculative attacks, and this is consistent with the view that retail investors are attracted by skewness (Barberis and Huang, 2008; Kumar, 2009; Barberis and Xiong, 2012) and, by doing so, bring more risk to the given market (De Long et al., 1990; Andrei and Hasler, 2015), playing an important role in the pricing process of the respective securities (Shleiffer and Summers, 1990; Barber et al., 2009).

Aiming to gauge whether the results so far are driven by alternative explanations such as sample period bias, Google search terminology, or the length chosen for the speculative attacks, the next section presents some robustness checks.

4. Robustness checks

4.1 Out-of-sample test

The findings documented thus far were obtained by examining the speculative attacks that affected some emerging economies during the second half of 2018. To investigate whether the results could be somehow biased by this sample period, I replicate the aforementioned tests in an out-of-sample test on the speculative attack on the Russian Ruble in December 2014. On this occasion, speculators began a massive attack on the Russian Ruble expecting that the Kremlin would not be able to hold the pegged currency regime due to the meltdown of the local economy. On this occasion, the Ruble price increased from 50.41 RUB/USD by the end of November/2014 to a peak of 67.51 RUB/USD 15 days later (an increase of 79% on monthly terms). The explanation for this choice is twofold. First, Russia is a leading emerging economy that is included in my first sample. Hence, the results of the out-of-sample and in-sample tests can be more appropriately compared, with lower interference of idiosyncratic features. Second, as the data of Google Trends begins in 2008, some of the most striking attacks on emerging economies, as on Mexico (1994), East Asian countries (1997) and Brazil (1999), are not covered by this tool, compelling me to use a more recent event for this analysis.

For consistency, I follow exactly the same assumptions explained in Section 2: a six-month analysis window (ranging from September 2014 to March 2015) and a speculative attack window of 45 days beginning 22 days before and after the currency's price peak (i.e., 12.17.2014). I also use the same terminology (i.e., the Russian Ruble) with the filter for "currency" to download the online search data and run an identical analysis to that described in Section 3. For brevity, I report in Table 6 only the main results (VAR models and OLS regressions)[8].

The results in Panel A indicate a bi-directional relationship between attention and return that is observable only during the attack. It is important to note that this mutual influence is much more pronounced than the one documented for the Russian Ruble during the 2018 analysis, which is consistent with the hypothesis that this relationship was driven by a speculative attack that was particularly strong for this currency in 2014, and much milder in 2018. Furthermore, the bi-directional relationship shown in Panel A is consistent with the behavior documented for the Argentine Peso and Turkish Lira in Section 3.1., which were the currencies that suffered particularly severe attacks in 2018. The influence of searches on returns (Panel B) is only significant during the attacks and, once again, short-lived (until lag 1). The impact is also economically important since a one-standard deviation on contemporaneous attention causes a daily increase in price of 1.9%. These features are also similar to the findings documented in Section 3.2 for the Argentine Peso and Turkish Lira.

(Table 6)

The investigation regarding online searches and currency variance is shown in Panels C and D. In this case, the results equally indicate a bi-direction relationship between these constructs that is restricted to speculative attack periods. Whereas changes in variance negatively affects investors' attention on the following day, the reverse relationship is always positive, following the same pattern observed in the in-sample analysis addressed in Section 3.3. Finally, the results in Panel D demonstrate that increases in attention positively affect volatility only during the attack, with no significant relationship out of this event. Overall, the results strongly support the previous findings and provide further support for the hypothesis that retail investors play a central role in currency price and risk during speculative attacks.

[8] The detailed results are available upon request.

4.2 Alternative specification for Google searches

As mentioned in Section 2, the data for investor attention were obtained by searching the name of the currency on Google Trends. Obviously, retail investors interested in trading currencies could employ alternative terminologies when searching for more information on a given currency. To determine whether the results documented in Section 3 are biased by the terminology that I chose as a proxy to attention, I download the Google Search Volume for alternative specifications of investor attention to currency prices. More precisely, I employ four alternative terminologies suggested in other papers (Goddard et al., 2015; Han et al., 2018; Wu et al., 2019) exemplified here for the Argentine Peso: "ARS USD", "USD ARS", "Argentine Peso Dollar" and "Dollar Argentine Peso". I add to these alternative specifications the data of the terminology employed in Section 2 (i.e., currency name), and in the time series of these different terminologies I run a Principal Component Analysis and extract the first component in an effort to capture the common factor among them[9]. The daily change in this factor is my alternative proxy to Searches. Using this new proxy, I run the same analysis detailed in Section 3. The results are presented in Table 7. For brevity, the table only shows the results for the Granger causality (Panels A and C) and OLS regressions (Panels B and D).

(Table 7)

The results in Panel A confirm the existence of a relationship between attention and return (or vice-versa) during speculative attacks that is restricted to the currencies that suffered these assaults (ARS, TRY, RUB and ZAR), while no association is found for the control groups (BRL and MXN). Consistently, outside of these circumstances, there is no causation between searches and prices for the currencies under speculative attacks, supporting part of the findings of Section 3. In Panel B, the findings indicate a contemporaneous influence of attention on prices for the attacked currencies during the assaults, as well as a lagged association for those currencies that experienced more intense assaults, notably ARS and TRY. For these currencies, the contemporaneous influence remains economically remarkable, since a one-standard deviation of online searches causes a change in price of

[9]For 5 out of 6 currencies, the Factor Analysis indicates only 1 factor, suggesting that these alternative terminologies are associated with one single factor that is closely related to the interest of retail investors in the given currency. The exception was Brazilian Reais, with two factors.

2.1% and 2.4%, respectively, on the same day. Out of the attacks, there is no significant relationship for these more exposed currencies.

With regard to the attention-variance relationship, Panel C confirms that volatility attracts the attention of investors only during attacks, with a negligible association outside of these occasions, or for those currencies under no relevant attacks, confirming the "pursuit for skewness" behavior of retail investors (Barberis and Huang, 2008; Kumar, 2009; Barberis and Xiong, 2012) documented in Subsection 3.4. Finally, the results in Panel D demonstrate that attention positively affects the variance of the attacked currencies during the assaults with virtually no influence found outside of these circumstances, which is an additional indication that the attention of noise traders increases the volatility of the market during turbulent events. Taken together, the results in Table 7 provide robust support for the findings previously reported and indicate that the main conclusions are not driven by the terminology employed to capture investors' online interests.

4.3 Alternative length for speculative attacks

In this study, I assume an event window of 45 days as the attack length. As mentioned in Section 2, this choice could be seen as subjective as well as permissive since an attack can be a short-lived occurrence, which could plausibly induce a reader to question whether the aforementioned results could not be biased by this choice. To address this issue, I shorten the previous event window by 15 days, and assume an alternative range of 30 days as the duration of the attacks[10] to run the same analysis reported in Section 3. For concision, Table 8 shows only the causality analysis between attention and return (or variance), and the influence of attention on return (or variance).

The Granger causality analysis (Panel A), in general, maintains the same features presented in Table 2: a bidirectional relationship between return and attention for the currencies under more severe attacks (ARS and TRY), no significant relationship for the control groups (BRL and MXN) during attacks, and no causation out of the attacks. The only exception is the South African Rand (ZAR), which did not show a significant relationship during the attacks, but only outside of these circumstances, which may indicate that this new window does not capture the full effect of the attack on this currency. In Panel B, the results

[10] Since the essence of the study contemplates the analysis during an attack, 30 continuous observations is the minimum required for statistical purposes to evaluate the influence of attention on both return and variance under these circumstances.

are very similar to those reported in Table 3: the contemporaneous influence of attention on return is positive and significant for the currencies under attack, while a lagged relationship is found only for the currencies that suffered more severe assaults (ARS and TRY). Out of these circumstances, this influence ceases, with ARS being the only exception, which is the pattern already observed for the 45-day window. It is interesting to note that the influence found for the contemporaneous attention employing the 30-day window is even stronger for the currencies under attack than reported previously. In concrete terms, the t-statistic for the lag 0 attention for the 30-day (45-day) window was 11.20 (9.33), 14.05 (6.36), 3.65 (2.51) and 4.05 (2.65) for ARS, TRY, RUB and ZAR respectively, which can be plausibly explained by the fact that speculative attacks are usually short lived.

(Table 8)

The results for the relationship between online searches and variance are shown in Panels C and D. The causality test indicates, once more, that changes in volatility attracts investor attention only during attacks for the affected currencies (ARS, TRY, RUB and ZAR), with no association documented for the control groups (BRL and MXN). Additionally, Panel D documents that online searches positively affects contemporaneous (ARS and RUB) and future (ARS, TRY and ZAR) variances during the attacks, as well as out of these occasions, even though this relationship is usually more intense in the former case, which is consistent with the behavior documented when employing the 45 event window definition (Table 5). Overall, the evidence reported in Table 8 indicate that the main findings of the paper are not driven by the length employed to define the assaults, providing further support for the view that retail investors play a central role in currency prices and risk during speculative attacks.

5. Conclusion

In this paper I use Google Search Volume (GSV) to capture investor attention to investigate whether retail investors play any significant role during speculative attacks. Focusing on the assaults that affected some important emerging countries in the second semester of 2018, I find that attention exerts an important influence on both the return and risk of the currencies under attack. In concrete terms, I document a bidirectional attention-return relationship for more affected currencies (Argentine Pesos and Turkish Lira) in a feedback process that increases the outcome of the attack. For currencies that suffered less severe assaults (Russian ruble and South Africa rand), there is a strong influence of attention on return, with no association in the reverse direction. For all affected currencies, the impact of attention on return is short lived and both statistically and economically significant. Moreover, no relationship is found out of these circumstances, or for those emerging currencies that did not experienced an attack in the sample period (Brazilian reais and Mexican pesos).

For the attention-variance relation, I register that variance attracts investor attention only during speculative attacks, which is consistent with the preference for a skewness framework (Barberis and Huang, 2008; Kumar, 2009; Barberis and Xiong, 2012; Han and Kumar, 2013). The results also show that attention exert an important influence on variance during those events. Investor attention actually shows greater explanatory power over future variance than the lagged variance. Consistent with the behavior described for the attention-return relationship for the currencies not affected by attacks during the period, there is virtually no influence of searches on variance or vice-versa. I also conduct some robustness checks and find that the results are not driven by alternative explanations such as in-sample bias, online search terminologies or the definition of event windows. Overall, the results demonstrate that retail investors affect securities' return and risk, as assumed in some economic models (De Long et al, 1990; Shleifer and Summers, 1990; Andrei and Hasler, 2015).

Finally, it is worth mentioning that the literature on speculative attacks documents contradictory findings regarding the importance of structural characteristics, such as interest rates or the reputation of Central Banks', to the success of an attack. How this influence can be driven by investor attention appears to be an interesting agenda that I leave to future studies.

