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Individual investor attention and the predictability of stock market volatility and returns

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Abstract

We study individual investor attention to the most important stock market index in Brazil and its dynamics with market volatility and returns. We find that attention is a leading indicator of future volatility and that returns are a leading indicator of future attention. The results are robust to different specifications.

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1 Introduction

Being attentive to something means concentrating mentally on a task or target. Attention implies selection since there are always alternative activities or things in which to be engaged. In addition to selection, attention is a matter of intensity as well. In the financial context, the incorporation of information into stock prices requires the efficient allocation of attention by investors. The need for fast decision making and the increasing amount of available information consume too much attention, which is a scarce resource for the decision maker. In the stock market, institutional (professional) and individual (retail) investors are two of the most relevant agents. Although they trade on the same set of assets, they most likely gather information from different sources. Institutional investors are mostly informed by fundamentals, whereas individual investors may favor media vehicles such as books, magazines, newspapers, radio, TV, and the Internet (Mondria, T. Wu, and Zhang 2010).

The measurement of the attention paid by market participants is a difficult task. Some indirect measures have been proposed as proxies for investor attention, such as advertising expenses (Grullon, Kanatas, and Weston 2004), media coverage (Chan 2003), price limits (Seasholes and G. Wu 2007), and stock abnormal trading volume and previous one-day return (Barber and Odean 2008). The validity of these measures relies on the assumption that if a company experienced an extreme stock return or was mentioned in the news media, then investors should have paid attention to it, which is not necessarily true (Da, Engelberg, and Gao 2011). A more direct measure of attention allocation, one based on Internet search queries, was first used by Mondria, T. Wu, and Zhang (2010) and Da, Engelberg, and Gao (2011). By exploring the information made available by Internet search engines, it is possible to measure the search frequency for specific phrases and quantify the amount of attention dedicated to satisfying someone's information needs.

In this paper, we use Google search data as a proxy for individual investor attention, as this search engine accounted for 97.54% of all search queries performed in Brazil in March 2019 (Statista 2019). Attention is then used to predict stock market volatility and returns. We find that a positive shock in investor attention is followed by an increase in stock market volatility and that a negative shock in stock returns is followed by an increase in investor attention.

2 Data and methodology

We obtain the Search Volume Index (SVI) from Google Trends for the keyword 'ibovespa' for searches originating in Brazil from January 2, 2006, to December 28, 2018. Ibovespa is a market cap-weighted index of the largest firms with stocks traded at the Sao Paulo Stock Exchange. We use this term because Ibovespa is the most important stock market index in Brazil. We use the algorithm of Chronopoulos, Papadimitriou, and Vlastakis (2018) to retrieve a consistent time series of the daily SVI for our sample period.

Ibovespa daily stock prices and trading volume are obtained from Economatica. Volatility is estimated using the GJR-GARCH$(1,1)$ model of Glosten, Jagannathan, and Runkle (1993) since our evidence suggests that positive and negative innovations to returns have different

Table I: Descriptive statistics

	log-Return	log-SVI	log-Volatility	log-Volume
Mean	0.0004	1.90	−4.19	22.40
Std. Dev.	0.02	0.71	0.28	0.47
Q1	−0.01	1.39	−4.38	22.23
Median	0.001	1.95	−4.24	22.45
Q3	0.01	2.40	−4.04	22.66
Skewness	0.16	−0.04	1.48	−0.58
Excess Kurtosis	6.05	−0.12	3.68	1.28

impacts on conditional volatility in the Brazilian market:

$$\sigma_t^2 = \omega + (\alpha_1 + \gamma_1 I_{t-1})\varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{1}$$

where γ_1 represents the leverage term, and the indicator function I is equal to 1 for $\varepsilon \leq 0$ and 0 otherwise. We assume that ε follows a standardized Student's t distribution. The Schwarz Bayesian information criterion (BIC) indicates that the Ibovespa daily log-returns follow a random walk with zero mean. We use logarithmic transformations of SVI, volatility and trading volume to avoid large skewness and excess kurtosis. The descriptive statistics are reported in Table I.

