ANALYSIS OF THE PERFORMANCE OF THE DIAMONDS ETF AROUND A GLITCH IN THE COMPUTATION OF THE DOW JONES INDUSTRIAL AVERAGE INDEX

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ABSTRACT

In this paper I examine the pricing deviation, pricing premium and discount, and tracking error of the Diamonds around the event of a glitch in the computation of the Dow Jones Industrial Average on February 27, 2007. That day a technical error in the computation of the Dow Jones Industrial Average caused a shock in the financial markets. This event provides for an excellent laboratory to examine the behavior of an ETF in extreme market conditions. I find that the pricing deviation and tracking error of this ETF increase and experience high volatility for a brief period of time after identifying the problem.

JEL: G01, G14

Key words: ETF, Pricing Deviation, Tracking Error, Technical Glitch

I. INTRODUCTION

In this paper I examine the pricing deviation, pricing premium and discount, and tracking error of Exchange Traded Funds (ETFs) around the event of a technical glitch in an index. ETFs are designed to track closely an index which they achieve due to their in-kind creation or redemption of ETF units by authorized participants. The units consist of cash or the underlying assets of the index which can be exchanged for ETF shares which can be then traded in the market. This arbitrage activity ensures that ETFs provide the closest performance in terms of price and return to their net asset value (NAV) which is representing the underlying index.

However, this is what ETFs do by design in normal conditions, when the NAV is close to the value of the index. The question that I attempt to answer in this study is with regards to the efficiency of this arbitrage mechanism under strenuous conditions. It is possible that in times of stress in markets the creation or redemption process might be slowed down thus impeding the ETFs performance. I find that the pricing deviation, pricing premium and discount, and tracking error of the DIA increase significantly after identifying the glitch. This suggests deterioration of ETF performance. However, this

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deterioration is brief with the breakdown right after the identification of the problem which might be due to overwhelming of the system with orders. This finding emphasizes the usefulness of the pricing deviation metric in times of distress.

This is the first study to the best of my knowledge to examine ETFs performance and behavior in severe market conditions. I study one of the oldest and most prominent ETFs: the Diamonds (DIA), the DJIA tracking ETF around the event of the Dow Jones Industrial Average (DJIA) "glitch" of February 27, 2007. At that time a technical error in the computation of the DJIA Index shocked the financial markets. This event provides an excellent laboratory to examine the efficiency of the ETF arbitrage mechanism. Bawden (2007) provides the following description of the "glitch":

> "Dow Jones faced a flurry of lawsuits last night after the business information provider acknowledged that a computer glitch had misled investors about the value of its benchmark stock index and potentially exacerbated some institutions' losses by millions of dollars.
>
> The company, which publishes The Wall Street Journal, said that it had miscalculated the Dow Jones industrial average index for 70 minutes on Tuesday. It added confusion to a market already reeling, helping US stocks to their biggest fall in four years. At 1.50pm in New York the Dow Jones computer system became overwhelmed by the heavy share trading triggered by plunging stock markets in China and growing economic uncertainty in America.
>
> The data backlog meant that for the following 70 minutes the 400 "live" Dow Jones indices fell by less than they should have done before plunging disproportionately at 3pm, when the backup system was activated and the backlog was cleared.
>
> The apparent 178-point plunge in the Dow Jones in less than a minute -as the index caught up -implied that US stocks were in far worse health than was the case and intensified panic among many already jittery traders.
>
> Lawyers will say that many costly investment decisions were made during the 70 minutes when the Dow Jones was miscalculated in the aftermath of the plunge that took place after the system caught up. Many derivative and index-linked mutual fund investments that are based on Dow Jones's own index calculations -as opposed to those conducted separately, based on individual stock prices -will have suffered investment losses from the computer glitch, lawyers will argue."

One might argue that such a sever event as the "glitch" is unlikely to happen again but unfortunately we were reminded yet again of the danger of occurrence of such rare adverse events with the "Flash Crash" of May 6, 2010 (Scannell and Lauricella, 2010).