References

Andrei, D., Hasler, M., 2015. Investor attention and stock market volatility. *Review of Financial Studies*, 28(1), 33-71

Angeletos, G., Hellwig, C., Pavan, A., 2006. Signaling in a global game: coordination and policy traps. *Journal of Political Economy*, 114 (3), 452–486.

Barber, B., Odean, T., Zhu, N., 2009. Do Retail Trades Move Markets? *Review of Financial Studies*, 22(1), 151-186

Barberis, N., Huang, M., 2008. Stock as lotteries: the implication of probability weighting for security prices, *American Economic Review,* 98 (5), 2066-2100

Barberis, N., Xiong, W., 2012, Realization utility. *Journal of Financial Economics*, 104, 251-271

Baur, D., Dimpfl, T., 2016. Googling gold and mining bad news. *Resources Policy*, 50, 306-311

Bijl, L., Kringhuag, G., Molnár, P., Sandvik, E., 2016. Google searches and stock returns. *International Review of Financial Analysis*, 45, 150-156

Da, Z., Engelberg, J., Gao, P., 2015. The sum of all FEARS. Investor sentiment and asset prices. *Review of Financial Studies*, 28(1), 1-31

Da, Z., Engelberg, J., Pengjie, G., 2011. In Search of Attention, *Journal of Finance*, 66(5), 1461-1498

Dastgir, S., Demir, E., Downing, G., Gozgor, G., Lau, C., 2019. The causal relationship between Bitcoin attention and Bitcoin returns: Evidence from the Copula-based Granger causality test. *Finance Research Letters*, In Press

De Long, J., Shleifer, A. Summers, L., Waldmann, R., 1990. Noise Trader Risk in Financial Markets. *Journal of Political Economy*, 98(4), 703-738

Dimpfl, T., Jank, S., 2016. Can Internet Search Queries Help to Predict Stock Market Volatility? *European Financial Management*, 22(2), 171-192

Eichengreen, B., Rose, A., Wyplosz, C., 1995. Exchange market mayhem: the antecedents and aftermath of speculative attacks. *Economic Policy*, 21, 249–312.

Eom, C., Kaizoji, T., Kang, S., Pichl, L., 2019. Bitcoin and investor sentiment: Statistical characteristics and predictability. *Physica A*, 514, 511-521

Erler, A., Bauer, C., Herz, B., 2014. Defending against speculative attacks – It is risky, but it can pay off. *Journal of Banking & Finance,* 47, 309-330

Goddard, J., Kita, A., Wang, Q., 2015. Investor attention and FX market volatility. *Journal of International Financial Markets, Institution & Money*, 38, 79-96

Han, B., Kumar, A., 2013. Speculative retail trading and asset prices. *Journal of Financial and Quantitative Analysis*, 48(2), 377-404

Han, L., Xu, Y., Yin, L., 2018. Does investor attention matter? The attention-return relationship in FX markets. *Economic Modelling*, 68, 614-660

Huang, C., 2017. Defending against speculative attacks: The policy maker's reputation. *Journal of Economic Theory,* 171, 1-34

Joseph, K., Wintoki, M., Zhang, Z., 2011. Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting*, 27, 1116-1127

Kelley, E., Tetlock, P., 2017, Retail short selling and stock prices. *Review of Financial Studies,* 30(3), 801-834

Kristoufek, L., 2013. BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific Reports*, 3, 3415, 1-7

Kumar, A., 2009, Who gambles in stock market? *Journal of Finance*, 64, 1889-1933

Shleifer, A., Summers, L., 1990. The Noise Trader Approach to Finance. *The Journal of Economic Perspectives*, 4(2), 19-33

Smith, G., 2012. Google internet search activity and volatility prediction in the market for foreign currency. *Finance Research Letters*, 9, 103-110

Tversky, A., Kahneman, D., 1992. Advances in Prospect Theory: cumulative representation of uncertainty. *Journal of Risk and Uncertainty,* 5(4), 297-323

Vozlyublennaia, N., 2014. Investor attention, index performance and return predictability. *Journal of Banking & Finance*, 41, 17-35

Wu, Y., Han, L., Yin, L., 2019. Our currency, your attention: contagion spillovers of investor attention on currency returns. *Economic Modelling,* 80, 49-61

Yao, T., Zhang, Y., Ma, C., 2017. How does investor attention affect international crude oil prices? *Applied Energy*, 205, 336-344.

Yung, K., Nafar, N., 2017. Investor attention and the expected return of reits. *International review of economics and finance*, 48, 423-439

Zhang, W., Wang, P., Li, X., Shen, D., 2018. Quantifying the cross-correlations between online searches and Bitcoin market. *Physica A*, 509, 657-672

Table 1: Summary Statistics
The first panel presents the summary statistics of daily returns for Argentine Peso (ARS), Turkish Lira (TRY), Russian Ruble (RUB), South-African Rand (ZAR), Brazilian Real (BRL) and Mexican Peso (MXN) from 2018.06.01 to 2018.12.31. Panel two shows the summary statistics of the daily variations of Google Search Volume for the currencies' names (e.g.: "Argentine Pesos").

	ARS	TRY	RUB	ZAR	BRL	MXN
Return						
Mean	0.0029	0.0011	0.0008	0.0009	0.0003	-0.0001
Std. Dev.	0.0200	0.0217	0.0081	0.0115	0.0108	0.0087
Min	-0.0473	-0.0769	-0.0232	-0.0267	-0.0508	-0.0253
Max	0.1392	0.1590	0.0328	0.0330	0.0294	0.0361
Skewness	2.5024	2.5198	0.2842	0.3502	-0.5706	0.4839
Kurtosis	15.246	19.425	1.229	-0.267	2.608	1.305
Search						
Mean	0.0103	0.0192	0.0005	0.0044	0.0020	0.0035
Std. Dev.	0.1779	0.3067	0.0592	0.1078	0.0860	0.0856
Min	-0.3590	-0.4286	-0.3088	-0.1967	-0.3014	-0.2800
Max	1.8571	3.3478	0.3651	0.6111	0.4085	0.5152
Skewness	7.5905	8.7262	0.8058	1.9831	1.2734	1.8432
Kurtosis	78.031	93.516	13.377	8.280	5.827	9.958

Table2: Causality between currency return and investor attention

Panel A presents the p-values for the Ganger Causality test between currency return (R) and online search changes (S). Entire Sample ranges from 2018.06.01 to 2018.12.31. The data on currency returns and attention are daily. Speculative Attacks are defined as the 22 days before and after the peak of a currency's price to USD.Bold means significant at 10% level. Panel B reports VAR estimation results that are displayed in two parts: the search equation is given in the upper section and the return equation in the lower section. For brevity, the panel shows only the results for the lags of the alternative variable in the VAR model (i.e.: Returns in the case of Searches and vice-versa) as well as for the intercept. The standard errors are in parentheses and the significant coefficients are in bold. All estimations contain 2 lags.

	Entire Sample						Speculative Attacks						Out-of speculattive attacks					
	ARS	TRY	RUB	ZAR	BRL	MXN	ARS	TRY	RUB	ZAR	BRL	MXN	ARS	TRY	RUB	ZAR	BRL	MXN
Panel A: Granger causality test																		
H0: R does not Granger cause S	**0.000**	**0.099**	**0.077**	0.027	0.923	0.422	**0.000**	**0.000**	0.253	0.667	0.165	0.348	0.388	0.932	0.469	0.922	0.918	0.111
H0: S does not Granger cause R	**0.000**	**0.001**	0.899	0.898	0.497	**0.037**	**0.000**	**0.033**	**0.076**	**0.008**	0.973	0.631	0.147	0.457	0.936	0.994	0.877	0.113
Panel B: VAR regression																		
Search																		
R_{t-1}	**4.359*** **	**2.808***	**1.139***	**1.557** **	-0.185	0.454	**3.249*** **	3.608	0.840	**1.13***	0.060	-0.235	**0.597***	-0.488	-0.048	$-4.1*10^{-4}$	-0.222	0.707
	(0.862)	(1.462)	(0.615)	(0.763)	(0.627)	(0.795)	(0.806)	(1.470)	(0.427)	(0.593)	(0.300)	(0.396)	(0.307)	(0.390)	(0.418)	(0.467)	(0.551)	(0.680)
R_{t-2}	-1.012	1.162	0.912	**1.342***	0.139	-0.857	-1.159	**1.298** **	0.588	**1.47** **	-0.026	0.258	-0.033	0.125	0.143	-0.053	0.138	-1.104
	(0.925)	(1.384)	(0.621)	(0.771)	(0.626)	(0.791)	(0.840)	(1.376)	(0.43)	(0.598)	(0.299)	(0.395)	(0.311)	(0.391)	(0.418)	(0.465)	(0.551)	(0.680)
Intercept	0.004	0.021	-0.002	0.003	0.003	0.004	$3.2*10^{-4}$	0.019	$-3.0*10^{-4}$	0.002	0.001	0.002	0.005	0.003	-0.001	0.001	0.002	0.003
	(0.014)	(0.025)	(0.005)	(0.009)	(0.007)	(0.007)	(0.013)	(0.023)	(0.003)	(0.006)	(0.003)	(0.003)	(0.006)	(0.008)	(0.003)	(0.005)	(0.006)	(0.006)
R^2	0.16	0.05	0.06	0.08	0.10	0.09	0.12	0.07	0.16	0.13	0.07	0.04	0.05	0.06	0.01	0.08	0.11	0.06
N	149						149						149					
Return																		
S_{t-1}	**-0.038*** **	**0.013** **	0.005	-0.004	$-1.4*10^{-4}$	-0.008	**-0.043*** **	**0.016** **	0.015	-0.010	**-0.011***	-0.005	-0.018	-0.002	0.002	0.006	0.003	-0.010
	(0.011)	(0.006)	(0.013)	(0.009)	(0.011)	(0.008)	(0.012)	(0.007)	(0.018)	(0.012)	(0.022)	(0.017)	(0.023)	(0.017)	(0.020)	(0.014)	(0.013)	(0.010)
S_{t-2}	**0.025** **	-0.018	-0.004	-0.001	0.012	**0.018** **	**0.043*** **	**-0.023*** **	-0.028	**-0.002***	0.037	0.022	-0.028	0.005	0.024	0.003	0.005	0.015
	(0.011)	(0.007)	(0.013)	(0.009)	(0.011)	(0.009)	(0.012)	(0.007)	(0.017)	(0.012)	(0.022)	(0.017)	(0.023)	(0.017)	(0.020)	(0.014)	(0.012)	(0.010)
Intercept	0.002	0.001	0.001	0.001	$1.9*10^{-4}$	$-2.8*10^{-4}$	0.002	0.001	0.001	0.001	$2.2*10^{-4}$	$-2.7*10^{-4}$	**0.003***	0.001	0.001	0.001	$2.2*10^{-4}$	$-2.5*10^{-4}$
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.14	0.18	0.03	0.02	0.03	0.07	0.18	0.21	0.16	0.02	0.05	0.04	0.06	0.11	0.03	0.02	0.07	0.11
N	149						149						149					

***Significant at 1%, **5% and *10% levels

Table3: Influence of investor attention on currency returns in and out of speculative attacks

The table presents the results for the regression between currency returns (R) and online search changes (S) for the entire dataset (one regime) as well as for during and out of speculative attacks (two regimes), according to the following equations:

$$R_{t,i} = a_0 + \sum_{n=0}^{2} b_{i,n} \cdot S_{i,t-n} + \sum_{n=1}^{2} c_{i,n} \cdot R_{i,t-n} + \varepsilon_t \quad (3)$$

$$R_{t,i} = a_0 + \sum_{n=0}^{2} b_{i,n} \cdot D_{i,t-n} \cdot S_{i,t-n} + \sum_{n=0}^{2} c_{i,n} \cdot (1 - D_{i,t-n}) \cdot S_{i,t-n} + \sum_{n=1}^{2} d_{i,n} \cdot R_{i,t-n} + \varepsilon_t \quad (4)$$

Where D is a dummy variable that assumes 1 during speculative attacks and 0 otherwise. Speculative Attacks are defined as the 22 days before and after the peak of currency's price to USD. Estimated coefficients are followed by robust standard errors in parentheses. The data on currency returns and attention are daily for the sample period of 2018.06.01 to 2018.12.31.

