

RARE EVENTS ANALYSIS OF HIGH-FREQUENCY FINANCIAL DATA

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ABSTRACT: In this work we present a methodology to detect unusual trading activity defined as high price movement with relatively little volume traded. The study is performed using all the trade data for some five thousand equities for five days. We analyze what happens after this unusual activity is detected and we find that in the majority of the cases the price of equities tends to bounce back. The methodology developed is based on non-parametric statistics and makes no assumption about the distributions involved.

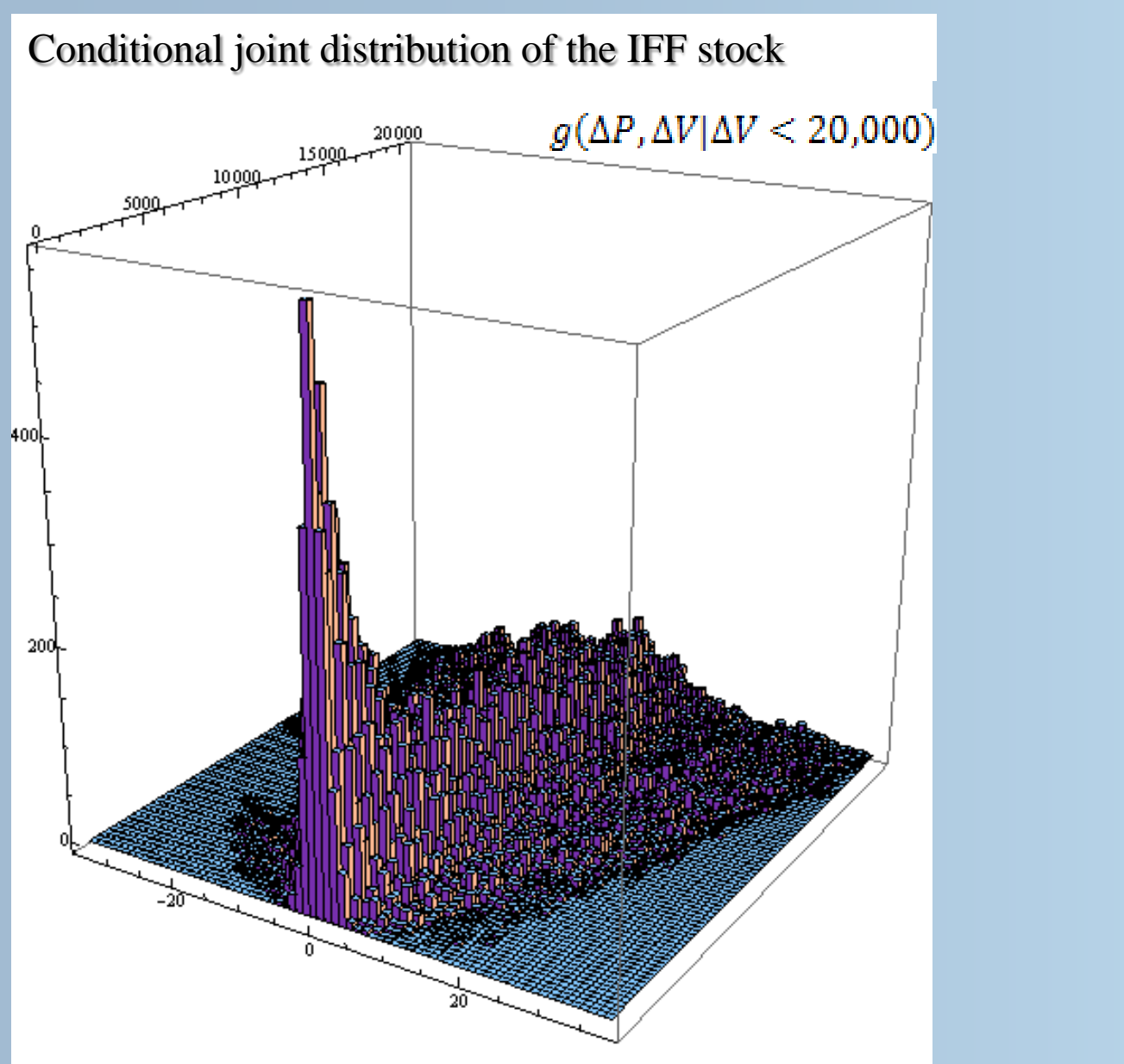
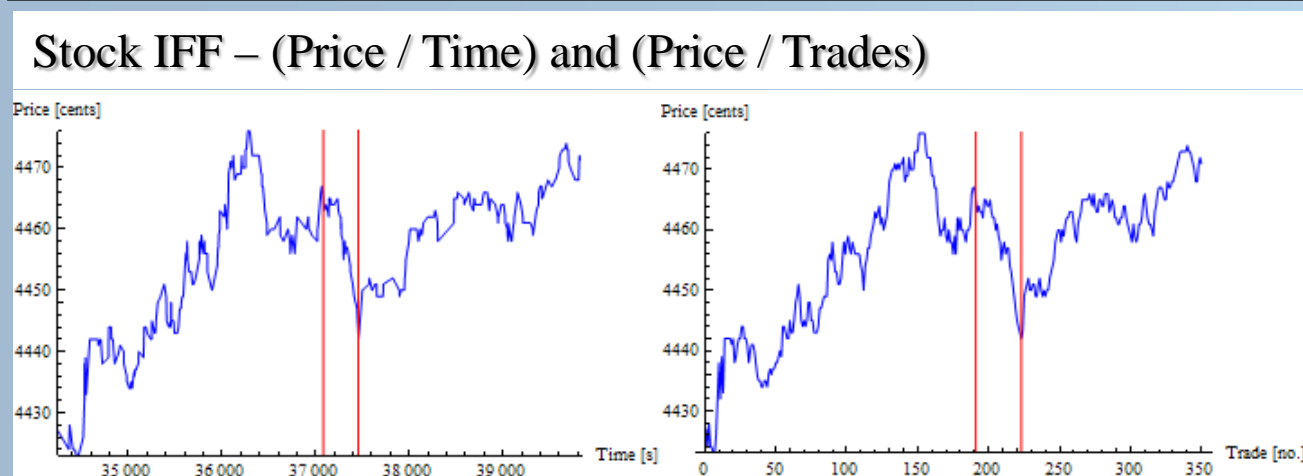
SPECIFIC OBJECTIVES OF THE STUDY

