CONSUMER SENTIMENT, RETURN, AND FLOW OF FUNDS TO SECTOR EXCHANGE TRADED FUNDS

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ABSTRACT

The impact of consumer sentiment on return and flow of funds to sector exchange traded funds (ETFs) is examined in this paper. The sample includes 29 sector ETFs sponsored by 3 different fund families, namely, SPDR, iShares and Vanguard for the period between 2005 and 2013. Considering potential endogeneity among the variables under investigation, a panel vector autoregressive (PVAR) is specified and estimated. Consumer sentiment is found to have an influence on both return and flow of funds to the sector ETFs analyzed in this study. In addition, sentiment is also affected by return and flow. Variance decomposition and impulse response analysis offer further insights, revealing the nature of the impact of consumer sentiment on return and flow of sector funds. Results from Granger causality tests also reconfirm the existence of bidirectional relationships regarding consumer sentiment, return and flow of funds. **JEL Classification:** C33, G11, G12

INTRODUCTION

Investor sentiment has the potential to affect financial decisions made by investors. Within the rational decision making framework, investor decision regarding which mutual funds to invest in depends only on fund characteristics and underlying economic fundamentals. In the behavioral finance paradigm, however, investors are also influenced by sentiment/psychology.

The purpose of this paper is to examine the relationship between consumer sentiment, return, and the flow of funds to sector ETFs. Specifically, this paper focuses on ETFs, which have become very popular investment vehicles for investors due to the ease of trading and their stock like behavior. A special class of ETFs are sector ETFs, that enable investors to diversify their portfolios across various U.S. industries. Additionally, this paper investigates whether consumer sentiment affects return on and flow of funds to a sample of sector exchange traded funds. Sentiment is measured using the consumer sentiment index from the University of Michigan[1].

Since first being introduced in the 1990's, ETFs have become increasingly popular investment vehicles, and are on the rise across different asset classes. Note: for a detailed review of the history if ETF's, please see the earlier paper by

Noman, Lawrence, Lajaunie and Connell (2017). There are a number of advantages of ETF investing compared to open ended mutual funds, such as intra–day trading opportunities, low fee structures and tax benefits. In addition, ETFs can be based on almost any asset class, including equities, bonds and commodities. Finally, a very popular style of ETF is industry ETFs that track the performance of benchmark industry level indices.

This paper is a follow up to a previous paper by Noman, Lawrence, Lajaunie, and Connell (2017) in which the authors analyze the relationship between ETF fund flow and return, as well as the relevance of this relationship for positive and negative returns. Additionally, the duration of these relationships was considered. Two hypotheses were developed and tested to determine if past return predicts future fund flow of ETFs and whether ETF fund flow predicts future return. The results from this study indicate that past return does have a significant effect on future fund flow to and from ETFs. However, the results overall do not indicate a clear causal pattern. With regard to the duration of the relationship, increased fund flow generally leads to significantly higher returns in the next month, but tapers off and is not significant in the second and third months following the event. Finally, negative fund flow has stronger predictive ability compared to positive flow, indicating that fund outflow following poor performance is greater than fund inflow following good performance. This implies that investors are more likely to engage in relatively significant selling in the wake of negative return than aggressive buying to "chase" positive return. This finding is consistent with the assumption of investor risk aversion.

This paper looks specifically at consumer sentiment and analyzes the affect it may have on ETF return and flow. It contributes to the existing literature on ETFs in general as well as adding a link between consumer sentiment and financial assets. Although research on different aspects of ETFs are abundant, studies that examine the interrelationship among return, flow, and sentiment are rather scarce. Moreover, the methodological contribution of the paper is that it combines potentially endogenous variables in single framework of panel vector autoregression (PVAR) enabling the authors to obtain consistent results. The rest of the paper is organized as follows. Section 2 delves into some of the underlying psychological factors that can sway consumer sentiment. Section 3 provides a brief literature review. Section 4 discusses data and methodological issues while section 5 presents the results and findings. Section 6 concludes the paper.