	ARS	TRY	RUB	ZAR	BRL	MXN
Panel A: One regime						
S_t	**0.065*** **	**0.037*** **	**0.038*** **	**0.025** **	0.014	0.016
	(0.007)	(0.006)	(0.015)	(0.010)	(0.010)	(0.012)
S_{t-1}	**-0.022* **	**0.015*** **	0.001	-0.001	0.004	-0.004
	(0.011)	(0.005)	(0.010)	(0.008)	(0.011)	(0.013)
S_{t-2}	**0.026** **	-0.009	-0.003	0.004	**0.016* **	**0.018* **
	(0.011)	(0.008)	(0.013)	(0.009)	(0.009)	(0.010)
R_{t-1}	0.165	0.153	**-0.074* **	0.013	-0.150	**-0.144* **
	(0.112)	(0.106)	(0.083)	(0.081)	(0.091)	(0.082)
R_{t-2}	-0.103	-0.115	0.125	0.102	-0.035	-0.010
	(0.092)	(0.109)	(0.075)	(0.072)	(0.070)	(0.079)
Intercept	**0.002* **	$2.4*10^{-4}$	0.001	0.001	$1.5*10^{-4}$	-3.4*10-4
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.43	0.44	0.10	0.07	0.03	0.09
N	149					
Panel B: Two regimes						
$D_t.S_t$	**0.072*** **	**0.044*** **	**0.080*** **	**0.047*** **	0.025	0.010
	(0.007)	(0.003)	(0.021)	(0.012)	(0.028)	(0.019)
$D_{t-1}.S_{t-1}$	**-0.032*** **	**0.020*** **	-0.009	-0.012	-0.004	-0.003
	(0.010)	(0.006)	(0.018)	(0.008)	(0.027)	(0.023)
$D_{t-2}.S_{t-2}$	**0.040*** **	-0.011	-0.020	0.012	**0.041* **	0.023
	(0.008)	(0.008)	(0.019)	(0.011)	(0.023)	(0.016)
$(1 - D_t).S_t$	**0.027* **	-0.018	0.001	-0.003	0.011	0.018
	(0.015)	(0.016)	(0.013)	(0.013)	(0.011)	(0.015)
$(1 - D_{t-1}).S_{t-1}$	-0.009	-0.008	0.003	0.005	0.006	-0.004
	(0.018)	(0.013)	(0.015)	(0.013)	(0.012)	(0.016)
$(1 - D_{t-2}).S_{t-2}$	-0.019	0.003	0.024	0.002	0.008	0.016
	(0.014)	(0.014)	(0.019)	(0.012)	(0.009)	(0.012)
R_{t-1}	**0.223** **	0.067	-0.111	0.014	-0.142	-0.147
	(0.110)	(0.122)	(0.087)	(0.080)	(0.088)	(0.083)

R_{t-2}	-0.139	-0.082	**0.140****	0.077	-0.035	**-0.003***
	(0.090)	(0.131)	(0.070)	(0.076)	(0.072)	(0.080)
Intercept	0.002**	$2.6*10^{-4}$	$6.9*10^{-4}$	$5.9*10^{-4}$	$1.5*10^{-4}$	-3.4*10-4
	(0.001)	(0.001)	($6.4*10^{-4}$)	($9.2*10^{-4}$)	($8.5*10^{-4}$)	($6.7*10^{-4}$)
R^2	0.49	0.53	0.20	0.13	0.06	0.10
N	149					

***Significant at 1%, **5% and *10% levels

Table4: Causality between variance and investor attention

Panel A presents the p-values for the Ganger Causality test between currency variance (σ^2) and online search changes (S). Variance is calculated using a GARCH (1,1) model. Entire Sample ranges from 2018.06.01 to 2018.12.31. The data on variance and attention are daily. Speculative Attacks are defined as the 22 days before and after the peak of a currency's price to USD. Bold means significant at 5% level. Panel B reports VAR estimation results that are displayed in two parts: the search equation is given in the upper section and the return equation in the lower section. For brevity, the panel shows only the results for the lags of the alternative variable in the VAR model (i.e.: Variance in the case of Searches and vice-versa) as well as for the intercept. The standard errors are in parentheses and the significant coefficients are in bold. All estimations contain 2 lags.

	Speculative Attacks						Out-of speculattive attacks					
	ARS	TRY	RUB	ZAR	BRL	MXN	ARS	TRY	RUB	ZAR	BRL	MXN
Panel A: Granger causality test												
H0: σ^2 does not Granger cause S	**0.000**	**0.000**	**0.059**	**0.000**	0.724	0.615	0.857	0.887	0.449	0.530	0.721	**0.001**
H0: S does not Granger cause σ^2	**0.010**	0.464	**0.007**	0.374	0.654	0.915	0.877	0.982	0.990	0.837	0.492	0.440
Panel B: VAR regression												
Search												
σ^2_{t-1}	$\mathbf{-56.826***}$	68.55	$\mathbf{-1435.233*}$	-316.079	-4.676	73.225	-0.453	-0.682	-285.501	-109.965	-103.824	228.053
	(19.476)	(68.098)	(800.481)	(403.051)	(48.641)	(206.094)	(3.409)	(7.020)	(727.999)	(288.954)	(89.576)	(356.375)
σ^2_{t-2}	$\mathbf{18.428*}$	-55.944	17.799	194.407	-44.799	-173.995	-1.261	-0.477	108.353	-168.968	16.96	-414.251
	(10.443)	(47.028)	(809.438)	(402.533)	(48.647)	(412.617)	(3.408)	(7.021)	(728.698)	(287.602)	(89.76)	(355.877)
Intercept	$\mathbf{0.025*}$	0.018	$\mathbf{0.093***}$	0.020	0.007	0.003	0.007	0.003	0.011	0.038	0.013	0.017
	(0.014)	(0.026)	(0.031)	(0.020)	(0.009)	(0.010)	(0.006)	(0.009)	(0.032)	(0.065)	(0.017)	(0.017)
R^2	0.08	0.03	0.19	0.09	0.08	0.05	0.02	0.05	0.01	0.08	0.11	0.10
N	149						149					
Variance												
S_{t-1}	$\mathbf{0.011***}$	$\mathbf{0.004***}$	$\mathbf{2.8*10^{-5}**}$	$\mathbf{9.4*10^{-5}***}$	$6.2*10^{-5}$	$2.1*10^{-5}$	0.001	$4.5*10^{-4}$	$\mathbf{1.2*10^{-5}***}$	$2.5*10^{-5}$	$-3.0*10^{-5}$	$\mathbf{5.7*10^{-5}***}$
	$(3.8*10^{-4})$	$(8.6*10^{-5})$	$(1.2*10^{-5})$	$(1.8*10^{-5})$	$(1.4*10^{-4})$	$(3.2*10^{-5})$	(0.002)	$(9.5*10^{-4})$	$(1.2*10^{-5})$	$(2.4*10^{-5})$	$(7.7*10^{-5})$	$(1.8*10^{-5})$
S_{t-2}	**-0.001**	$2.5*10^{-4}$	$-9.0*10^{-6}$	$1.2*10^{-5}$	$1.0*10^{-4}$	$2.7*10^{-5}$	-0.001	$-3.0*10^{-5}$	$-8.0*10^{-6}$	$-3.0*10^{-6}$	$4.3*10^{-5}$	$\mathbf{5.4*10^{-5}***}$
	$(9.0*10^{-4})$	$(2.9*10^{-4})$	$(1.0*10^{-5})$	$(1.9*10^{-5})$	$(1.4*10^{-4})$	$(3.2*10^{-5})$	(0.002)	$(9.5*10^{-4})$	$(1.2*10^{-5})$	$(2.4*10^{-5})$	$(7.7*10^{-5})$	$(1.9*10^{-5})$
Intercept	$\mathbf{2.4*10^{-4}***}$	$\mathbf{8.3*10^{-5}***}$	$\mathbf{1.5*10^{-5}***}$	$\mathbf{2.3*10^{-4}***}$	$\mathbf{1.4*10^{-4}*}$	$\mathbf{1.2*10^{-5}***}$	$\mathbf{3.5*10^{-4}**}$	$\mathbf{1.8*10^{-4}*}$	$\mathbf{1.5*10^{-5}***}$	$\mathbf{2.0*10^{-4}***}$	$\mathbf{1.4*10^{-4}***}$	$\mathbf{1.2*10^{-5}***}$
	$(6.2*10^{-5})$	$(2.7*10^{-5})$	$(3.8*10^{-6})$	$(2.0*10^{-5})$	$(1.5*10^{-5})$	$(4.0*10^{-6})$	$(1.5*10^{-4})$	$(1.0*10^{-4})$	$(3.7*10^{-6})$	$(1.9*10^{-5})$	$(1.5*10^{-5})$	$(3.9*10^{-6})$
R^2	0.89	0.96	0.60	0.38	0.01	0.67	0.25	0.39	0.59	0.08	0.01	0.69
N	149						149					

***Significant at 1%, **5% and *10% levels

Table 5: Influence of investor attention on currency variance in and out of speculative attacks
The table presents the results for the regression between currency variance and online search changes (S) for the entire dataset (one regime) as well as for during and out of speculative attacks (two regimes), according to the following equations:

$$\sigma^2{}_{t,i} = a_0 + \sum_{n=0}^{1} b_{i,n} \cdot S_{i,t-n} + c_{i,t} \cdot \sigma^2{}_{i,t-1} + \varepsilon_t \quad (5)$$

$$\sigma^2{}_{t,i} = a_0 + \sum_{n=0}^{1} b_{i,n} \cdot D_{i,t-n} \cdot S_{i,t-n} + \sum_{n=0}^{1} c_{i,n} \cdot (1 - D_{i,t-n}) \cdot S_{i,t-n} + d_{i,t} \cdot \sigma^2{}_{i,t-1} + \varepsilon_t \quad (6)$$

Where D is a dummy variable that assumes 1 during speculative attacks and 0 otherwise.Variance is calculated using a GARCH (1,1) model. Speculative Attacks are defined as the 22 days before and after the peak of a currency's price to USD. Estimated coefficients are followed by robust standard errors in parentheses. The data on currency returns and attention are daily for the sample period of 2018.06.01 to 2018.12.31.