We utilize three-equation vector autoregressive (VAR) models to uncover the relation between SVI and volatility and between SVI and returns. Both models control for traded volume. Let $\mathbf{x}_t$ be a vector containing the variables of interest, and the VAR(9) model is as follows:

$$\mathbf{x}_t = \boldsymbol{\phi}_0 + \sum_{j=1}^{9} \boldsymbol{\Phi}_j \mathbf{x}_{t-j} + \mathbf{a}_t, \tag{2}$$

where $\boldsymbol{\phi}_0$ is a three-dimensional vector of constants, $\boldsymbol{\Phi}_j$ are 3×3 matrices, and $\mathbf{a}_t$ is a vector of white noise innovations. The lag length is determined using the BIC. The stationarity of all variables is assessed via the augmented Dickey-Fuller test, which suggests that all of the variables are stationary. Furthermore, we use Wald tests to uncover Granger causalities between pairs of variables.

3 Results

Table II shows the results of the two VAR models. All coefficient estimates are presented in Panel A, and the results of the Granger causality tests are presented in Panel B. In model 1, we find significant estimates of the autoregressive coefficients for SVI for all included lags. Volatility shows significant autoregressive coefficients for lags 1, 2, and 3. Only the autoregressive coefficients for lags 6 and 7 are not significant for trading volume. The results indicate that past volatility coefficients are not significant in the SVI equation. This finding is supported by the Granger causality test result. On the other hand, there is strong evidence that past SVI provides significant information about future volatility. These results indicate that an increase in volatility is not sufficient for increasing investor attention, but an increase in investor attention increases the levels of volatility.

In model 2, we substitute volatility for returns and find that all lagged autoregressive coefficients are significant for the SVI equation. Returns show significant autoregressive coefficients for lags 2, 3, 6, and 7. Only the autoregressive coefficients for lags 6 and 7 are not significant for trading volume. The results indicate that some past return coefficients are significant in the SVI equation. This finding is supported by the significance result in the Granger causality test. On the other hand, and contrary to the volatility case, there is no evidence that past SVI provides significant information about future returns. The results for this VAR model indicate that an increase in SVI has no effect on future returns, but past returns help to predict SVI.

Table II: Estimation results.

Panel A: VAR estimation

	Model 1			*Model 2*		
	log SVI	log TV	log σ	log SVI	log TV	r
log SVI_{t-1}	0.14***	0.02	0.01***	0.14***	0.02	0.0000
log SVI_{t-2}	0.16***	−0.01	0.003	0.16***	−0.01	−0.0003
log SVI_{t-3}	0.11***	−0.04***	0.0004	0.11***	−0.04***	0.002**
log SVI_{t-4}	0.08***	−0.01	−0.003	0.08***	−0.01	0.0004
log SVI_{t-5}	0.12***	0.01	−0.005*	0.12***	0.01	−0.0003
log SVI_{t-6}	0.04**	0.02*	−0.01*	0.04**	0.02*	−0.001
log SVI_{t-7}	0.08***	0.01	0.01**	0.08***	0.005	−0.0001
log SVI_{t-8}	0.13***	−0.01	−0.003	0.13***	−0.01	−0.001
log SVI_{t-9}	0.09***	0.02	−0.002	0.09***	0.02	0.001
log TV_{t-1}	0.20***	0.35***	0.04***	0.21***	0.35***	0.002
log TV_{t-2}	−0.01	0.09***	−0.02***	0.001	0.09***	−0.001
log TV_{t-3}	−0.06*	0.05**	−0.01	−0.05	0.05***	−0.0001
log TV_{t-4}	−0.01	0.12***	−0.004	−0.01	0.11***	−0.001
log TV_{t-5}	−0.002	0.09***	0.004	−0.003	0.09***	−0.001
log TV_{t-6}	−0.03	0.03	−0.01*	−0.03	0.03	−0.001
log TV_{t-7}	−0.04	−0.02	0.01	−0.05	−0.02	−0.002
log TV_{t-8}	−0.03	0.04**	0.01*	−0.03	0.04**	−0.0002
log TV_{t-9}	−0.001	0.13***	−0.001	−0.02	0.13***	0.0004
log σ_{t-1}	0.22*	0.02	0.93***			
log σ_{t-2}	−0.07	0.07	0.08***			
log σ_{t-3}	−0.07	−0.26***	−0.05**			
log σ_{t-4}	−0.02	0.05	0.01			
log σ_{t-5}	0.15	0.05	0.02			