UNDERSTANDING CONSUMER SENTIMENT

One of the main tenets in understanding consumer sentiment is that one must accept the fact that individuals may not behave rationally when making financial decisions. Emotions, as well as cognitive errors, may cause investors to make bad decisions. This problem has become more pronounced in recent years as technological advancements in investing and a barrage of information has caused the increased turnover of investment account allocations, but not increased returns. Some common psychological pitfalls of investing, that affect consumer sentiment, are discussed below.

Loss Aversion

The pain of losing money is much worse for investors psychologically than the elation of making money. As a result, after a market downturn investor sentiment is generally one of extreme conservatism. For example, after suffering losses in equities, investor sentiment is usually to sell out of losing positions and go into safer investments with potentially lower but more stable returns. All this strategy accomplishes is to lock in losses while eliminating the potential for adequate future gains. This issue is particularly relevant given the market volatility in recent years. If caught in a market downturn, the best option for an investor is to have patience and stay the course.

Market Timing

Now that virtually anyone with a computer and a brokerage account can become a trader, many investors have tried to time the equity markets by buying low and selling high. The problem is that psychological biases often result in just the opposite. There seems to be a herd mentality in investing. That is, investors tend to buy equities that are rising in price and sell equities that are declining in price when they should be doing just the opposite. In addition, trying to time the market may result in an investor selling too soon (and foregoing potential earnings), then getting back in the market when prices are too high.

Keeping Losers too Long, Selling Winners too Fast

Another psychological bias with investing is that investors may be reluctant to sell out of a losing equity, as this is an admission of failure. Conversely, investors tend to sell their winners too fast due to the temptation to take profits.

Overconfidence

Investors typically remember their stock market gains more vividly than their losses. As a result, investors may become overconfident, causing them to overestimate their knowledge. This can cause investors to misinterpret information or overestimate their analytical skills, resulting in excessive trading, risk taking, and ultimately, financial losses.

Recency Bias

Recency bias is tendency for investors to place more importance in recent events. For example, during the great bull market of 1995-1999, many investors assumed that the market would continue its enormous gains, forgetting the fact that bear markets do occasionally occur and will happen eventually.

Anchoring

This is when investors cling to a fact or figure that should have no bearing on their decision making. For example, in a volatile market investors may count their losses from the market highs, which is irrelevant to investment decisions.

CURRENT LITERATURE

The existing literature regarding consumer sentiment and ETFs is somewhat scarce; however, there a few noteworthy studies. Specifically, Brown and Cliff (2004) document the link between investor sentiment and stock market returns in the near term. Their findings indicate that past returns are one of the determinants of investor sentiment, along with other common measures of investor sentiment. An important finding of their paper is that investor sentiment and stock market returns are related at the contemporaneous level and the former has little predictive power over the latter. Moreover, the authors find that the relationship between these variables exists beyond individual investors or small stocks only. In addition, the authors report the existence of a relationship between common and direct measures of investor sentiment and market returns.

A number of papers have investigated the relationship between consumer sentiment and stock market valuation (e.g. Brown and Cliff, 2005) as well as options market valuation (Han, 2008). Brown and Cliff (2005) demonstrate that investor sentiment does indeed play a role in asset valuation. Specifically, their findings indicate that future returns and sentiment are inversely related. Han (2008) extends the relevant literature by examining the relationship between sentiment and the options market, particularly S&P 500 options. The results indicate the existence of a significant impact of sentiment on options, which can form a barrier to arbitrage.

Lemmon and Portniaguina (2006) investigate the impact of consumer sentiment on asset prices within a time series framework. In particular, the authors study the time series relationship between sentiment and premiums for small stocks while controlling for time variation in stock betas. Their results are consistent with the idea of noise trader sentiment as consumer confidence, as a measure of sentiment, which is related to stocks with low intuitional ownership. Schmeling (2009) extends this analysis to international stock markets. Specifically, Schmeling (2009) utilizes predictive regressions to study the impact of market sentiment in international stock markets. The results indicate the existence of significant effects of market sentiment on stock returns in a number of countries. Sentiment and future stock returns are found to be inversely related across different prediction horizons.

