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The Application of Event Study Method in Virtual Goods Markets: Based on CS:GO Skin Prices

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Abstract

With the rapid advancement of information technology, virtual assets have experienced significant growth, both in terms of market value and variety. Among these, a new category of virtual assets rooted in online gaming has emerged. Specifically, decorative items (commonly referred to as "skins") in Counter-Strike: Global Offensive 2 (CS2) exhibit key characteristics of financial assets, such as price volatility, liquidity, and responsiveness to market events-making them a unique subject of economic analysis. Despite the growing economic significance of CS2 skins, there remains a lack of systematic methods to quantify how specific events influence their price dynamics. Existing studies often focus on broader virtual asset markets, with limited attention to the nuanced relationships between event-specific factors and price fluctuations of single highly-related item in gaming ecosystems. This gap blocks both players (as casual traders) and investors from understanding market responses and managing associated risks. To address this, the present study proposes a precise analytical framework to assess the extent to which events impact the prices of specific CS2 items. By doing so, it aims to clarify the causal links between same types of events and market reactions in this understudied domain. This work makes two key contributions: (1) It develops a scientific and replicable method to determine whether an event has a statistically significant impact on specific in-game items; (2) It provides actionable insights into the risks associated with different types of events, enabling more informed estimation of potential losses for market participants.

Keywords

Event Study Method; Counter-Strike; Skin Market; Price Fluctuation; Financial.

1. Introduction

Nowadays, with the rapid development of technology and form of entertainment, game industry obtained an in- credible evolution from both entertainment and commercial value. Among different types of games, there are some specific ones with a tradable skin market, such as Counter-Strike: Global Offensive 2 (CS2) and Defense of the Ancients 2 (Dota2). Belongs with the accumulation of player base day by day, the virtual goods market of these games gradually grow, becoming a large scale, hectic trading world. For example,the skins belong to the game CS:GO not only particular due to its decorative and collectible value, but also formed a secondary market according to the basis of the tradable attribute of the items. Therefore, players will no longer purchase for only amusement, the investment behavior is also notable.

The phenomenon leading to the price fluctuation of the virtual goods possessing some characteristics of financial-assets, which show price fluctuate significantly according to supply and demand, market sentiment, scarcity and external events. Unlike traditional financial market, these prices of game-related goods have direct correlation with game update,

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adjustments on trade policies and some other factors. Hence, it provide an unique sample for academic research.

Therefore, study will select some example events and the related item, to analyze the significance of effect of the events apply to the items through a reliable and persuasive study method. dedicating to conclude different types of game's events' affection to the short-term and medium-term price fluctuations of related item. In order to summarize some generally applicable conclusions of the fluctuation of prices with some event-related items in CS2 while facing events of the same type. That is significance to help making a rough prediction of the price tendency while encountering similar events, and enable to offer guidance for players to avoid latent price risks among game events. Based on the findings, the study will provide practical suggestions for game players to better understand market risks and avoid potential losses caused by events.

Also, for those who intend to seize the market opportunities belong with the events, one of the expected out- comes of the research is to provide an insight that allows them to benefit from the effects that events bring.

2. Literature Review

For various researches about the trading market of CS2, scholars have studied from several aspects. From psycho- logical perspective, studies has showed several factors such as cultural backgrounds, gender differences, and game design elements (scarcity, random rewards) can significantly drive purchase behavior, guiding global monetization strategies[1,2]. Such behaviors and some other elements promote the form and further developments of CS2 skins market[3,4].

Meanwhile, there are significant effects on market price of skins causing by different types of events and elements, such as adjustments on trading policies and existing quantity of specific skin[5]. Thus it is easy to speculate that the skin market is highly related with various of factors.