I study the pricing deviation of the DIA. Pricing deviation is defined as the difference between the underlying index price and the ETF price by DeFusco, Ivanov, Karels (2009). The DIA is designed to track the DJIA index and have a price of 1/100 of the value of the DJIA Index. Therefore, the pricing deviation of the DIA is found as the difference between the value of the DJIA index divided by 100 and the price of the ETF. The pricing premium and discount is the difference between the log price of the index and the log price of the ETF. Thus it is similar to the pricing deviation but is different from it in that it is in logs, not dollars.

I also study the tracking error of the DIA. There are numerous definitions of tracking error. In this study I use the simplest tracking error measure possible among many as defined in Chen, Noronha and Singal (2006). The tracking error measure is the difference between the intra-daily returns of the underlying index and the ETF summed over the period. I examine the pricing deviation, pricing premium and discount, and tracking error of ETFs with ultra-high frequency data at one minute intervals.

II. METHODOLOGY

DeFusco, Ivanov, Karels (2009) find that the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model best describes the properties of the three oldest ETFs: DIA, SPY and QQQQ. Connolly (1989) suggests that the predictability of volatility and the use of GARCH models might have an impact on the results in the prior day-of-the-week and weekend effects literature. Considering that the day-of-the-week and weekend effects are typical event studies the findings of Connolly (1989) can be generalized to mean that event studies might benefit from allowing for volatility predictability and the use of GARCH models. In this study I examine the transmission of a shock from the underlying index to the tracking ETF. The shock is the technical glitch in the computation of the Dow Jones Industrial Average on February 27, 2007. Accordingly, I allow for volatility predictability in this study by employing a GARCH model.

Engle and Ng (1993) find that the EGARCH (Exponential GARCH) model captures best the asymmetry in predictability of futures stock volatility.[2] Engle and Ng (1993) state that the EGARCH model differs from the standard GARCH model and other GARCH model specifications in that:

> "1. The EGARCH model allows good news and bad news to have a different impact on volatility, while the standard GARCH model does not, and
> 2. the EGARCH model allows big news to have a greater impact on volatility than the standard GARCH model." (Engle and Ng (1993), p. 1753)

Fu (2009) uses the EGARCH model to show that the idiosyncratic volatilities are time varying and thus require special treatment. Fu (2009) uses the Akaike Information Criterion to select a best fitting EGARCH(p,q) model to fit the time varying idiosyncratic volatility in monthly data of stock returns. Kim and Kon (1994) also find that Nelson's EGARCH model specification is best suited for stock indexes. Reyes (2001) studies the asymmetric volatility spillover between size based Japanese stock indexes by using a bivariate AR(1)-EGARCH(1,1) model. In this study I follow to a certain extent Reyes (2001)

[2] Ross (1989), Lo and MacKinlay (1990), Conrad, Gultekin, and Kaul (1991), Ewing, and Malik (2005), Hassan, and Malik (2007) are among the studies examining the effects of volatility predictability and news transmission between large and small firms.

methodology in studying the behavior of shock transmission between indexes and ETFs by employing a bivariate AR(1)-EGARCH(p,q) .

The bivariate AR(1)-EGARCH(p,q) model specification which I use in this study is as follows:

$$r_{1,t} = \beta_{1,0} + \beta_{1,1} r_{1,t-1} + \beta_{1,2} r_{2,t-1} + e_{1,t}, \quad (1)$$

$$r_{2,t} = \beta_{2,0} + \beta_{2,1} r_{1,t-1} + \beta_{2,2} r_{2,t-1} + e_{2,t}, \quad (2)$$

$$\sigma^2_{1,t} = e^{\omega_{1,0} + \sum_{i=1}^{q} \alpha_{i,1} f(z_{1,t-i}) + \sum_{j=1}^{p} \gamma_j \ln(\sigma^2_{1,t-j})}, \quad (3)$$

$$\sigma^2_{2,t} = e^{\omega_{1,0} + \sum_{i=1}^{q} \alpha_{i,1} f(z_{2,t-i}) + \sum_{j=1}^{p} \gamma_j \ln(\sigma^2_{2,t-j})} \quad (4)$$