Other relevant studies include Akhtar et al. (2011, 2012) and Johnson and Naka (2014). Akhtar et.al. (2012) find that the U.S. stock market is influenced by the announcement effects of consumer sentiment news. However, this effect is asymmetric. Specifically, they report that stock returns react negatively when a negative change in sentiment index is announced. On the other hand, stock returns do not respond significantly when the sentiment index improves compared to the previous month. Johnson and Naka (2014) employ asymmetric response models to examine the impact of consumer sentiment on short and long horizon stock returns. They report that the consumer sentiment index can predict stock returns over a long-term time horizon. Moreover, the magnitude of predictability is greater for negative changes in consumer sentiment compered to positive changes.

A few studies have documented the empirical interrelationship between mutual fund flow and investor sentiment. Specifically, mutual fund flow is found to reflect investor sentiment in the market (Frazzini and Lamont, 2008 and Ben-Rephael et al. 2012). Frazzinni and Lemmont (2008) use an indirect measure of investor sentiment

based on mutual funds flow and find the existence of sentiment's predictive ability for future return, particularly over longer time horizons. However, their study shows that reallocation of mutual fund investments by small investors do not turn out to be profitable in the long run. The authors term this as the dumb money effect for the individual investors. Ben-Rephael, Kandel and Wohl, A. (2012) also use mutual funds flow as a measure of investor sentiment. Specifically, they adopt a proxy for sentiment, which is the monthly shift between bond and equity funds. Their findings indicate that this new measure is negatively related with changes in the VIX index. In addition, the authors find that the impact of sentiment on return is short lived and typically reverses within four months. Finally, as mentioned in the introduction section of this paper, Noman et al. (2017) examine the flow and return relationship for a sample of sector ETFs. They document results that indicate the presence of short-term return chasing behavior among investors.

DATA AND METHODOLOGY

Monthly return and total net assets (TNA) were obtained for all major sector ETFs managed by SPDR, iShares and Vanguard fund families for the period spanning January 2005 to December 2013. The list of ETFs used in this study is provided in Table 1. Since different fund families began their ETFs at different times, a sample period was selected in which data was available for all funds. Consumer sentiment data was collected from the University of Michigan Surveys of Consumers[2]. Data is pooled for each time series across all ETFs within each family. This created three subsamples: SPDR, iShares and Vanguard. In addition, a full sample comprising all 29 ETFs is also created. This helps us to see how the results in our study vary across fund families, while also getting the overall picture of the sector ETFs as a whole. On average, SPDR funds have more assets under management compared to iShares and Vanguard. Table 2 presents the summary statistics of the variables and other helpful statistics illustrating the characteristics of the funds in the sample.

Panel Vector Autoregression (PVAR)

We specify a Panel Vector Autoregression (PVAR) to study the relationship among fund flow, return and consumer sentiment. These variables are potentially endogenous and are treated as such in this paper. A vector autoregressive model is specified to examine the interrelationship among the variables. Consider a vector of three endogenous variables Z_{it}=[$Flowp_{it}$, $MRet_{it}$, $\Delta Sent_{it}$ where $Flowp_{it+1} \equiv \{TNA_{it+1} - [TNA_{it} \times (1+MRet_{it+1})]\}/TNA_{it}$ is the percentage net flow of funds to an ETF; TNA_{it} is its total net asset; $MRet_{it}$ is the monthly return on an ETF over the previous period as reported in the Center for Research in Stock Prices (CRSP) database; and $\Delta Sent_{it}$ is the change in the consumer sentiment index. The unrestricted VAR in the level with these variables can be written as:

$$Z_{it}=A_0+A_1Z_{(it-1)}+f_i+U_{it} \qquad (1)$$

where and are vector of constant and slope coefficients, and *f* is individual ETF–

specific fixed effects, and is a vector containing three variables as defined before. The vector error terms, , are allowed to have unrestricted interaction among them[3].

RESULTS AND ANALYSIS

The optimum lag of the VAR system is chosen to minimize Modified AIC (MAIC). Table 3 presents the results of the Panel VAR where, coefficients of each equation are presented, followed by their associated *t*–statistics. Interpretation of the coefficients is straightforward as the variables on both sides of the equation are expressed in percentage change. The main focus is on the full sample results, while subsamples provide additional insight. In the full sample, sentiment is found to have influenced both return and flow. In addition, return and flow is found to affect sentiment.