3. Method

3.1. Research Framework and Methods

The study will take some iconic game events occurring between 2023,September,27 and 2025,November,1 as examples. In the study,the selected game events will be analyzed using a combination of qualitative and quantitative methods. Different events firstly will be categorized(e.g.release and removal of weapon cases, or market policies' changes). The study will take the price fluctuation data from Buff(buff.163.com,one of the largest third-party virtual item trading platforms in China's mainland.)and Steam Community Market. Buff is selected due to its active trading and high data accessibility. Meanwhile, in order to enhance the external validity of the result, the sample from Steam Community Market will be used for testing the robustness□if there is collectible data on Steam Community Market of the single item. The price data of the same time point of each day will be selected from both buff and steam community market. The study will set t=0 as the specific date the chosen events commenced, and sets the event window to 14 days before and after each event(i.e., [-14,+14]days)to examine the short-term and medium-term impacts that different kinds of events brought on related items' prices. Moreover, the research will evaluate the extend that different kinds of events' affect on related item's market price by event study method. Specifically, the price fluctuation during the defined event window(14 days before and after the event happened) will be collected from buff and steam community market. Then its Abnormal returns(AR) and cumulative abnormal returns(CAR) will be calculated to evaluate the short-term market impact. Next, according to the quantitative analysis of events' effect on price from when the event

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started to 14 days after, daily returns and abnormal returns will be calculated, to quantify the actual effects of different events on related items' price fluctuation. Finally t-test will be used in order to analyze the significance of the specific event affect on designated items.

Here is the specific calculate method:

Firstly, the study will take some iconic game events as examples. It will firstly set the event date as t=0, with an event window of [-14,+14]. Then, the price fluctuation of event-related items will be collected from both buff and steam community market, for further calculation of the daily log returns with the formula:

$$R_t = \ln\frac{P_t}{P_{t-1}} \tag{1}$$

Meanwhile, the benchmark market return ($R_{m,t}$) was derived from the overall Market Composite Index counted on www.steamdt.com(a stat website that recording price fluctuation of each items on different trading platform), which represents the weighted average price performance of all tradable CS2 items on market, by using the function:

$$R_{m,t} = \frac{Inde\ \ _t - Index_{t-1}}{Inde\ \ _{t-1}} \tag{2}$$

Furthermore, compute the original expected return with applying the Market Model:

$$E(R_{i,t}) = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \tag{3}$$

The price data of the specific item and the daily benchmark market return from 14 days before the event happened will be collected as an estimation window. These data can be utilized into the calculation of α and β in the market model, which can significantly improve the accuracy of the expected return estimation, meanwhile ensure an reliable baseline for abnormal return analysis. For the step above, the parameters α and β will be estimated according to the Ordinary Least Squares(OLS),which is:

$$\min_{\alpha_i,\beta_i} \sum_{t=1}^{T} \left(R_{i,t} - \alpha_i - \beta_i R_{m,t}\right)^2 \tag{4}$$

Then, define abnormal return as:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{5}$$

Accumulate the abnormal return generated as the event commences:

$$CAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{6}$$

Using statistical testing, conduct two-tailed one-sample t-tests on AR and CAR to get a specific type of events' significance:

$$t = \frac{\bar{AR}}{s/\sqrt{n}} \tag{7}$$

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$$\begin{cases} H_0: \mu = \mu_0 & (No\ significant\ effect, average\ AR = 0) \\ H_1: \mu \neq \mu_0 & (Have\ significant\ effect) \end{cases} \tag{8}$$

$$p = 2 \times (1 - F_{t(df)}(|t|)), \quad df = n - 1 \tag{9}$$

Which N refers to the amount of samples of same type of events. Meanwhile the standard deviation s denotes the sample standard deviation of abnormal returns observed during the event window.

Finally, p-value of different kinds of events are available for further comparison with p=0.05. The threshold of p is conventionally used in social sciences and finance research, represents the maximum acceptable probability of committing a Type I error-i.e., incorrectly rejecting the null hypothesis that the mean abnormal return is zero (i.e., no significant event impact) when it is actually true. A test result with $p \leq 0.05$ was interpreted as sufficient evidence to reject the null hypothesis, inferring a statistically significant event impact. Conversely, $p > 0.05$ suggested insufficient evidence to conclude a significant impact, and the null hypothesis was maintained.