$$f(z_{1,t}) = \theta_1 z_{1,t-1} + |z_{1,t-1}| - E(|z_{1,t-1}|), \quad (5)$$

$$f(z_{2,t}) = \theta_2 z_{2,t-1} + |z_{2,t-1}| - E(|z_{2,t-1}|), \quad (6)$$

$$z_{1,t} = e_{1,t} / \sigma_{1,t}, \quad (7)$$

$$z_{2,t} = e_{2,t} / \sigma_{2,t}, \quad (8)$$

$$\sigma_{12,t} = \rho_{12} \sigma_{1,t} \sigma_{2,t}. \quad (9)$$

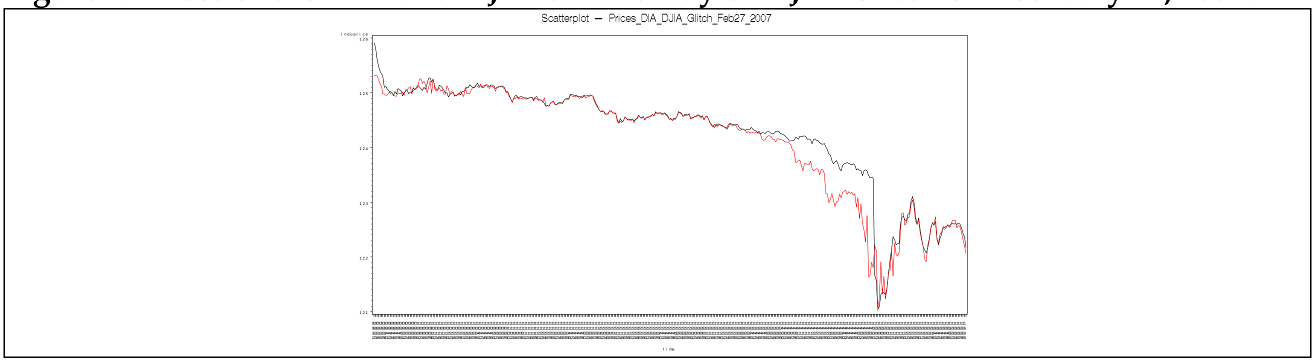
The $r_{1,t}$ is the minute rate of return on the index and $r_{2,t}$ is the minute rate of return on the ETF, $\sigma^2_{1,t}$ is the underlying index conditional variance, $\sigma^2_{2,t}$ is the ETF conditional variance and $\sigma_{12,t}$ is the conditional variance between the index and ETF. The coefficients $\beta_{i,j}$ capture the price spillover effects and $\alpha_{i,j}$ capture the volatility spillover effects between the index and ETF. If $\beta_{1,2}$ is statistically significant then the price spillover is from ETF to index and if $\beta_{2,1}$ is statistically significant then the price spillover is from index to ETF. Naturally, I expect that the $\beta_{1,2}$ coefficient is insignificant and that $\beta_{2,1}$ is significant because the technical glitch is in the DJIA index, not the ETF. As Reyes (2001) suggests the price spillover is bi-directional if both coefficients are statistically significant.

Similarly, if $\alpha_{1,2}$ is statistically significant then the volatility spillover is from ETF to index and if $\alpha_{2,1}$ is statistically significant then the volatility spillover is from index to ETF. Again, I expect that the $\alpha_{1,2}$ coefficient is insignificant and that $\alpha_{2,1}$ is significant because the technical glitch is in the DJIA index, not the ETF. If all of the $\alpha_{m,n}$ coefficients are significant there are bi-directional spillover effects between the index and ETF. The θ_i coefficients capture the relation between news and volatility and the γ_i coefficients capture the persistence of volatility. Thus, if coefficient $\theta_i \in (-1,0)$ then a positive news shock would increase volatility less than a negative news shock, and if $\theta_i \in (-\infty,-1)$ then a good news shock would decrease volatility and a bad news shock would increase volatility.