For the SPDR sample, sentiment does not seem to influence either return or flow of funds. However, consumer sentiment is positively influenced by return on ETFs. For the iShares sample, sentiment affects return but not flow. This is limited to the first lag only. Similar to the SPDR case, sentiment is influenced by return on sector ETFs. In the Vanguard sample, sentiment affects flow but not return, and this happens in both lags. Conversely, both return and flow influence consumer sentiment. In order to ensure robustness of our results reported above, the panel VAR equations were re-estimated by changing the order of variables. The results are very similar and hence, not reported.

Variance Decomposition and Impulse Response Analysis

In order to gain further insight, we also report variance decomposition of the PVAR. The results are presented in Table 4. The results of variance decomposition can be summarized as follows. In all subsamples, accumulated variances over 10 periods for return and flow are almost entirely (over 99%) explained by themselves. This is also true of the full sample. On the other hand, variance in consumer sentiment is partly (around 5%) caused by return and the rest by itself.

Impulse functions were run to provide further insight into our findings. All responses taper off in the first of the second periods with respect to different shocks, and converge. The results indicate the shocks are short lived, and these returns adjust rather quickly, supporting the notion of informational efficiency.

Granger Causality Tests

In order to ensure robustness of our analysis, Granger causality tests are conducted. The null hypothesis is that a set of excluded variables do not Granger-cause the left hand side variable. On the other hand, the alternative hypothesis is that the right hand side variables do Granger-cause the left hand side variable. Within this framework, we apply the test for each of the potentially endogenous variables in the system. The results are presented in Table 5.

As in the full sample, one can see that the null hypotheses have been rejected for all cases at hand indicating the existence of significant relationships among the

variables in the system. The results reconfirm the findings reported in the previous tables. Given the empirical evidence of bidirectional causality, a VAR specification is the more appropriate choice.

Granger causality tests also give us an opportunity to see the adequacy of the model specifications. The null hypothesis in this case is that the specified model is inadequate (i.e. the included variables have no explanatory power for the dependent variable). Low p–value for a test would provide evidence against the null hypothesis. To test the hypothesis, we consider the results reported in the last row for each equation in Table 5. First, for the return equation, we reject the null hypothesis for all subsamples as well as for the full sample. Second, for the flow equation, although the null hypothesis for the iShares subsample cannot be rejected, we can reject the null hypothesis for the other two subsamples, as well as for the full sample. Finally, for the sentiment equation, the null hypothesis is also rejected for all cases at hand. Overall, we find the specification in the VAR system is adequate and all variables are integral to the model.

CONCLUDING REMARKS

ETFs are very popular investment vehicles for individual investors because of the ease of trading and their stock like behavior. A special class of ETFs are sector ETFs that enable investors to diversify their portfolios across various U.S. industries. This paper examines the relationship among consumer sentiment, return and flow of funds for the sector exchange traded funds in the U.S. The sample includes 29 ETFs sponsored by 3 different fund families, namely, SPDR, iShares and Vanguard for the period between 2005 and 2013. Considering potential endogeneity among the variables under investigation, a panel vector autoregressive (PVAR) is specified and estimated.

For the full sample, sentiment is found to have influence on both return and flow, and vice versa. However, the results for the sub-samples of the ETFs were mixed. Variance decomposition and impulse response analysis offer further insight revealing the nature of the impact of consumer sentiment on return and flow of sector funds. Specifically, results from Granger causality tests reconfirm the existence of bidirectional relationships among consumer sentiment, return and flow of funds.

The paper has certain limitations. First, it investigates the return–flow relationship at the fund level, not at the individual investor level. The findings of the paper indicate the existence of a relationship among the variables of interest, but it is important to recognize that the results hold at the fund level. Individual investors' reactions to consumer sentiment may vary depending on their characteristics, such as investment objectives, risk tolerance, age, etc. Second, this paper does not include all sector ETFs in the market but rather focuses on a set of ETFs that are sponsored by three large and well–known fund management companies. Therefore, the reported results may have limited applicability.