The main objectives this study are:

1. Develop a method to detect *large price movements* corresponding to *small volume of shares traded*.
2. Analyze the evolution of price after these unusual events and study the probability of price recovery.
3. Estimate the *expected return* if a trade is placed at the detected event.
4. Compare the result obtained with “normal” price evolution simulated using Monte Carlo technique.

METHODOLOGY

In this analysis we use tick-by-tick data of 5,369 equities (TAQ).



First we note that the trades are recorded in consecutive order and, though the time between trades is not necessarily constant, the price versus time and the price versus trade distributions are very similar. As a way to visualize this similarity, we present a small segment of the stock IFF from Apr. 14 2008 (the two images on the left).

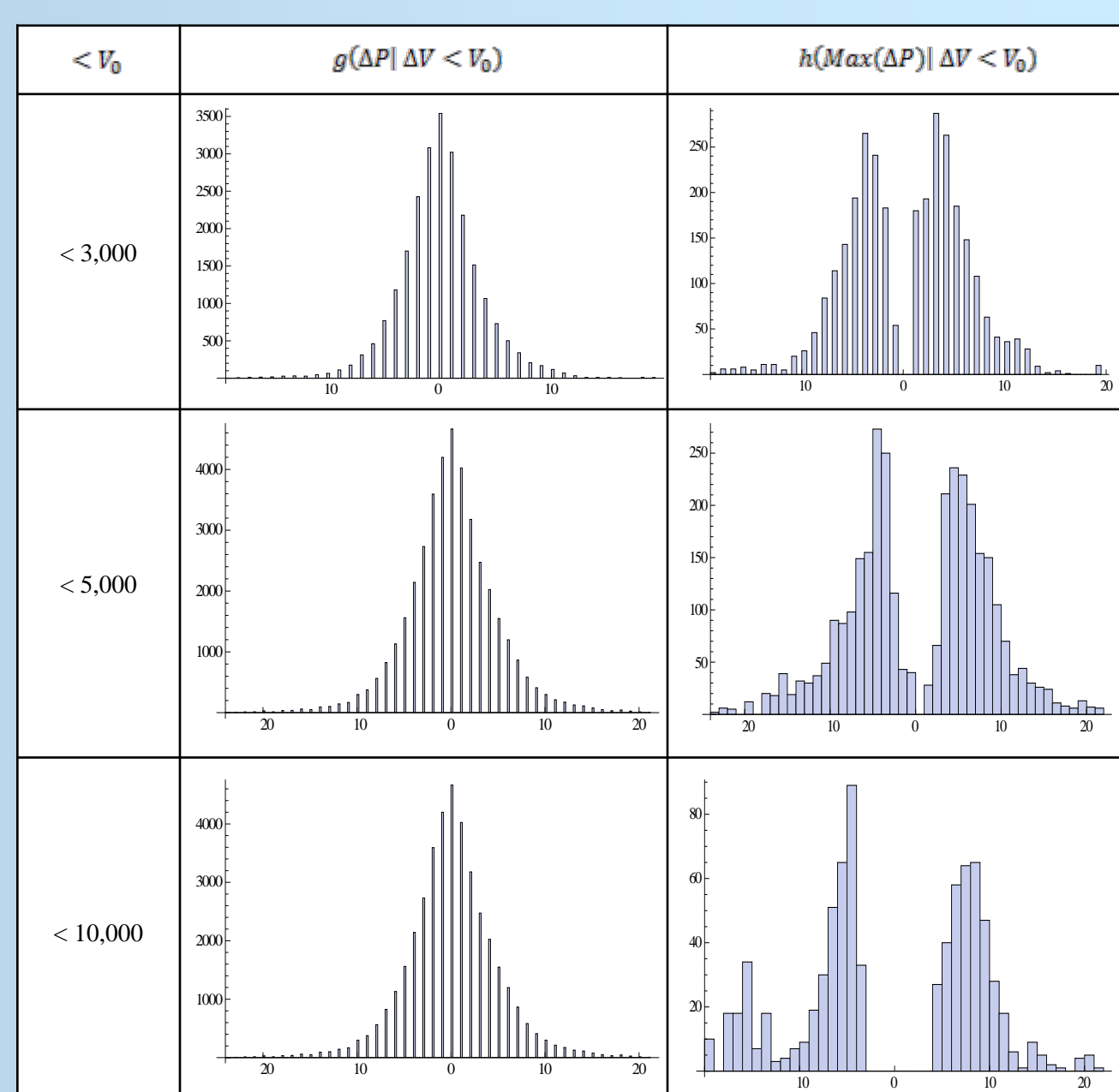
The 3D image on left represents the joint distribution of volume and price movement. The total number of pairs used for this distribution is 159,583. This is an extremely large number of data points to be calculated and analyzed for every stock and for every day.

To further simplify we retain only the maximum price movement with respect to change in volume for each window with $\Delta V < V_0$. Consequently, all the analysis that follows is based on the following distribution:

$$h(\text{Max}(\Delta P) | \Delta V < V_0)$$

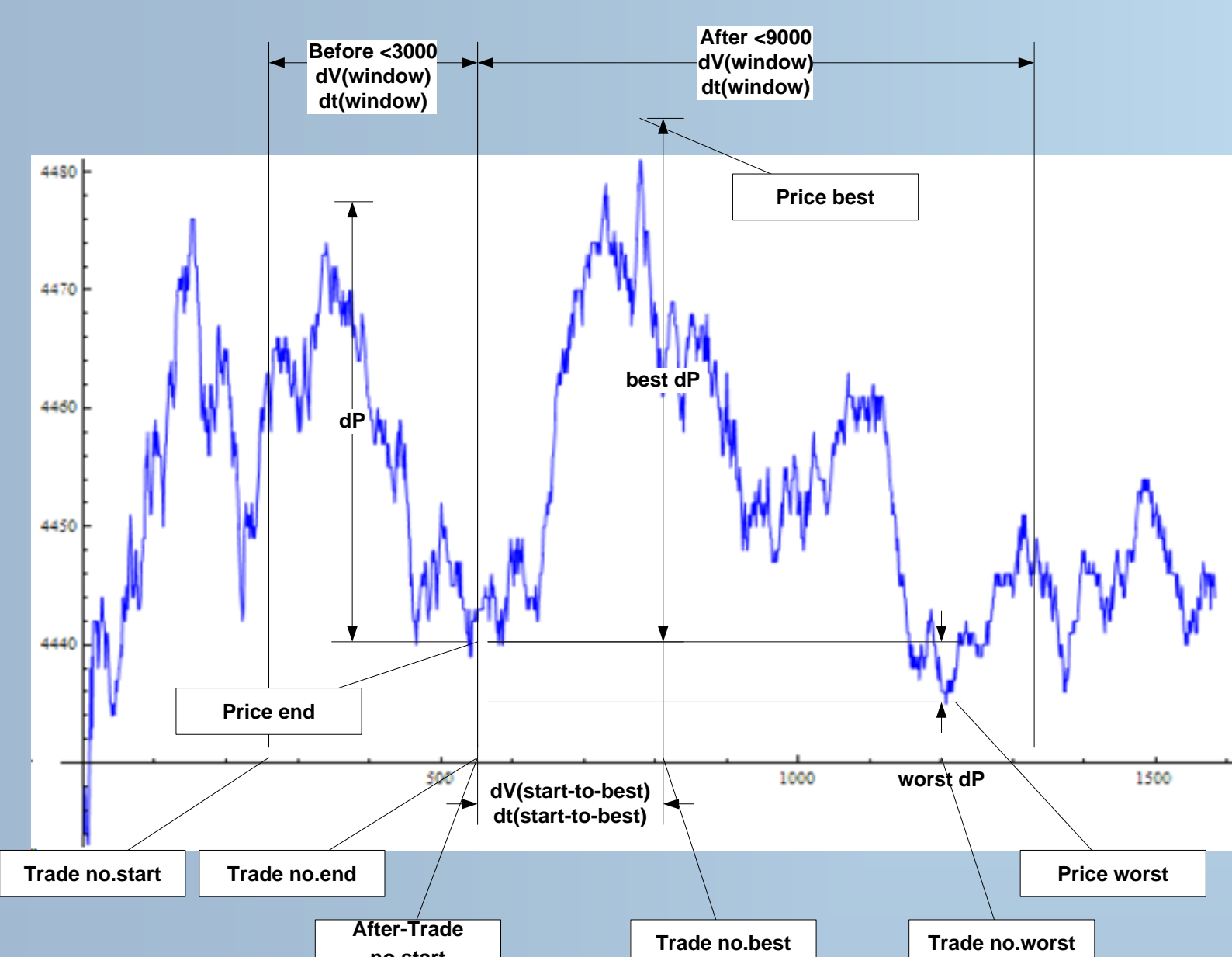
For example for the IFF stock, we obtain 1,570 observations for $V_0 = 3,000$ shares, 1,562 observations for $V_0 = 5,000$ shares and 1,544 observations for $V_0 = 10,000$ shares.

The proposed sampling technique generates new distributions that share similar behavior of the tails and provides a computationally feasible approach to this analysis.



RARE EVENTS DETECTION AND ANALYSIS

Consider the distribution $h(\text{Max}(\Delta P) | \Delta V < V_0)$ with $V_0 = 5,000$ for stock IFF on Apr. 14, 2008. The sampling distribution is performed by using a moving window with cumulative volume smaller than 5,000 shares. The observation that has the maximum price change within the window is recorded. A typical output of such analysis has the following form:



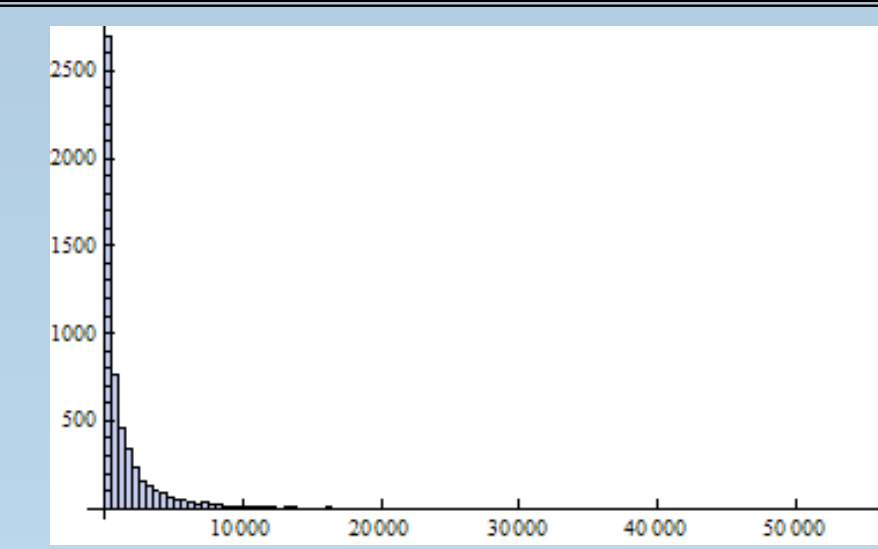
ΔP	ΔV	Start	End	PriceEnd	dt	τ
-24	4900	189	222	4443	389	0.537273
-23	4900	191	223	4442	374	0.515118
-23	4900	188	221	4444	397	0.514887
-22	4900	192	224	4443	369	0.492721
-22	4800	188	220	4445	393	0.492501
-21	4900	2	27	4444	453	0.474791
-21	4900	1	26	4444	541	0.474791
-21	4900	108	136	4471	261	0.47191
-21	4900	104	134	4471	272	0.47191
-20	4900	636	664	4462	537	0.450248
-20	4800	634	663	4462	540	0.450248
-20	4800	111	137	4470	257	0.449438
-20	4900	107	135	4470	265	0.449438
-20	4900	103	133	4470	277	0.449438
-20	4900	102	132	4470	289	0.449438

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COMPARATIVE STUDY OF STOCK GROUPS

Herein, we analyze the change in price from the volume perspective; therefore, we recognize the need for classifying stocks into classes based on the average daily traded volume. We refer to this classification as the *multi-scale volume classification*. The histogram corresponds to the average daily trading volume of the total universe of 5,369 stocks considered in this study.