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Table II – continued from previous page

	Model 1			*Model 2*		
	log SVI	log TV	log σ	log SVI	log TV	r
log σ_{t-6}	−0.16	−0.10	−0.02			
log σ_{t-7}	−0.001	0.06	−0.004			
log σ_{t-8}	−0.07	0.05	−0.02			
log σ_{t-9}	0.01	−0.004	0.02			
r_{t-1}				−0.23	−0.02	−0.03
r_{t-2}				−0.48	0.13	−0.03*
r_{t-3}				−0.84*	−0.33	−0.06***
r_{t-4}				−1.08**	0.24	−0.02
r_{t-5}				−0.59	−0.04	−0.01
r_{t-6}				−0.43	0.03	−0.03*
r_{t-7}				−0.33	0.64**	−0.04**
r_{t-8}				−1.12***	0.02	0.01
r_{t-9}				0.49	0.16	−0.003
Constant	−0.32	2.57***	−0.45***	−0.34	2.87***	0.09***

Panel B: Granger causality test

	Model 1			*Model 2*		
	log SVI	log TV	log σ	log SVI	log TV	r
log SVI		22.6***	30.4***		20.5**	11.0
log TV	57.0***		93.9***	61.5***		18.1**
log σ	9.5	22.5***				
r				20.9**	9.0	

SVI is the search volume index for the keyword 'ibovespa', TV is the trading volume of the stocks that comprise the index, σ is the estimated volatility of the index, and r is the log-return of the index. Statistical significance: $^{*}p < 0.10$; $^{**}p < 0.05$; and $^{***}p < 0.01$.

Figure 1 shows the orthogonalized impulse-response functions for the variables of interest obtained via Cholesky decomposition. We can see from Figure 1a that after a positive shock in investor attention (SVI), volatility increases in the first few days and subsequently slowly decreases to zero. Figure 1b shows that a shock in volatility has no significant effect on investor attention. Figure 1c shows no significant effect to returns after a shock in attention. Figure 1d shows that a negative shock in returns increases investor attention and that the effect slowly moves toward zero.

Our findings show that lagged SVI affect the stock market volatility, but not the other way around. In order to incorporate this result in the volatility estimation, we add the first lag of the log of SVI as an external regressor to an exponential GARCH model of Nelson (1991). The first lag is chosen because this is the most significant lag in the VAR equation for volatility. Additionally, we choose the exponential GARCH for this new estimation because