Finally, further research could extend the data to include all sector ETFs to examine whether or not the results from this study would hold when conducted with a more comprehensive sample. In addition, future studies involving different time periods, in which there is significant volatility, would add insight to this somewhat underrepresented field of research.

END NOTES

[1]http://www.sca.isr.umich.edu/

[2]http://www.sca.isr.umich.edu/

[3]As the number of regressors equals that of instruments, the model is just–identified.

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TABLE 1: LIST OF SECTOR ETFs INCLUDED IN THIS PAPER

Sector Fund Name	Ticker	Inception Date	AUM
Benchmark: Standard and Poor's Select Sector Indexes			
The Consumer Discretionary Select Sector SPDR Fund	XLY	12/16/1998	$8.95B
The Consumer Staples Select Sector SPDR Fund	XLP	12/16/1998	10.29B
The Energy Select Sector SPDR Fund	XLE	12/16/1998	12.68B
The Financial Select Sector SPDR Fund	XLF	12/16/1998	18.62B
The Health Care Select Sector SPDR Fund	XLV	12/15/1998	13.27B
The Industrial Select Sector SPDR Fund	XLI	12/15/1998	8.28B
The Materials Select Sector SPDR Fund	XLB	12/15/1998	3.07B
The Technology Select Sector SPDR Fund	XLK	12/15/1998	13.26B
The Utilities Select Sector SPDR Fund	XLU	12/15/1998	7.29B
Benchmark : Dow Jones U.S. Sector Indexes			
iShares Dow Jones U.S. Consumer Services Sector Index Fund	IYC	6/11/ 2000	931.50M
iShares Dow Jones U.S. Consumer Goods Sector Index Fund	IYK	6/11/ 2000	663.2M
iShares Dow Jones U.S. Energy Sector Index Fund	IYE	6/12/ 2000	1.32B
iShares Dow Jones U.S. Financial Sector Index Fund	IYF	5/21/2000	1.33B
iShares Dow Jones U.S. Healthcare Sector Index Fund	IYH	6/12/ 2000	2.18B
iShares Dow Jones U.S. Industrial Sector Index Fund	IYJ	6/11/ 2000	869.78M
iShares Dow Jones U.S. Basic Materials Sector Index Fund	IYM	6/11/ 2000	520.96M
iShares Dow Jones U.S. Technology Sector Index Fund	IYW	5/14/2000	3.07B
iShares Dow Jones U.S. Telecommunications Sector Index Fund	IYZ	5/21/2000	514.66M
iShares Dow Jones U.S. Utilities Sector Index Fund	IDU	6/11/ 2000	1.52B

Benchmark: MSCI US Investable Markets Indexes			
Vanguard Consumer Discretionary ETF	VCR	1/25/2004	1.74B
Vanguard Consumer Staples ETF	VDC	1/26/2004	2.97B
Vanguard Energy ETF	VDE	9/22/2004	4.46B
Vanguard Financials ETF	VFH	1/26/2004	2.71B
Vanguard Health Care ETF	VHT	1/25/2004	5.55B
Vanguard Industrials ETF	VIS	9/22/2004	2.12B
Vanguard Information Technology ETF	VGT	1/25/2004	7.66B
Vanguard Materials ETF	VAW	1/26/2004	1.52B
Vanguard Telecommunications Services ETF	VOX	9/23/2004	989.26M
Vanguard Utilities ETF	VPU	1/25/2004	2.39B

Notes*: Assets Under Management (AUM) for each ETF are as of 2/27/15 and were retrieved on 3/6/15 from http://finance.yahoo.com*