	ARS	TRY	RUB	ZAR	BRL	MXN
Panel A: One regime						
S_t	**0.002*** **	1.700	**$3.3*10^{-5}$***	**$3.5*10^{-5}$****	$-3.3*10^{-5}$	$1.6*10^{-5}$
	($3.6*10^{-4}$)	(0.092)	($2.0*10^{-5}$)	($1.7*10^{-5}$)	($6.0*10^{-5}$)	($1.5*10^{-5}$)
S_{t-1}	**0.009*** **	**0.003*** **	$9.0*10^{-6}$	**$6.6*10^{-5}$*****	$-2.9*10^{-5}$	$3.9*10^{-5}$
	($1.6*10^{-3}$)	($5.6*10^{-4}$)	($9.0*10^{-6}$)	($2.0*10^{-5}$)	($5.7*10^{-5}$)	($5.5*10^{-5}$)
σ^2_{t-1}	**0.435*** **	**0.653*** **	**0.792*** **	**-0.554*** **	-0.077	**0.816*** **
	(0.079)	(0.062)	(0.063)	(0.054)	(0.081)	(0.033)
Intercept	**$2.1*10^{-4}$*****	**$1.1*10^{-4}$*****	**$1.36*10^{-5}$*****	**$2.0*10^{-4}$*****	**$1.3*10^{-4}$*****	**$1.36*10^{-5}$*****
	($6.7*10^{-5}$)	($3.9*10^{-5}$)	($4.0*10^{-6}$)	($7.1*10^{-6}$)	($9.5*10^{-6}$)	($2.4*10^{-6}$)
R^2	0.43	0.90	0.67	0.38	0.01	0.67
N	150					
Panel B: Two regimes						
$D_t.S_t$	**0.002*** **	**$-9.6*10^{-5}$*****	**$6.6*10^{-5}$****	**$5.7*10^{-5}$*****	$-8.6*10^{-5}$	$-1.6*10^{-7}$
	($3.8*10^{-4}$)	($7.1*10^{-5}$)	($2.7*10^{-5}$)	($2.1*10^{-5}$)	($7.9*10^{-5}$)	($1.7*10^{-5}$)
$D_{t-1}.S_{t-1}$	**0.010*** **	$3.9*10^{-3}$	$-9.2*10^{-6}$	**$8.5*10^{-5}$*****	$1.8*10^{-5}$	$1.6*10^{-5}$
	($7.4*10^{-4}$)	($2.7*10^{-4}$)	($1.6*10^{-5}$)	($2.7*10^{-5}$)	($8.6*10^{-5}$)	($1.7*10^{-5}$)
$(1 - D_t).S_t$	**0.001***	**$1.4*10^{-4}$***	**$8.5*10^{-6}$***	$1.8*10^{-5}$	$-1.9*10^{-5}$	$2.2*10^{-5}$
	($6.8*10^{-3}$)	($1.1*10^{-4}$)	($5.0*10^{-6}$)	($1.8*10^{-5}$)	($7.2*10^{-5}$)	($2.2*10^{-5}$)
$(1 - D_{t-1}).S_{t-1}$	**0.002***	$5.0*10^{-4}$	$1.4*10^{-5}$	$2.0*10^{-5}$	$-4.5*10^{-5}$	$-4.7*10^{-5}$
	($8.0*10^{-4}$)	($2.8*10^{-4}$)	($8.8*10^{-6}$)	($1.6*10^{-5}$)	($7.1*10^{-5}$)	($7.4*10^{-5}$)
σ^2_{t-1}	**0.422*** **	**0.652*** **	**0.84*** **	**-0.579*** **	-0.074	0.817
	(0.061)	(0.060)	(0.077)	(0.055)	(0.085)	(0.034)
Intercept	**$2.6*10^{-4}$*****	**$1.1*10^{-4}$*****	**$1.0*10^{-5}$****	**$2.1*10^{-4}$*****	$1.3*10^{-4}$	**$1.4*10^{-5}$*****
	($4.9*10^{-5}$)	($3.0*10^{-5}$)	($4.8*10^{-6}$)	($7.3*10^{-6}$)	($9.8*10^{-6}$)	($2.4*10^{-6}$)
R^2	0.90	0.95	0.72	0.43	0.01	0.67
N	150					

***Significant at 1%, **5% and *10% level

Table 6: Out-of sample analysis of the relationship between investor attention, currency return and variance for the Russian ruble

Panel A reports VAR estimation results between currency return (R) and online searches (S) that are displayed in two parts: the search equation is given in the left section and the return equation in the right section. For brevity, the panel shows only the results for the lags of the alternative variable in the VAR model (i.e.: Returns in the case of Searches and vice-versa) as well as for the intercept. Panel B presents the results for the regression between currency returns and online search changes as expressed in Equations (3) and (4). The regression includes a dummy variable that assumes 1 during speculative attacks and 0 otherwise. Speculative Attacks are defined as the 22 days before and after the peak of the RUB price to USD. Estimated coefficients are followed by robust standard errors in parentheses. Panel C reports VAR estimation results between currency variance (σ^2), calculated using a GARCH (1,1) model and online searches (S) that are displayed in two parts: the search equation is given in the left section and the variance equation in the right section. For brevity, the panel shows only the results for the lags of the alternative variable in the VAR model (i.e.: Variance in the case of Searches and vice-versa) as well as for the intercept. Panel D presents the results for the regression between currency variance and online search change as expressed in Equations (5) and (6). The regression includes a dummy variable that assumes 1 during speculative attacks and 0 otherwise. The standard errors are in parentheses and the significant coefficients are in bold. The data on currency returns, variance and attention are daily for the sample period of 2014.09.01 to 2015.03.31.

Panel A: VAR analysis between return and attention (N = 149)

Influence on S				**Influence on R**			
R_{t-1}	R_{t-2}	Intercept	R^2	S_{t-1}	S_{t-2}	Intercept	R^2
During Speculative Attacks							
3.493***	0.701	-0.004	0.28	**-0.037*****	0.011	0.003	0.05
(0.580)	(0.620)	(0.013)		(0.013)	(0.012)	(0.002)	
Out of Speculative Attacks							
0.137	-0.066	0.006	0.05	0.016	-0.008	0.003	0.01
(0.247)	(0.247)	(0.006)		(0.027)	(0.027)	(0.002)	

Panel B: Regression between return and attention (N = 149)

$D_t.S_t$	$D_{t-1}.S_{t-1}$	$D_{t-2}.S_{t-2}$	$(1 - D_t).S_t$	$(1 - D_{t-1}).S_{t-1}$	$(1 - D_{t-2}).S_{t-2}$	R_{t-1}	R_{t-2}	Intercept	R^2
0.059***	**-0.042****	0.007	0.038	0.032	-0.003	-0.102	0.118	0.003	0.21
(0.020)	(0.020)	(0.008)	(0.028)	(0.024)	(0.020)	(0.112)	(0.104)	(0.002)	

Panel C: VAR analysis between variance and attention (N = 149)

Influence on S	**Influence on σ^2**

σ^2_{t-1}	σ^2_{t-2}	Intercept	R^2	S_{t-1}	S_{t-2}	Intercept	R^2
During Speculative Attacks							
-178.279* **	**146.108*** **	0.028	0.19	**0.695*** **	**0.240*** **	0.028	0.92
(49.367)	(50.492)	(0.017)		(0.075)	(0.077)	(0.017)	
Out of Speculative Attacks							
-132.49	112.567	0.008	0.06	3.2*10-4	1.1*10-4	3.9*10-5	0.87
(185.016)	(185.266)	(0.007)		(3.6*10-4)	(3.6*10-4)	(3.3*10-5)	

Panel D: Regression between variance and attention (N = 150)

$D_t.S_t$	$D_{t-1}.S_{t-1}$	$(1 - D_t).S_t$	$(1 - D_{t-1}).S_{t-1}$	σ^2_{t-1}	Intercept	R^2
$9.3*10^{-4}$* **	$4.8*10^{-5}$	$4.1*10^{-5}$	$3.6*10^{-4}$	**0.973*** **	$3.2*10^{-6}$	0.90
$(3.2*10^{-4})$	$(6.8*10^{-5})$	$(1.4*10^{-4})$	$(2.5*10^{-4})$	(0.055)	$(2.2*10^{-5})$	

***Significant at 1%, **5% and *10% levels

Table 7: Analysis of the relationship between investor attention and currencies' returns/variance using alternative terminologies for online searches.

Panel A presents the p-values for the Granger Causality test between currencies' daily return (R) and online search changes (S). Online searches are measured by the daily change of the first factor extracted from the Principal Component Analysis using five different terminologies of online searches (e.g.: "Argentine Peso", "ARS USD", "USD ARS", "Argentine Peso Dollar" and "Dollar Argentine Peso"). Bold means significant at 10% level. Panel B presents the results for the regression between currency returns and online search changes as expressed in Equations (3) and (4). The regression includes a dummy variable that assumes 1 during speculative attacks and 0 otherwise. Speculative Attacks are defined as the 22 days before and after the peak of a currency's price to USD. Estimated coefficients are followed by robust standard errors in parentheses. The sample period is from 2018.06.01 to 2018.12.31. Panels C and D replicate the analysis of the previous panels for the variance-attention relation, using Equations (5) and (6) in the case of Panel D. Variance is calculated using a GARCH (1,1) model.