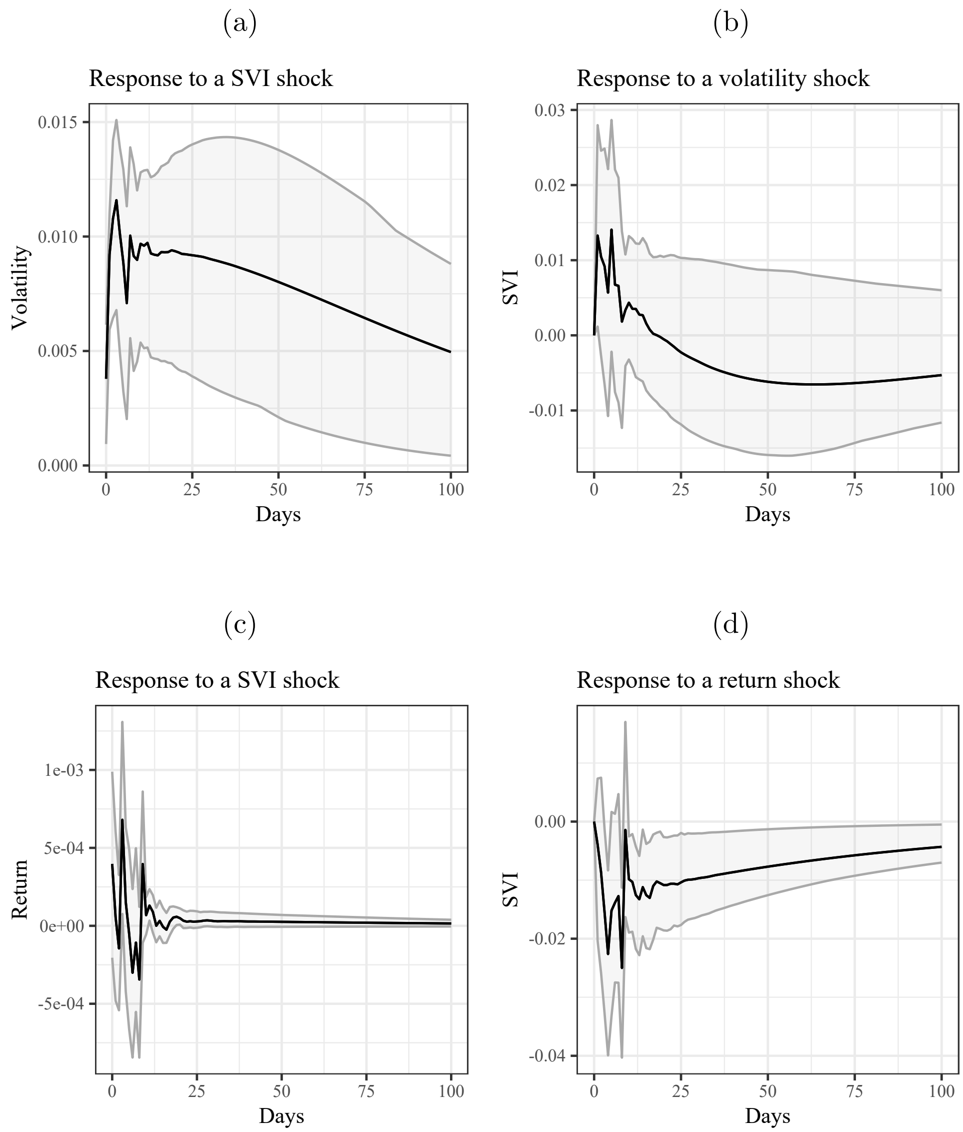

Figure 1: Orthogonalized impulse-response function plots with 95% confidence intervals.

the dependent variable in this specification is the log of variance, making the relationship similar to that of the VAR model.

The coefficient of the first lag of SVI in the volatility estimation is 0.008, with a t-statistic of 2.57, being therefore significant at the 1% level. We also used other transformations in the SVI variable, such as the log of SVI squared and the root of SVI, and the results remained qualitatively the same. Other lags were also added to the variance equation, but the first lag proved to be the most significant in all specifications. We also estimate volatility using the GJR-GARCH model. Again the results are not significantly different.

As a robustness check, we use results for the keyword 'bovespa' instead of 'ibovespa' since individual investors may use them interchangeably when searching for information about the Brazilian stock market and find qualitatively similar results.

4 Conclusion

This paper uses the search volume index obtained from Google Trends to investigate the dynamics between individual investor attention, volatility and market returns. We find that the SVI is a leading indicator of future volatility. The relationship between these two variables is unidirectional, so volatility is not a good predictor of future investor attention. On the other hand, returns are the leading indicator of future investor attention. Particularly, after a negative shock in returns, investor attention increases.

Declaration of interest statement

None.

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