TABLE 2: SUMMARY STATISTICS

	Flow ($m)		% Return		% Prem	Size (m$)	% Exp	% TO	% Spread
SPDR Sector Funds									
Consumer Discretionary	39.98	282.37	0.85	5.40	–0.003	7.15	0.22	8.67	0.07
Consumer Staples	27.61	291.14	0.83	3.04	–0.007	7.82	0.22	9.17	0.07
Energy	17.32	727.14	1.18	6.63	–0.012	8.60	0.22	9.86	0.04
Financial	162.00	769.35	0.14	7.25	–0.006	8.48	0.22	11.75	0.08
Health Care	33.89	264.85	0.79	3.88	–0.015	7.92	0.22	5.31	0.06
Industrial	57.37	296.36	0.81	5.61	0.008	7.59	0.22	6.03	0.07
Materials	20.85	194.98	0.81	6.25	–0.001	7.32	0.22	12.44	0.08
Technology	67.21	303.51	0.72	5.05	–0.036	8.22	0.22	7.25	0.08
Utilities	2.22	284.43	0.67	3.85	–0.054	8.09	0.22	5.92	0.06
iShares Sector Funds									
Consumer Services	0.31	21.75	0.83	4.70	–0.029	5.47	0.51	6.69	0.09
Consumer Goods	–1.69	23.92	0.79	3.62	0.011	5.89	0.51	6.72	0.11
Energy	3.15	57.30	1.11	6.38	–0.018	6.79	0.51	7.47	0.12
Financial	9.81	100.30	0.23	6.66	0.032	6.22	0.51	9.47	0.09
Healthcare	2.29	68.84	0.83	3.88	0.001	6.78	0.51	5.50	0.10
Industrial	8.63	39.60	0.83	5.65	–0.026	5.91	0.51	5.33	0.11
Basic Materials	0.39	43.17	0.87	7.22	–0.026	6.36	0.50	8.86	0.10
Technology	15.30	63.42	0.75	5.55	0.707	6.92	0.51	6.11	0.08
Telecommunications	–1.06	43.42	0.56	5.28	0.32	6.37	0.51	25.06	0.14
Utilities	–3.51	71.35	0.66	3.84	–0.034	6.49	0.51	6.50	0.11
Vanguard Sector Funds									
Consumer Discretionary	8.43	34.51	0.88	5.68	–0.006	5.13	0.41	8.50	0.11
Consumer Staples	8.80	94.37	0.88	3.09	0.009	6.05	0.22	11.00	0.11
Energy	14.83	94.64	1.16	6.67	–0.005	6.69	0.22	15.50	0.13
Financials	12.84	65.31	0.24	6.66	0.024	5.89	0.22	9.78	0.14
Health Care	13.98	92.87	0.85	3.92	0.017	6.30	0.22	8.72	0.10
Industrials	10.21	73.59	0.85	5.79	–1.841	5.39	0.22	8.61	0.12
Information Technology	28.05	69.92	0.80	5.53	–0.009	6.42	0.22	8.28	0.10
Materials	5.16	40.09	0.90	6.51	0.006	5.68	0.22	10.17	0.12
Telecommunications	3.10	39.95	0.75	4.78	–0.017	5.15	0.22	27.22	0.14
Utilities	8.09	98.38	0.70	3.82	0.005	5.97	0.22	9.11	0.10