III. DATA

In this study I use intra-daily one minute interval data from http://pitrading.com. The data are available for both the ETFs and their underlying indexes. The DIA is designed to be one hundredth of the value of the DJIA. The way the price is ensured to be close to this value is by the arbitrage activities which ETF authorized participants perform. Authorized participants are institutional investors who can create and redeem ETF units, either in cash or in baskets of securities which represent the underlying asset of the ETF. These participants have until 16:00 EST to create or redeem ETF units. Thus, if the ETF market price is higher than the underlying benchmark/ net asset value the authorized participant will buy the underlying benchmark securities, exchange these securities for ETF units, i.e. create units, and sell the ETF shares in the marketplace, thus forcing the ETF price to get in line with the value of the underlying benchmark.

Figure 1: Prices of the DIA and DJIA on The Day of DJIA Glitch on February 27, 2007.



As we see on Figure 1 up to the time of the glitch at 13:50 this arbitrage activity is very efficient. However, naturally at the start of the glitch the value of the DIA drops in a greater amount than the value of the DJIA. In other words in this 70 minute window the DIA is the more accurate representative of the DJIA securities not the reported DJIA. On the Figure the DIA price is in red and the DJIA price is in black. The interesting part of this graph is what happens to the performance of the arbitrage activity after the correction of the glitch. It is difficult to delineate the DIA price from the DJIA price on this graph. That is why we compute the pricing deviation of the DIA at that time as defined by DeFusco, Ivanov, Karels (2009).

Figure 2: Pricing Deviation of the DIA on the Day of the DJIA Glitch on February 27, 2007.

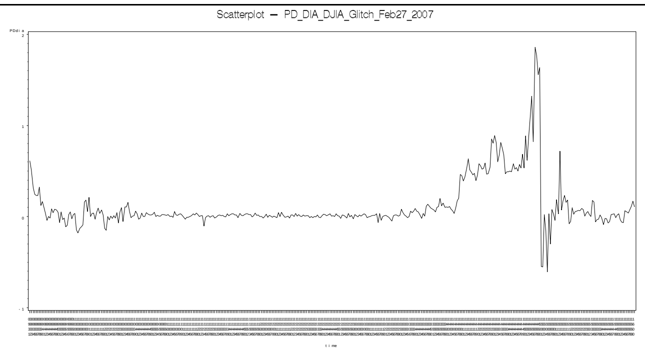


Figure 2 displays the intra-daily behavior of the pricing deviation of the DIA on the day of the DJIA technical glitch on February 27, 2007. The figure clearly shows the increase in DIA pricing deviation at the time of the error and fast correction in the pricing deviation after the 70 minutes of the error. However, what becomes immediately transparent is the large volatility and difficulty of the arbitrage mechanism to bring the DIA and DJIA prices back together.

Table 1: Pricing Deviation of the DIA on The Day of the DJIA Glitch on February 27, 2007.

PD	Day of Glitch	Minutes Before Glitch	Minutes After Glitch
N	390	260	130
Mean	0.1149	0.0231	0.2984
St Dev	0.2776	0.0759	0.4122
Min	-0.6056	-0.1787	-0.6056
Max	1.8591	0.6149	1.8591
Skewness	2.9022	3.4723	1.2792
Kurtosis	11.9522	22.1340	2.8298
Jarque-Bera Normality Test	<0.0100	<0.0100	<0.0100
Kolmogorov-Smirnov Normality Test (p-value)	<0.0100	<0.0100	<0.0100

Table 1 reinforces this observation it reports the average pricing deviations of the DIA. The pricing deviation is computed based on prices. DeFusco, Ivanov, Karels (2009) study closing daily prices in the period 1999 to 2007 for DIA and SPY, and 1999 to 2005 for QQQQ. The authors find that DIA's, SPY's and QQQQ's pricing deviations are -0.08, -0.29 and 0.25, respectively. I use intradaily data and find that in the minutes before the glitch which can be interpreted as the typical pricing deviation of the DIA in normal circumstances the pricing deviation of the DIA is 0.0231. Thus, the DIA pricing deviation is positive but economically very small which is in contrast to the findings of DeFusco, Ivanov, Karels (2009). The average pricing deviations for the rest of the trading day are the quite large positive number 0.2984 with maximum as high as 1.8591. The volatility increases significantly as well with the standard deviation of the pricing deviation being 0.0231 right before the glitch and 0.2984 in the minutes after the glitch.