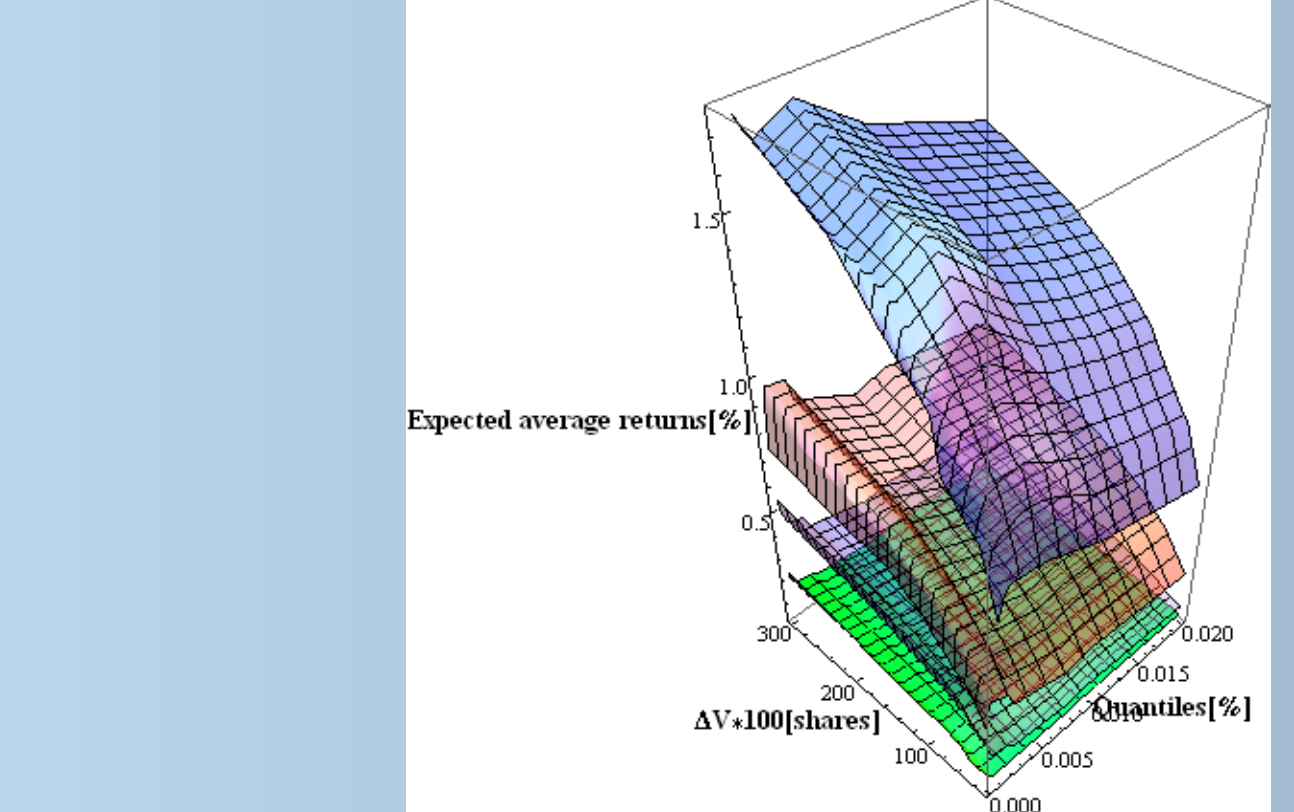
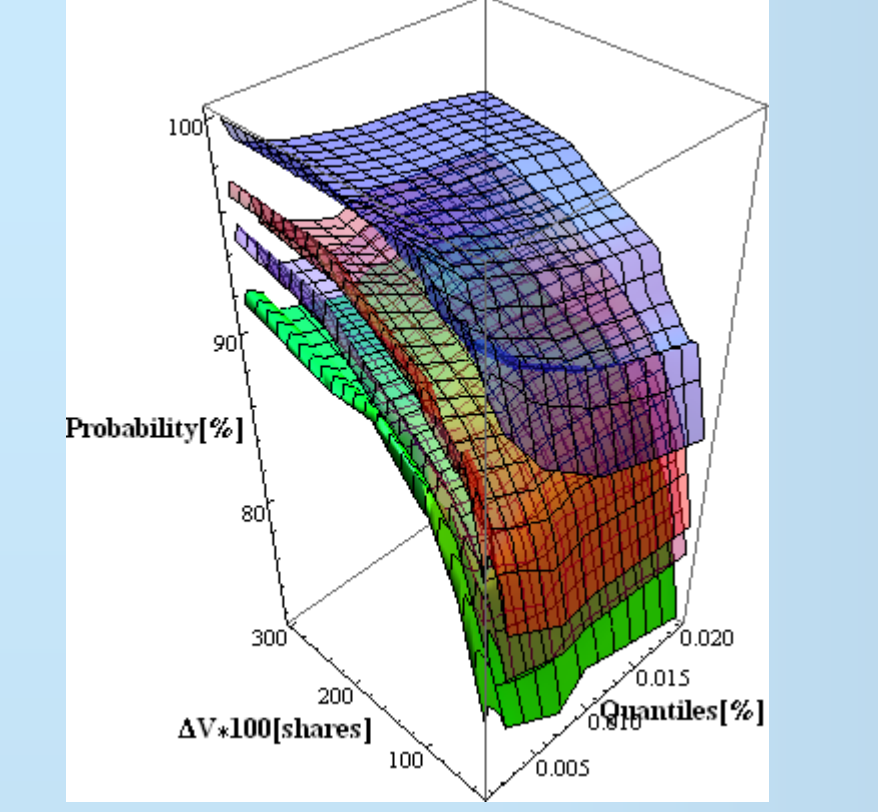
Group	Average daily volume (shares)	Number equities
1	$ADV \leq 30,000$	1,305
2	$30,000 < ADV \leq 100,000$	1,088
3	$100,000 < ADV \leq 1,000,000$	2,117
4	$1,000,000 < ADV \leq 10,000,000$	799
5	$10,000,000 < ADV$	60

For a consistent approach to the rare events detection, we calculate the quantiles for all equities individually over a 5 day period. The tables present an example of quantile calculations for a few exemplifying stocks. Based on the previous classification JPM belongs to class 1, GS to class 2, IFF to class 3, and STAN to class 4.