	ARS	TRY	RUB	ZAR	BRL	MXN
Panel A: Granger causality between return and attention						
During speculative attacks						
H0: R does not Granger cause S	**0.034**	**0.001**	0.585	0.753	0.700	0.199
H0: S does not Granger cause R	**0.008**	0.228	**0.034**	**0.020**	0.982	0.497
Out of speculative attacks						
H0: R does not Granger cause S	0.795	0.711	0.803	0.505	0.700	0.223
H0: S does not Granger cause R	0.998	0.544	0.662	0.848	0.675	**0.007**
Panel B: Regression between return and attention						
$D_t.CGT_t$	**0.053*****	**0.053*****	**0.037*****	**0.035*****	-0.010	-0.004
	(0.008)	(0.005)	(0.010)	(0.009)	(0.012)	(0.009)
$D_{t-1}.CGT_{t-1}$	-0.013	**0.017***	0.010	-0.010	-0.007	0.004
	(0.013)	(0.010)	(0.008)	(0.008)	(0.014)	(0.011)
$D_{t-2}.CGT_{t-2}$	**0.020****	-0.009	-0.003	0.010	0.005	0.017
	(0.010)	(0.013)	(0.008)	(0.009)	(0.010)	(0.010)
$(1 - D_t).CGT_t$	0.004	-0.003	0.003	-0.008	**0.009***	0.014
	(0.008)	(0.010)	(0.006)	(0.010)	(0.005)	(0.007)
$(1 - D_{t-1}).CGT_{t-1}$	0.010	-0.003	0.003	0.007	-0.002	-0.003
	(0.008)	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)
$(1 - D_{t-2}).CGT_{t-2}$	0.006	0.008	0.006	0.007	0.004	0.003
	(0.008)	(0.009)	(0.008)	(0.008)	(0.005)	(0.005)
R_{t-1}	0.152	0.114	-0.138	0.004	-0.143	**-0.182***
	(0.115)	(0.114)	(0.092)	(0.08)	(0.090)	(0.092)
R_{t-2}	-0.129	-0.102	0.108	0.097	-0.032	0.061
	(0.094)	(0.119)	(0.075)	(0.077)	(0.072)	(0.084)
Intercept	0.002	0.000	0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.39	0.52	0.15	0.13	0.05	0.13
Panel C: Granger causality between variance and attention						
During speculative attacks						

H0: σ^2 does not Granger cause S	**0.000**	**0.000**	**0.036**	**0.000**	0.340	0.681
H0: S does not Granger cause σ^2	0.112	0.611	**0.010**	0.167	0.712	0.340
Out of speculative attacks						
H0: σ^2 does not Granger cause S	0.911	0.962	0.697	0.538	0.084	0.113
H0: S does not Granger cause σ^2	0.950	0.924	0.988	0.504	0.092	**0.000**
Panel D: Regression between variance and attention						
$D_t.CGT_t$	**$1.2*10^{-3}$*****	$-2.8*10^{-4}$	**$3.2*10^{-5}$****	**$3.9*10^{-5}$****	$-3.0*10^{-5}$	$8.2*10^{-6}$
	($3.3*10^{-4}$)	($3.2*10^{-4}$)	($1.3*10^{-5}$)	($1.5*10^{-5}$)	($4.6*10^{-5}$)	($9.3*10^{-6}$)
$D_{t-1}.CGT_{t-1}$	**$7.1*10^{-3}$*****	**$4.2*10^{-3}$*****	$1.7*10^{-6}$	**$6.8*10^{-5}$*****	$4.7*10^{-5}$	$-8.6*10^{-6}$
	($1.3*10^{-3}$)	($1.1*10^{-3}$)	($6.2*10^{-6}$)	($2.2*10^{-5}$)	($3.0*10^{-5}$)	($8.8*10^{-6}$)
$(1 - D_t).CGT_t$	$1.5*10^{-4}$	$8.0*10^{-5}$	$2.4*10^{-6}$	**$-1.2*10^{-5}$***	$-2.2*10^{-5}$	$5.3*10^{-6}$
	($3.1*10^{-4}$)	($8.4*10^{-5}$)	($2.2*10^{-6}$)	($1.2*10^{-5}$)	($5.3*10^{-5}$)	($9.1*10^{-6}$)
$(1 - D_{t-1}).CGT_{t-1}$	$8.1*10^{-5}$	$2.7*10^{-4}$	$6.6*10^{-7}$	$1.5*10^{-5}$	$2.4*10^{-5}$	$2.9*10^{-5}$
	($2.3*10^{-4}$)	($1.8*10^{-4}$)	($2.7*10^{-6}$)	($1.3*10^{-5}$)	($2.4*10^{-5}$)	($3.5*10^{-5}$)
σ^2_{t-1}	**0.399*****	**0.635*****	**0.827*****	**-0.583*****	-0.074	**0.815*****
	(0.068)	(0.082)	(0.064)	(0.055)	0.080	(0.034)
Intercept	**$2.7*10^{-4}$*****	**$1.2*10^{-4}$****	**$1.1*10^{-5}$*****	**$2.1*10^{-4}$*****	**$1.3*10^{-4}$*****	**$1.4*10^{-5}$*****
	($6.9*10^{-5}$)	($4.5*10^{-5}$)	($4.1*10^{-6}$)	($7.3*10^{-6}$)	($9.7*10^{-6}$)	($2.4*10^{-6}$)
R^2	0.83	0.85	0.71	0.43	0.02	0.68

***Significant at 1%, **5% and *10% levels

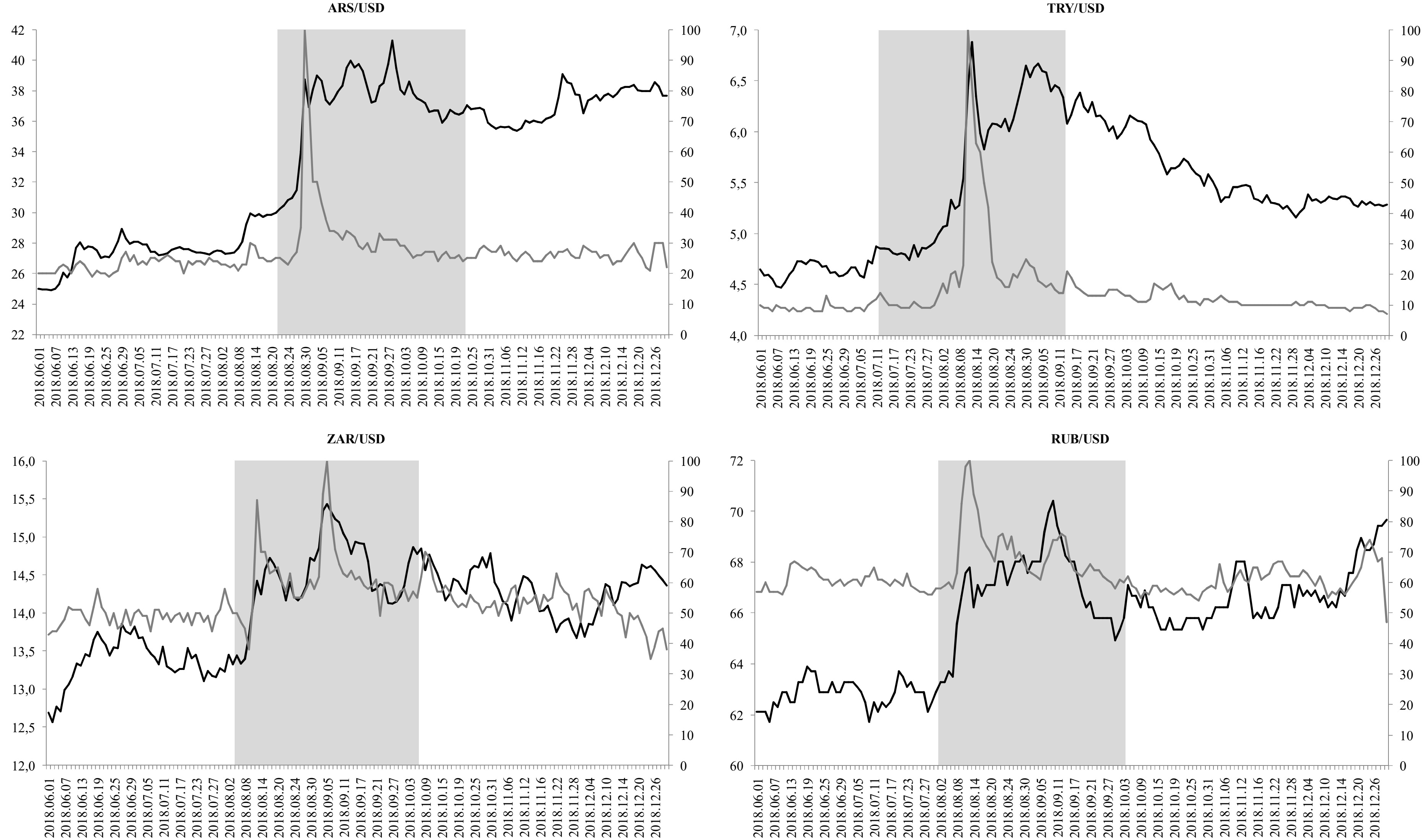
Table 8: Analysis of the relationship between investor attention and currencies' returns/variance using a 30-day event window as an alternative length of speculative attacks.

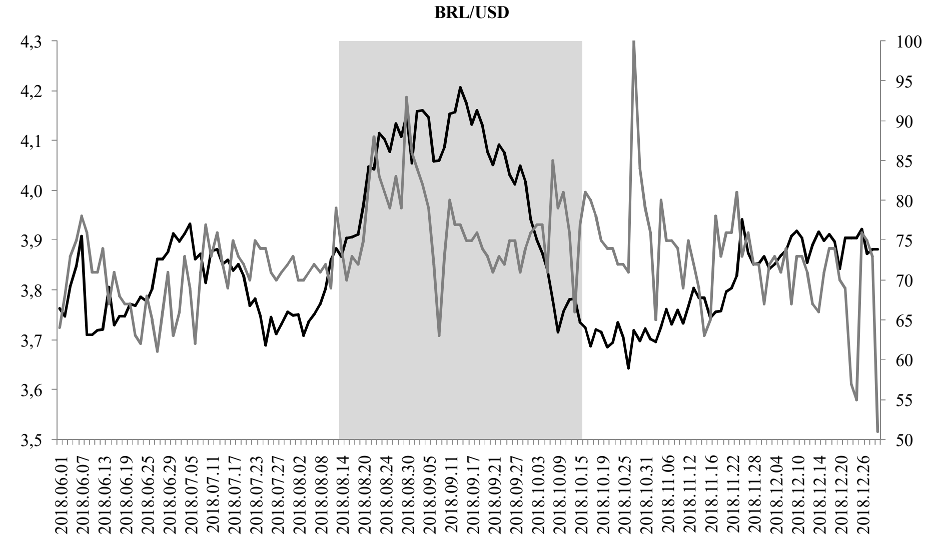
Panel A presents the p-values for the Ganger Causality test between currency daily return (R) and online search changes (S).Bold means significant at 10% level. Panel B presents the results for the regression between currency returns and online search changes as expressed in Equations (3) and (4). The regression includes a dummy variable that assumes 1 during speculative attacks and 0 otherwise. Speculative Attack window is defined as the 30 days surrounding the peak of a currency's price to USD. Estimated coefficients are followed by robust standard errors in parentheses. The sample period is from 2018.06.01 to 2018.12.31. Panel C and D replicate the analysis of the previous panels for the variance-attention relationshipusing Equations (5) and (6) in the case of Panel D. Variance is calculated using a GARCH (1,1) model.