Table 2 reports the pricing deviation premiums and discounts of the DIA. Engle and Sarkar (2006) study the mispricing of ETFs by defining ETF premium as the difference between the log price of the ETF and the log price of the ETF Net Asset Value (NAV). They find that the mispricing is very narrow, less than 5 basis points for domestic ETFs and is smaller than bid-ask spreads. The lPD measure which I use in this study is similar to the Engle and Sarkar (2006) measure in that log prices are used but in order to be consistent with the pricing deviation (PD) measure of DeFusco, Ivanov, Karels (2009) the log price of the ETF is subtracted from the log price of the index. The reason that this consistency is required is because the DeFusco, Ivanov, Karels (2009) measure can be use to supplement the Engle and Sarkar (2006) measure to compute the total premium or discount of the ETF. Total premium or discount is the deviation of the NAV of the ETF and the theoretical price of the index.

Table 2: Pricing Premium or Discount of the DIA on The Day of the DJIA Glitch on February 27, 2007.

lPD	Day of Glitch	Minutes Before Glitch	Minutes After Glitch
N	390	260	130
Mean	0.0009	0.0002	0.0024
St Dev	0.0023	0.0006	0.0034
Min	-0.0050	-0.0014	-0.0050
Max	0.0152	0.0049	0.0152
Skewness	2.9213	3.4489	1.2895
Kurtosis	12.1655	21.9153	2.9038
Jarque-Bera Normality Test	<0.0100	<0.0100	<0.0100
Kolmogorov-Smirnov Normality Test (p-value)	<0.0100	<0.0100	<0.0100

Engle and Sarkar (2006) find that the DIA trades at a premium of -0.79 basis points, which is for all practical purposes a discount. In this study, I find that the DIA trades at pricing deviation premium of 0.0009 basis points. Naturally, the Engle and Sarkar (2006) premium or discount are by definition different from the pricing deviation premium or discount used in this study, thus direct comparison between these numbers is not applicable. The reason I compute the different measure, the pricing deviation premium or discount but not the Engle and Sarkar (2006) premium or discount measure is because I do not have data on the ETF intradaily net asset values (NAV).

Next, I examine the tracking error of the ETF. The tracking error is of interest to ETF investors. It represents how well the ETF management team fares in reaching their goal of replicating the return of the underlying index. However, before I do that let's examine the DIA and DJIA returns which are shown in Figure 3. The DIA return is in red and DJIA return is in black. What this figure suggests is that there are significant volatility clustering and GARCH effects in returns around the glitch. Formal tests of ARCH are presented next.

Figure 3: Returns of the DIA and DJIA on The Day of the DJIA Glitch on February 27, 2007.

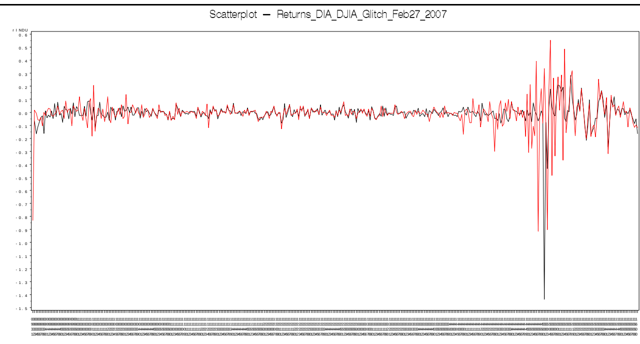


Table 3 reports the ETF's tracking error defined as the difference between the intra-daily returns of the underlying index and the ETF summed over the day. Based on the results in the table the DIA overperforms its underlying index (the tracking error result is -0.4243) on the day of the glitch and in the minutes prior to the glitch, however it underperforms in the minutes after the glitch, 0.0162.