Symbol	0.01	0.99	0.0075	0.9925	0.005	0.995	0.0025	0.9975	0.001	0.999	0.00075	0.99925	0.0005	0.9995	0.00025	0.99975	0.0001	0.9999
JPM	-4	4	-4	4	-5	5	-6	6	-7	7	-8	8	-9	9	-10	10	-12	12
GS	-22	22	-23	23	-25	24	-27	27	-31	32	-33	34	-34	36	-37	38	-40	42
IFF	-14	13	-15	14	-16	16	-17	18	-21	20	-21	20	-22	20	-23	23	-24	23
STAN	-42	44	-43	45	-51	46	-63	48	-83	51	-87	78	-87	78	-87	78	-87	78

Definition 1: We say that a favorable price movement occurred if either the price level within the after-event window raises above the event price for at least one trade if the event was generated by a negative quantile, or the price level within the after-event window decreases below the event price level for at least one trade if the event was generated by a positive quantile.

Ave Daily Vol.	Quantile	3000	4000	5000	6000	8000	10000	15000	20000	30000
< 100,000 Small stocks	0.02	84.1287	85.9725	81.0485	89.5041	92.6293	94.056	90.7398	95.727	96.3553
< 100,000 Medium Stocks	0.02	78.4629	84.5194	87.5394	83.2973	85.2792	90.349	85.8366	92.1489	93.3992
< 100,000 Large Stocks	0.02	76.5631	81.1437	84.1431	80.5959	84.5403	89.7239	81.6483	89.1845	91.7845
Greater than 100,000 Major indices and super large cap stocks	0.02	71.5077	79.7572	83.5179	77.3566	83.9958	87.0469	81.4939	86.9276	89.2139



We can see that unlike the probability plots these surfaces seem to have different curvatures. Each surface has a maximum level which is remarkably obtained using the same quantile level for all volume window sizes. The optimum quantile level is different within each surface. The 3D plots are providing details of the optimal after-event window size for stock groups considered.

At the top of the table to the right we present the realized probabilities of price rebound for JPM for various quantiles and window sizes. The bottom line estimates these probabilities using Monte Carlo simulations.

Quantile	Day 1	Day 2	Day 3	Day 4	Day 5
0.02	73.01	79.85	82.30	76.87	82.51
0.01	72.28	79.21	83.17	77.89	83.51
0.005	71.05	81.58	86.84	72.79	81.62
0.002	66.67	100.00	100.00	66.67	90.91
0.0015	0.00	100.00	100.00	66.67	88.89
0.001	0.00	100.00	100.00	76.92	100.00
0.0005	-	-	-	100.00	100.00
0.0002	-	-	-	100.00	100.00
Monte Carlo results	61.396	74.824	81.002	67.001	78.121

CONCLUSIONS

- As expected stocks behave differently depending on the daily average volume of trades. In particular, from the data under consideration we saw the expected return attains its maximum for the following quantile levels:

Class	Quantile
< 100,000 (ADV)	0.0025
< 1,000,000 (ADV)	0.0005
< 10,000,000 (ADV)	0.0001
> 10,000,000 (ADV)	less than 0.0001
- The estimation of optimal window size produced the following results (with the data under study).

Class	Before event window size	After event window size
< 50,000 (ADV)	3,000	9,000
< 1,000,000 (ADV)	3,000	6,000
> 10,000,000 (ADV)	3,000	10,000
- In more general terms we determined:
 1. We observed the existence of information embedded in the stock movement
 2. The events we discover exhibit increased probability of price recovery
 3. The method is possibly more appropriate as a measuring tool for market reaction to singular events rather than a trading tool. These singular events may be viewed as suspicious or events that go against the information available to all market participants and in this light it could be developed further for forensic analysis.