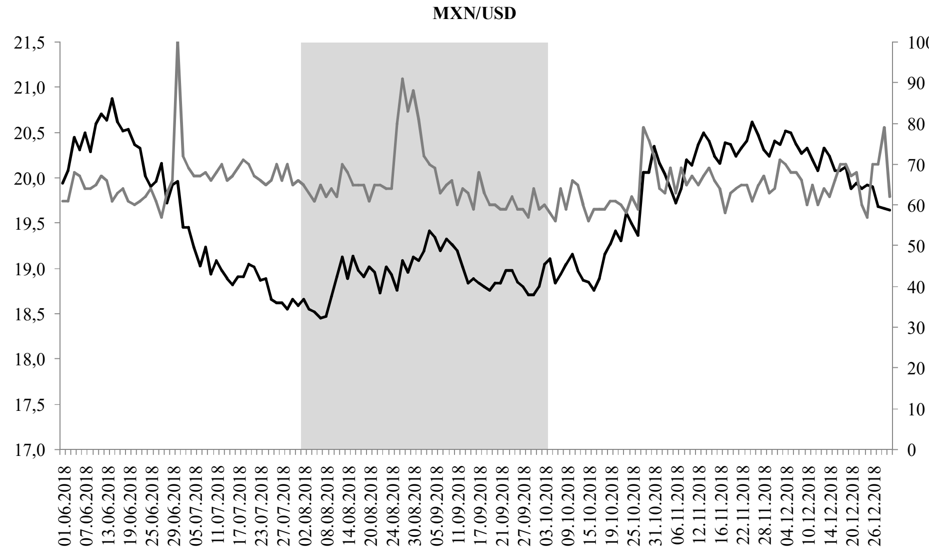
	ARS	TRY	RUB	ZAR	BRL	MXN
Panel A: Granger causality between return and attention						
During speculative attacks						
H0: R does not Granger cause S	**0.000**	**0.000**	0.164	0.672	0.215	0.855
H0: S does not Granger cause R	**0.000**	**0.039**	**0.045**	0.608	0.973	0.780
Out of speculative attacks						
H0: R does not Granger cause S	0.559	0.821	0.274	0.718	0.728	**0.039**
H0: S does not Granger cause R	0.147	0.727	0.832	**0.037**	0.932	0.207
Panel B: Regression between return and attention						
$D_t.CGT_t$	**0.072*****	**0.045*****	**0.081*****	**0.063*****	**0.072****	0.003
	(0.006)	(0.003)	(0.022)	(0.016)	(0.031)	(0.021)
$D_{t-1}.CGT_{t-1}$	**-0.034*****	**0.019*****	-0.011	0.003	-0.018	-0.002
	(0.009)	(0.006)	(0.018)	(0.014)	(0.038)	(0.027)
$D_{t-2}.CGT_{t-2}$	**0.039*****	-0.013	-0.026	0.002	**0.053***	0.011
	(0.008)	(0.008)	(0.022)	(0.016)	(0.032)	(0.015)
$(1 - D_t).CGT_t$	**0.034****	-0.017	0.005	0.013	0.007	0.018
	(0.015)	(0.014)	(0.014)	(0.012)	(0.011)	(0.014)
$(1 - D_{t-1}).CGT_{t-1}$	-0.004	0.000	0.011	-0.002	0.005	-0.003
	(0.018)	(0.012)	(0.016)	(0.01)	(0.011)	(0.015)
$(1 - D_{t-2}).CGT_{t-2}$	-0.012	0.008	0.031	0.007	0.011	0.019
	(0.016)	(0.012)	(0.019)	(0.01)	(0.009)	(0.012)
R_{t-1}	**0.227****	0.091	-0.121	0.028	-0.13	**-0.147***
	(0.11)	(0.12)	(0.084)	(0.082)	(0.092)	(0.082)
R_{t-2}	-0.134	-0.061	**0.155****	0.116	-0.047	-0.007
	(0.091)	(0.131)	(0.071)	(0.079)	(0.073)	(0.079)
Intercept	**0.002**	0.000	0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.49	0.54	0.20	0.11	0.08	0.10
Panel C: Granger causality between variance and attention						
During speculative attacks						
H0: σ^2 does not Granger cause S	**0.000**	**0.000**	**0.049**	**0.000**	0.793	0.410

H0: S does not Granger cause σ^2	**0.003**	0.356	**0.010**	**0.002**	0.906	0.648
Out of speculative attacks						
H0: σ^2 does not Granger cause S	0.820	0.857	0.467	**0.017**	0.752	**0.002**
H0: S does not Granger cause σ^2	0.846	0.992	0.871	0.652	0.470	0.391
Panel D: Regression between variance and attention						
$D_t.CGT_t$	$\mathbf{1.9*10^{-3}}$***	$-1.0*10^{-4}$	$\mathbf{6.5*10^{-5}}$**	$4.0*10^{-6}$	$\mathbf{-2.6*10^{-4}}$**	$-1.3*10^{-5}$
	$(2.7*10^{-4})$	$(6.8*10^{-5})$	$(2.9*10^{-5})$	$(3.0*10^{-5})$	$(1.1*10^{-4})$	$(1.7*10^{-5})$
$D_{t-1}.CGT_{t-1}$	$\mathbf{1.0*10^{-2}}$***	$\mathbf{3.9*10^{-3}}$***	$-7.3*10^{-6}$	$\mathbf{1.3*10^{-4}}$**	$-9.9*10^{-5}$	$3.0*10^{-5}$
	$(6.3*10^{-4})$	$(2.4*10^{-4})$	$(1.6*10^{-5})$	$(5.1*10^{-5})$	$(1.1*10^{-4})$	$(2.3*10^{-5})$
$(1 - D_t).CGT_t$	$8.4*10^{-4}$	$\mathbf{2.1*10^{-4}}$*	$\mathbf{1.1*10^{-5}}$**	$\mathbf{4.1*10^{-5}}$**	$-5.2*10^{-6}$	$2.3*10^{-5}$
	$(6.4*10^{-4})$	$(1.2*10^{-4})$	$(5.2*10^{-6})$	$(1.9*10^{-5})$	$(6.4*10^{-5})$	$(2.2*10^{-5})$
$(1 - D_{t-1}).CGT_{t-1}$	$\mathbf{1.5*10^{-3}}$**	$\mathbf{5.0*10^{-4}}$*	$1.2*10^{-5}$	$\mathbf{4.6*10^{-6}}$***	$-1.7*10^{-5}$	$4.3*10^{-5}$
	$(7.3*10^{-4})$	$(2.6*10^{-4})$	$(8.3*10^{-6})$	$(1.5*10^{-5})$	$(6.2*10^{-5})$	$(6.8*10^{-5})$
σ^2_{t-1}	**0.418*****	**0.654*****	**0.833*****	**-0.591*****	-0.072	0.819
	(0.056)	(0.061)	(0.077)	(0.063)	(0.085)	(0.034)
Intercept	$\mathbf{2.6*10^{-4}}$***	$\mathbf{9.1*10^{-5}}$***	$\mathbf{1.1*10^{-5}}$**	$\mathbf{2.1*10^{-4}}$***	$\mathbf{1.3*10^{-4}}$***	$\mathbf{1.3*10^{-5}}$***
	$(4.6*10^{-5})$	$(3.0*10^{-5})$	$(4.6*10^{-6})$	$(8.2*10^{-6})$	$(9.8*10^{-6})$	$(2.4*10^{-6})$
R^2	0.91	0.95	0.72	0.41	0.02	0.67

Figure 1: Currency prices (Currency/USD) and online searches during speculative attacks

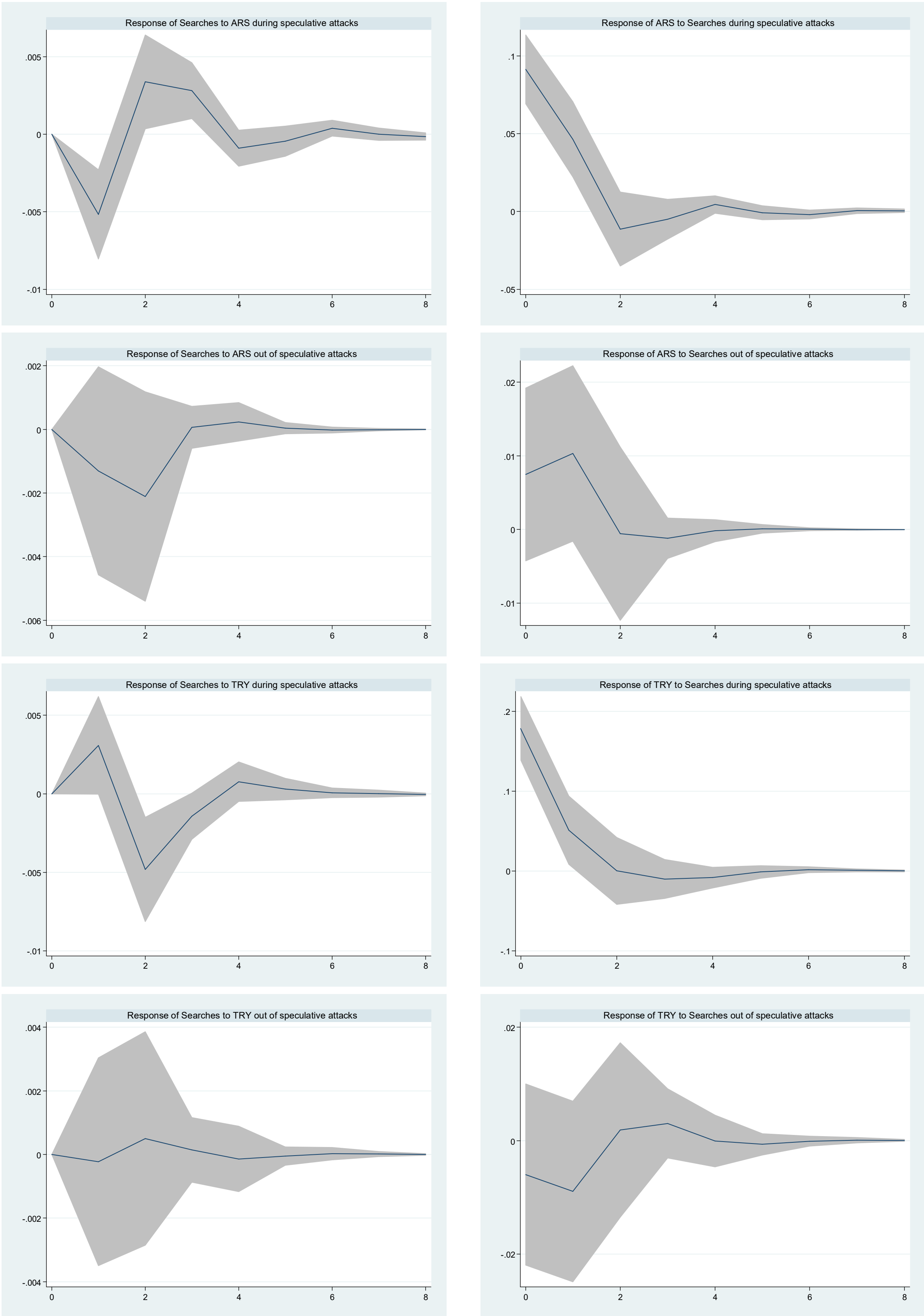






Note: The charts present the currency price to USD of some emerging countries during the second semester of 2018. The gray area indicates the speculative attacks, defined as the 22 days before and after the price peak, (in the case of Mexican pesos, for comparison purposes, the peak was considered during the range between July 2018 and September 2018 to meet the attacks on emerging markets). The black line refers to currency prices (left axis) and the gray line to Google Searches of the currency names (right axis).