The Ljung-Box $Q^2(12)$ statistic indicates that the return series prior to the glitch are white noise which cannot be said for the series after the glitch at 13:50. The Ljung-Box $Q^2(12)$ statistic suggests presence of linear dependence and presence of GARCH effects. Therefore, our analysis focuses on testing GARCH model on the data after the glitch.

Table 3: Tracking Error (%) and Returns (%) of the DIA and the DJIA on The Day of the DJIA Glitch on February 27, 2007.

	Day Of Glitch		Before Glitch		After Glitch	
Variable	rDJIA	rDIA	rDJIA	rDIA	rDJIA	rDIA
N	389	390	259	260	130	130
Sum	-3.0026	-3.4255	-1.2957	-1.7024	-1.7069	-1.7231
Mean	-0.0077	-0.0088	-0.0050	-0.0065	-0.0131	-0.0133
Std Dev	0.0930	0.1212	0.0362	0.0663	0.1528	0.1882
Minimum	-1.4356	-0.9124	-0.1649	-0.8310	-1.4356	-0.9124
Maximum	0.2838	0.5526	0.0876	0.2080	0.2838	0.5526
Skewness	-9.4926	-2.5228	-0.6279	-7.3772	-6.3838	-1.3349
Kurtosis	144.7751	22.7831	2.4844	92.4498	58.8577	7.5975
Tracking Error		-0.4081		-0.4243		0.0162
First Order Autocorrelation	0.1358	-0.2533	0.0218	-0.1221	0.1472	-0.2875
Ljung-Box $Q^2(12)$	0.0475	0.0368	0.1793	<0.0100	0.2585	0.2783

Jarque-Bera Normality Test	<0.0100	<0.0100	<0.0100	<0.0100	<0.0100	<0.0100
Kolmogorov-Smirnov Normality Test (p-value)	<0.0100	<0.0100	0.1065	<0.0100	<0.0100	<0.0100
Kruskal-Wallis Test		0.1495		0.1613		0.3889
Van Der Waerden Test		0.1134		0.1522		0.3687
Savage Chi-Square Test		0.0838		0.1215		0.3580

Examining only the interval after the glitch at 13:50 we find that the Kruskal-Wallis, Van Der Waerden and Savage non-parametric tests with null hypotheses equality between the distributions of the two returns fail to reject similarity between the two returns. This fact suggests that despite the computational error in the DJIA the ETF management team has been successful at replicating the return of the index, with the exception of a brief period after the identification of the glitch. This difficulty might be due to the overwhelming of the system with orders at the time as suggested in the article by Bawden (2007).

IV. EMPIRICAL ANALYSIS

The presence of GARCH effects requires special treatment in our analysis of the behavior of the ETF. Following Fu (2009) methodology I identify that the best fitting AR(1)-EGARCH(p,q) model is the AR(1)-EGARCH(5,5) model, based on the lowest Akaike Information Criterion (AIC). The empirical analysis of the bivariate AR(1)-EGARCH(5,5) models developed in equations (1) – (9) yields results which are reported in Table 4. The analysis is performed on data after the announcement of the glitch at 13:50 on February 27, 2007 by using minute intradaily data.

Table 4: Estimation Results of the bivariate AR(1)-EGARCH(1,1) of the DIA and the DJIA on Data After 13:15 on The Day of The DJIA Glitch on February 27, 2007.