TABLE 3: PANEL VAR RESULTS

	Impact on					
Impact of	$MRet_{it}$	$Flowp_{it}$	$\Delta Sent_{it}$	$MRet_{it}$	$Flowp_{it}$	$\Delta Sent_{it}$
Panel A		**Full Sample**			**SPDR**	
$MRet_{it-1}$	0.133** (4.62)	–0.176 (–0.87)	0.185** (8.62)	0.138** (2.65)	–0.588 (–1.25)	0.201** (5.30)
$Flowp_{it-1}$	0.011** (3.02)	0.161* (1.85)	0.003* (1.73)	0.001 (0.50)	0.057 (0.63)	–0.001 (–0.20)
$\Delta Sent_{it-1}$	0.036* (1.82)	–0.304** (–2.12)	0.053** (2.82)	0.017 (0.48)	0.099 (0.40)	0.048 (1.43)
$MRet_{it-2}$	–0.045* (–1.83)	0.707** (4.12)	–0.016 (–0.77)	–0.055 (–1.17)	0.231 (1.15)	0.002 (0.06)
$Flowp_{it-2}$	–0.006** (–3.04)	–0.014 (–1.15)	–0.003** (–2.41)	–0.002** (–3.40)	0.013 (1.17)	–0.001 (–1.20)
$\Delta Sent_{it-2}$	–0.048** (–2.74)	0.429** (3.88)	–0.244** (–15.69)	–0.046 (–1.50)	0.22 (1.37)	–0.243** (–8.77)
Panel B		**iShares**			**Vanguard**	
$MRet_{it-1}$	0.133** (2.70)	0.079 (0.63)	0.153** (4.22)	0.126** (2.64)	–0.044 (–0.13)	0.206** (5.44)
$Flowp_{it-1}$	–0.002 (–0.37)	0.172 (0.78)	0.001 (0.13)	0.023** (6.17)	0.259** (2.61)	0.007** (3.86)
$\Delta Sent_{it-1}$	0.063* (1.86)	–0.045 (–0.46)	0.058* (1.82)	0.035 (1.05)	–0.901** (–3.11)	0.054* (1.66)
$MRet_{it-2}$	–0.036 (–0.89)	0.050 (0.42)	–0.054 (–1.45)	–0.044 (–1.14)	1.795** (4.34)	0.006 (0.16)
$Flowp_{it-2}$	–0.003 (–1.22)	–0.002 (–0.07)	–0.005 (–1.08)	–0.013** (–4.31)	–0.069** (–2.40)	–0.007** (–4.63)
$\Delta Sent_{it-2}$	–0.051 (–1.64)	0.072 (0.91)	–0.243** (–9.15)	–0.040 (–1.41)	1.012** (4.25)	–0.242** (–9.09)

Notes: *Variables in rows are independent variables affecting the variables in column, separately. . The optimum lag length of 2 for the VAR system is chosen to minimize Modified AIC. (MAIC). One and two asterisks denotes significance of a parameter at 10% and 5% levels, respectively.*

TABLE 4: VARIANCE DECOMPOSITION

	Impact on					
Impact of						
Panel A	**Full Sample**			**SPDR**		
$MRet_{it}$	98.65%	0.91%	0.44%	99.62%	0.08%	0.30%
$Flowp_{it}$	1.12%	98.39%	0.49%	0.38%	99.54%	0.08%
$\Delta Sent_{it}$	4.45%	0.19%	95.36%	4.65%	0.04%	95.32%
Panel B	**iShares**			**Vanguard**		
$MRet_{it}$	99.19%	0.04%	0.77%	94.52%	4.90%	0.58%
$Flowp_{it}$	0.34%	99.59%	0.07%	4.43%	93.35%	2.22%
$\Delta Sent_{it}$	4.16%	0.10%	95.74%	4.79%	0.91%	94.30%

***Note**: Percentage of variation in a row variable explained by a column variable. The numbers represent accumulated variances in the last 10 periods*

TABLE 5: GRANGER CAUSALITY TESTS

Equation	Excluded	Full Sample	SPDR	iShares	Vanguard
$MRet_{it}$	$Flowp_{it}$	16.210	11.593	1.745	50.003
		(0.000)	(0.003)	(0.418)	(0.000)
	$\Delta Sent_{it}$	11.072	2.501	6.065	3.316
		(0.004)	(0.286)	(0.048)	(0.190)
	All	27.555	12.505	8.577	53.640
		(0.000)	(0.014)	(0.073)	(0.000)
$Flowp_{it}$	$MRet_{it}$	17.078	1.592	2.403	19.383
		(0.000)	(0.451)	(0.301)	(0.000)
	$\Delta Sent_{it}$	18.931	3.623	1.016	18.522
		(0.000)	(0.163)	(0.602)	(0.000)
	All	24.093	8.787	5.414	27.065
		(0.000)	(0.067)	(0.247)	(0.000)
$\Delta Sent_{it}$	$MRet_{it}$	75.401	28.422	19.987	29.903
		(0.000)	(0.000)	(0.000)	(0.000)
	$Flowp_{it}$	7.882	1.780	1.227	36.175
		(0.019)	(0.411)	(0.541)	(0.000)
	All	84.163	29.976	21.408	59.725
		(0.000)	(0.000)	(0.000)	(0.000)