Figure 2: Impulse response function for VAR of return and investor attention in and out of Speculative Attacks



Note: The figure plots impulse response to one standard deviation of the VAR model between currency returns and corresponding investor attention with 2 lags in and out of speculative attacks. Speculative Attacks are defined as the 22 days before and after the peak of a currency's price to USD. The data on currency returns and attention are daily for the sample period of 2018.06.01 to 2018.12.31

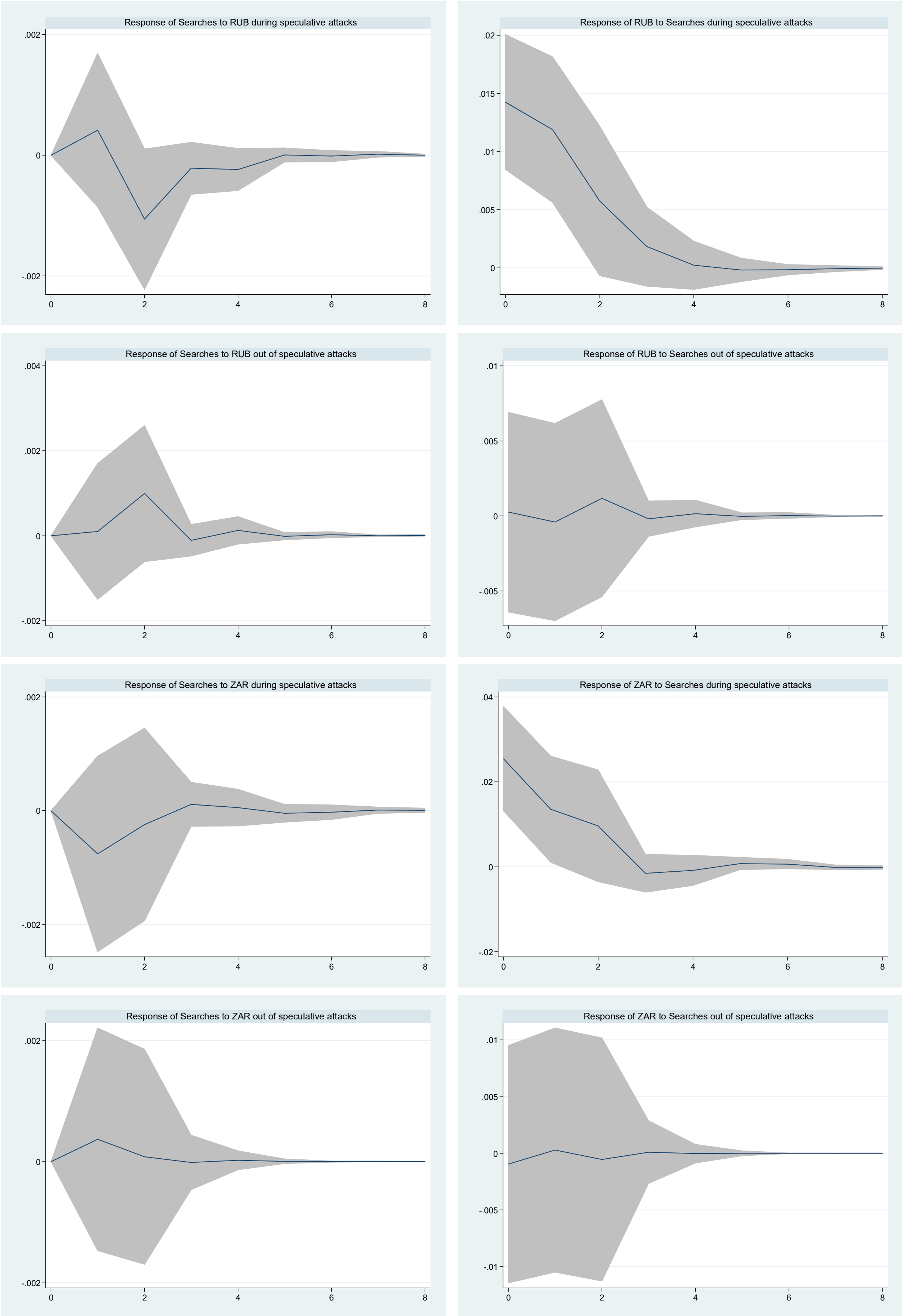


Fig. 2*(Continued)*

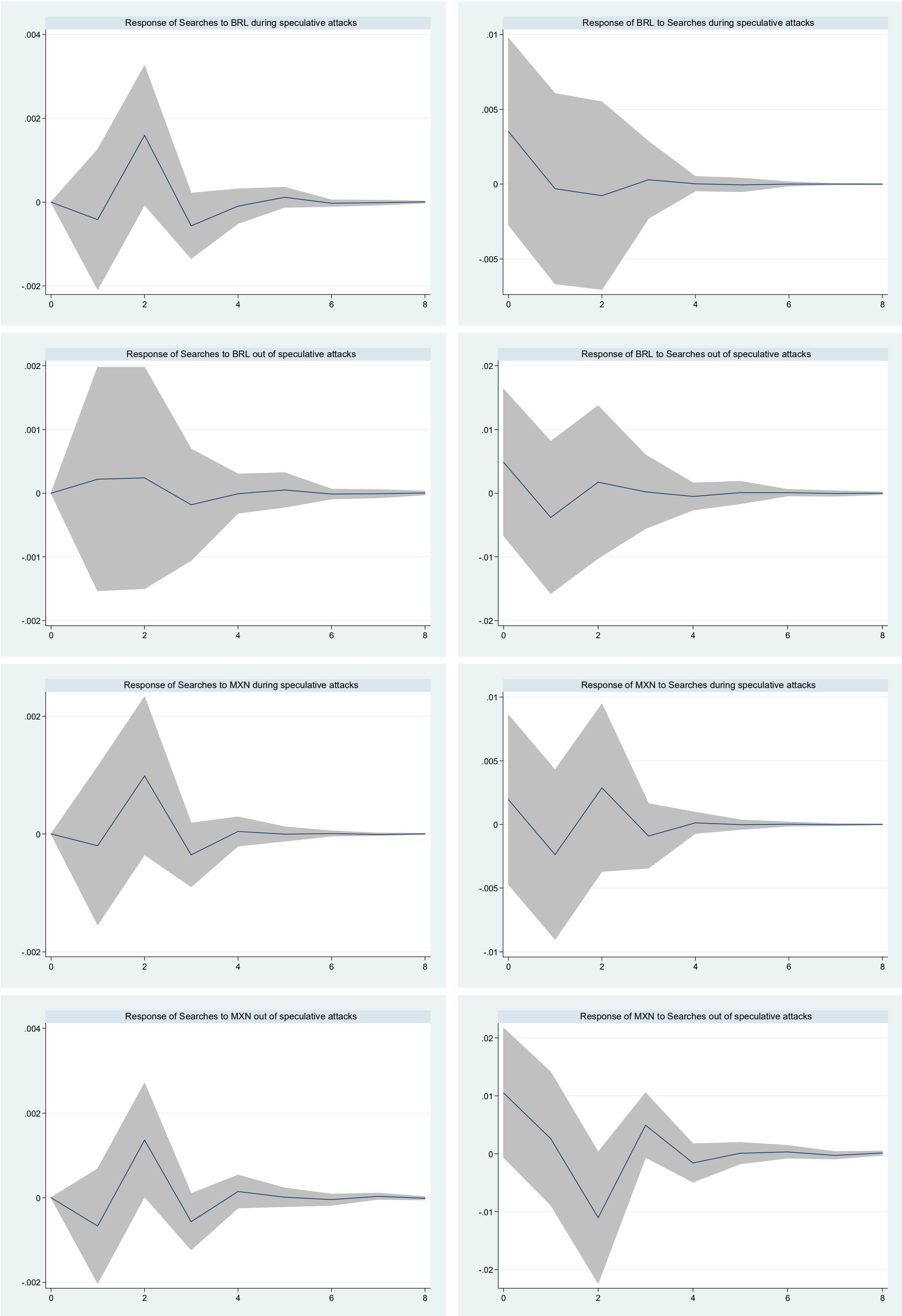
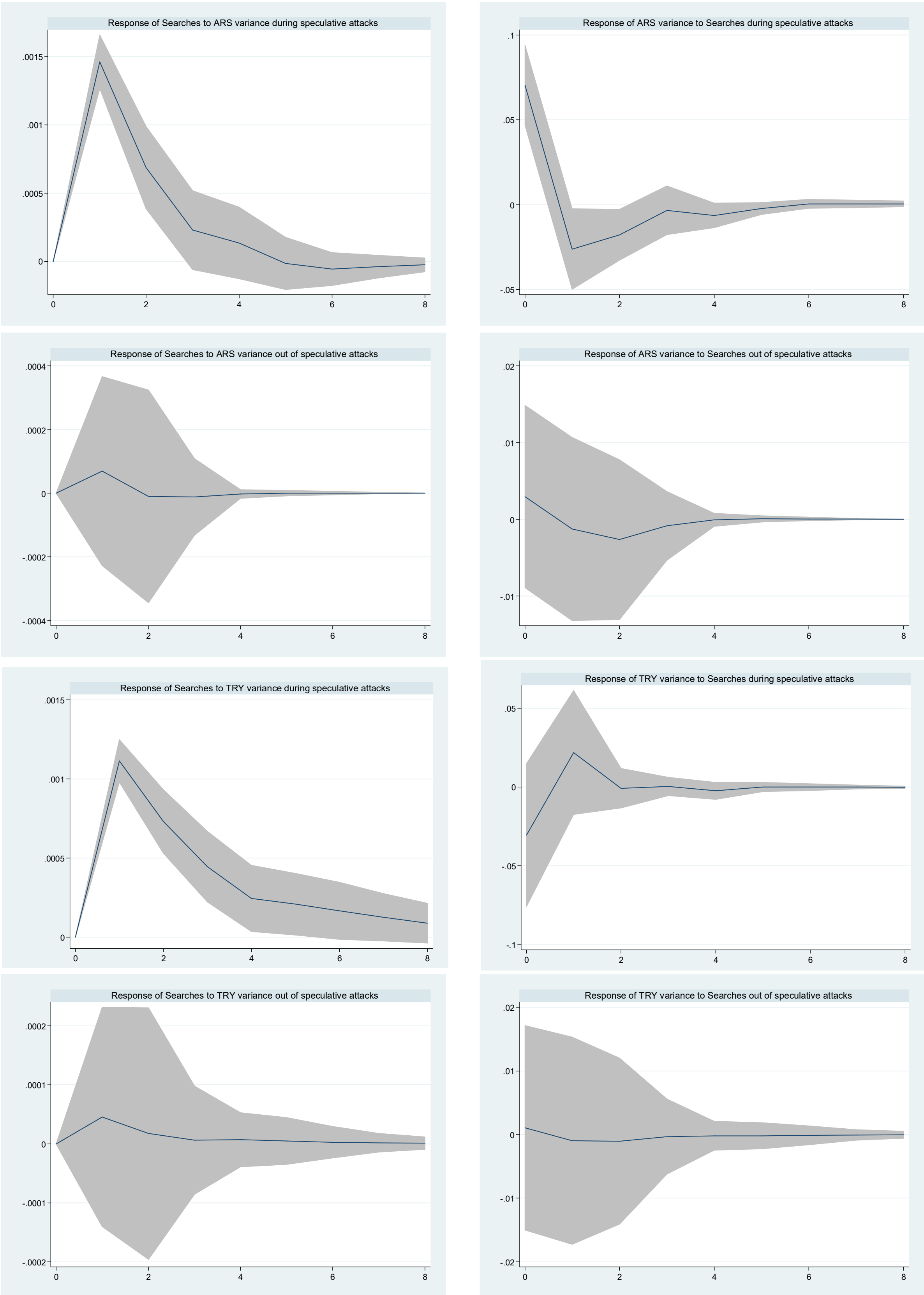