	DJIA			DIA		
Intercept	-0.0060	<.0001	***	0.0003	0.5848	
$\beta_{1,1}$	0.2531	<.0001	***			
$\beta_{2,1}$				0.9478	<.0001	***
$\beta_{1,2}$	-0.0878	<.0001	***			
$\beta_{2,2}$				0.4120	<.0001	***
ω_0	-3.9410	<.0001	***	-3.0568	<.0001	***
α_1	-0.2147	<.0001	***	0.6879	<.0001	***
α_2	0.6650	<.0001	***	1.1857	<.0001	***
α_3	0.7980	<.0001	***	0.1855	0.0041	***

α_4	0.9052	<.0001	***	0.0550	0.3888	
α_5	0.1525	0.0684	*	0.8036	<.0001	***
γ_1	0.0383	0.0140	**	-0.1303	0.0005	***
γ_2	0.3386	<.0001	***	0.2098	<.0001	***
γ_3	-0.0534	0.0069	***	0.0528	<.0001	***
γ_4	-0.5248	<.0001	***	0.5640	<.0001	***
γ_5	0.5395	<.0001	***	-0.3417	<.0001	***
θ	-0.2132	<.0001	***	0.0980	<.0001	***
OLS Normality Test (p-value)		<.0001	***		<.0001	***
AR-EGARCH Normality Test (p-value)		0.2352			0.4324	
First Order Autocorrelation	-0.0416			0.0800		
Ljung-Box $Q^2(12)$		0.0758	*		0.0102	**
AIC	-349.8381			-238.0344		
SBC	-306.8251			-195.0214		
Log Likelihood	189.9190			134.0172		

After correcting for GARCH the Ljung-Box $Q^2(12)$ statistic indicates that the residuals are white noise and the AR-EGARCH normality tests fail to reject the null hypothesis of normally distributed residuals. The $\alpha_{i,j}$ and $\beta_{i,j}$ coefficients are statistically significant indicating bi-directional price and volatility spillover effects between the index and ETF contrary to our original expectations. The θ_i coefficients which capture the relation between news and volatility are also significant and so are the γ_i coefficients which capture the persistence of volatility. The θ_i coefficients of the DJIA and the DIA are -0.2132 and 0.0980 respectively and both are greater than -1 indicating that a positive news shock increases volatility less than a negative news shock.

Thus, it is not a surprise that the announcement of the error in the computation of the DJIA increases volatility. The announcement of the error is negative news because it revealed that the DJIA is actually lower than reported. Also, as Bawden (2007) suggests the system has been overwhelmed with orders at the time. Therefore, it is reasonable to assume that even though the authorized participants made an effort to alleviate the price disparity between the DIA price and DJIA level because of flaws in the infrastructure this could not be achieved.

In retrospect, at the time of the occurrence of large pricing deviations between the DIA and DJIA level investors must have been wondering, is this pricing deviation due to inaccuracy in the ETF price or the index? Now we know that the ETF price was right and that the DJIA level was inaccurate. It would be fair to assume that investors should be more concerned with inaccuracies with index computations than with the ETF arbitrage mechanism. This only emphasizes the efficiency of the arbitrage mechanism between the ETF and its NAV and accentuates the importance of using the pricing deviation metric.

V. CONCLUSION

In this paper I study the behavior and performance of the Diamonds (DIA) by using pricing deviation, pricing premium and discount, and tracking error around the event of the Dow Jones Industrial Average "glitch" of February 27, 2007. That day a technical error in the computation of the DJIA caused a shock in the financial markets. This event provides for an excellent laboratory to test whether the arbitrage activities which ensure that ETFs perform as well as their underlying indexes fail in extreme market conditions.

I find that the pricing deviation, pricing premium and discount, and tracking error of the DIA on average increase significantly after identifying the glitch and experience increased volatility for the rest of the day. This suggests deterioration of ETF performance after announcing the error at 15:00. This deterioration might be due to the overwhelming of the system with orders and the breakdown in order flow processing right after the identification of the problem. This suggests failure in the ETF arbitrage mechanism for a brief period of time, which can be endowed to infrastructure issues not the arbitrage methodology.

Additional analysis along the lines of Engle and Sarkar (2006) methodology which examines the deviation of ETF prices from NAV is required to determine whether the DIA price is close to NAV. However, this would be possible if intradaily NAV data becomes available. Also, additional analysis is required to determine what has happened to the ETF creation and redemption flows at that time. Naturally, this analysis would be possible if ETF flows data on intradaily basis is collected. Also, it would be interesting to examine the behavior of ETFs around the "Flash Crash" of May 6, 2010.

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