Fig. 2*(Continued)*

Figure 3: Impulse response function for VAR of variance and attention in and out of Speculative Attacks



Note: The figure plots impulse response to one standard deviation of the VAR model between currency variance and corresponding investor attention with 1 lag in and out of speculative attacks. Variance is calculated using a GARCH (1,1) model. Speculative Attacks are defined as the 22 days before and after the peak of a currency's price to USD. The data on currency returns and attention are daily for the sample period of 2018.06.01 to 2018.12.31.

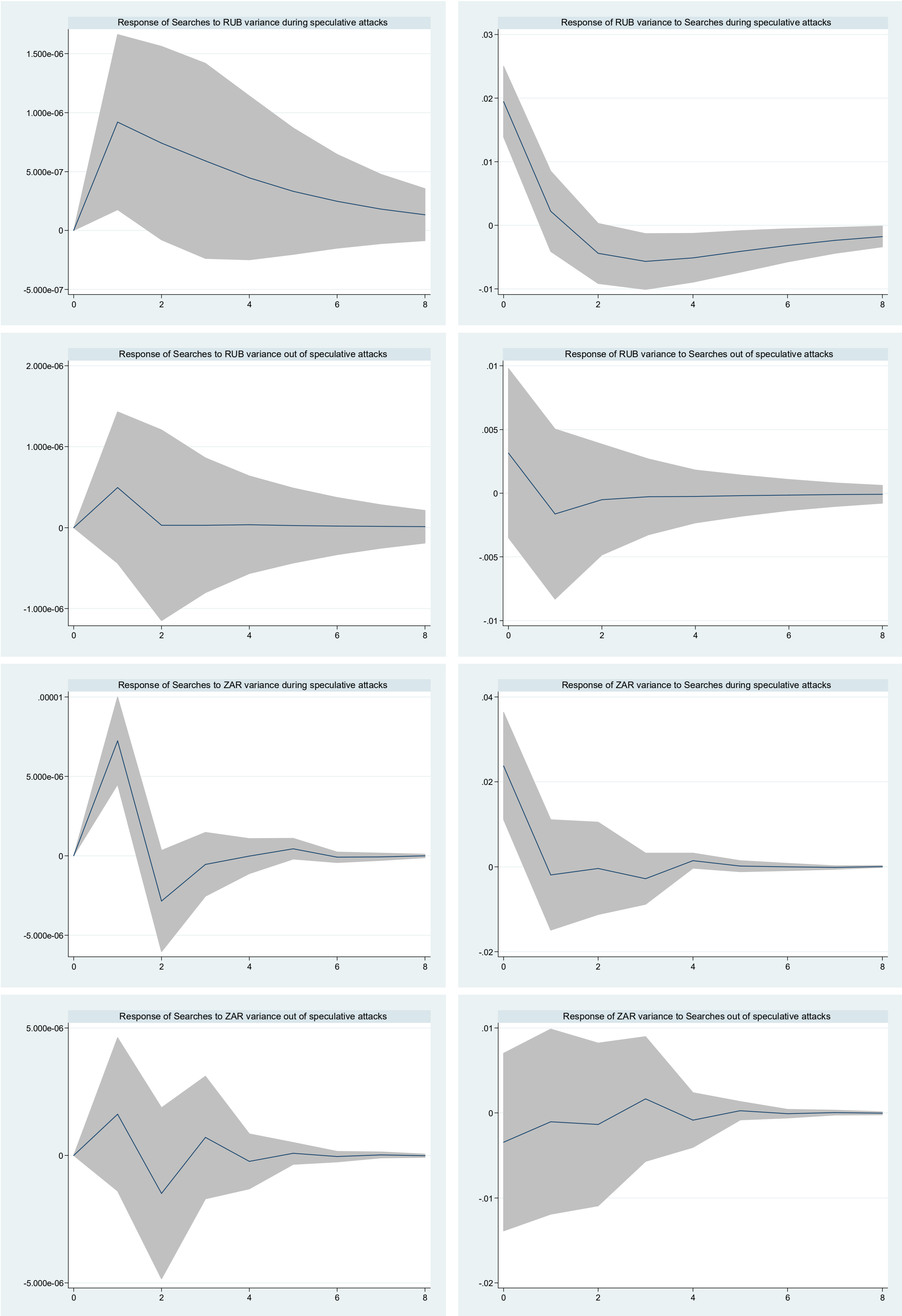


Fig. 3*(Continued)*

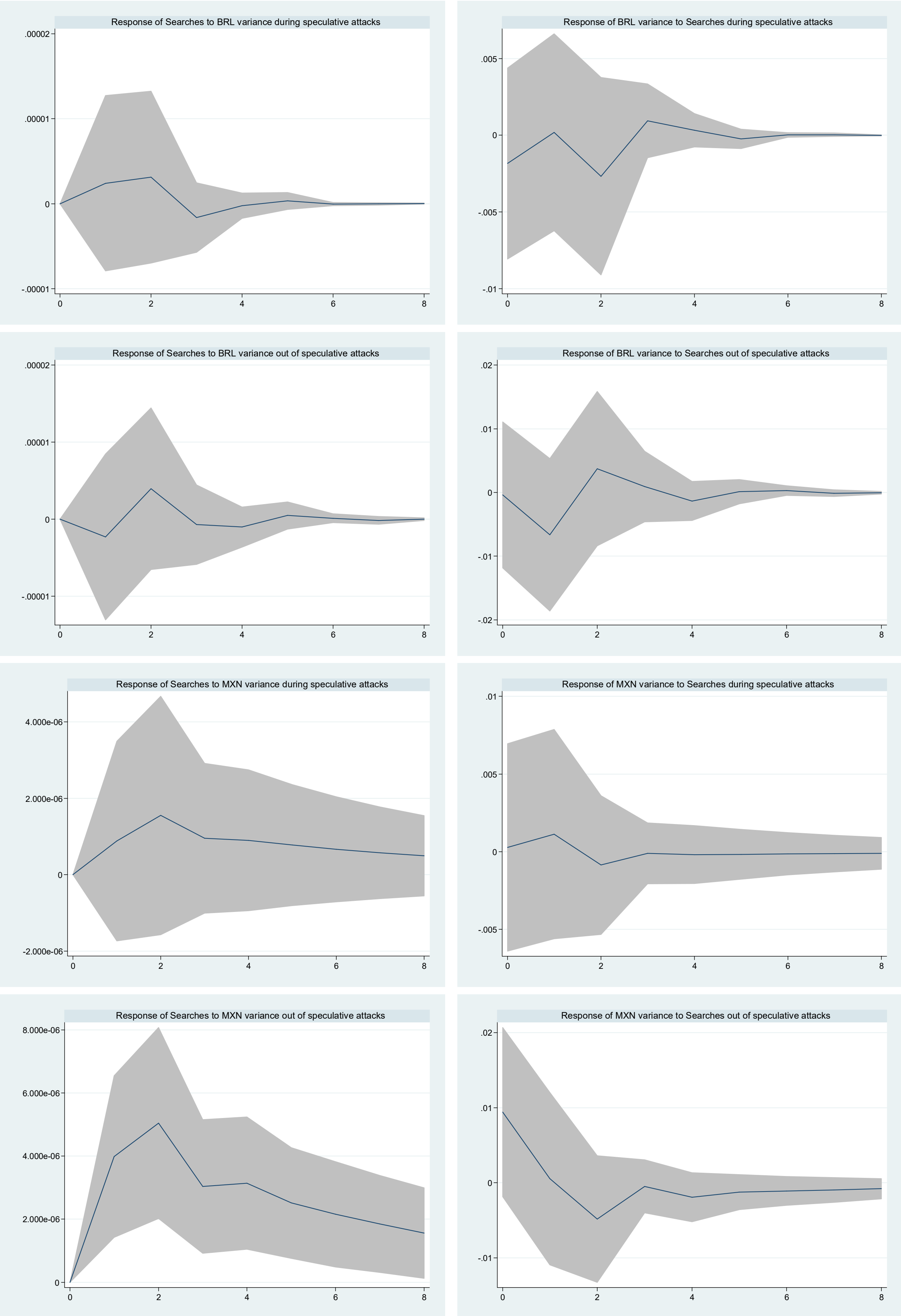


Fig. 3*(Continued)*