3.2. Effect of Game Content Update Events

The definition of game content update event is the update that only generates changes to the in-game contents, such as skins released and removed. According to the definition, the research will choose the remove of Gallery Case from game and the remove of Fracture Case from active drop pool as two sample. For the first event, the Gallery Cases were directly removed from game and will not have any new drops at all; And the second case, the remove of Fracture case from active drop pool means that the possibility of the cases' drop was decreased significantly, which implies the output of both cases reduced sharply. Since the price of the cases are directly related in these events, the study will applies the line chart of the price of both cases, to study such cases-remove event will carries out short-term effect to what extend.

Firstly, the price data of both cases and the benchmark market return of each day are collected, which is shows as below:

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Table 1. Price of Gallery Case with Market Return Data of each day

Days from event	Price from buff(CNY)	Price from Steam(CNY)	Benchmark Market Return
-14	7.12	9.84	0.005062
-13	7.11	9.13	0.008851
-12	6.94	9.22	-0.000415
-11	6.70	8.94	-0.004594
-10	6.50	8.53	-0.008460
-9	6.78	9.26	-0.008003
-8	6.84	9.17	0.003049
-7	7.16	9.01	-0.000987
-6	7.24	8.96	0.008573
-5	7.23	8.88	0.004365
-4	7.17	8.96	-0.003023
-3	7.20	8.88	0.007662
-2	7.43	8.96	-0.004045
-1	7.56	9.08	-0.002082
0	8.17	10.46	0.002642
1	8.14	10.68	0.005022
2	8.40	10.03	0.006720
3	8.20	9.96	0.001532
4	8.07	9.90	0.003629
5	7.95	9.95	0.007985
6	8.05	10.25	-0.000846
7	8.13	10.47	0.000080
8	9.50	12.04	-0.000031
9	11.85	13.91	0.008132
10	11.00	13.89	-0.001324
11	11.20	13.79	0.010671
12	11.19	13.89	-0.000437
13	11.07	13.77	-0.004038
14	10.80	13.68	0.016087

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Table 2. Price of Fracture Case with Market Return Data of each day

Days from event	Price from buff(CNY)	Price from Steam(CNY)	Benchmark Market Return
-14	2.19	3.35	0.003255
-13	2.29	3.35	0.010941
-12	2.2	3.49	-0.00144
-11	2.29	3.56	-0.004247
-10	2.29	3.49	0.000378
-9	2.29	3.56	0.011676
-8	2.28	3.56	0.007952
-7	2.29	3.49	0.000754
-6	2.5	3.56	0.018506
-5	2.49	3.63	0.009051
-4	2.48	3.7	-0.037823
-3	2.39	3.7	0.020479
-2	2.39	3.7	-0.027892
-1	2.48	3.77	0.014535
0	3.3	5.83	0.006483
1	3.97	7.09	0.005064
2	3.69	5.96	0.008845
3	3.45	5.83	-0.000415
4	3.3	5.69	-0.0046
5	3.43	5.26	-0.008477
6	3.19	4.9	-0.007988
7	3.19	4.69	0.003046
8	3.19	4.7	-0.000987
9	3.29	4.63	0.008581
10	3.3	4.71	0.004369
11	3.39	4.64	-0.00302
12	3.39	4.57	0.007665
13	3.29	4.48	-0.00404
14	3.37	4.41	-0.002088

With all the available data collected, showed in table 1 and 2, we can calculate the actual daily log return and the expected daily log return after the date of the event occurred of both cases according to the functions provided, which the data generated after calculating is as follow(days form event are arranged in the order of-14 to 14 from top to bottom. The specific values are showed in table 3 and 4. In order for better observation, the data on event happened date will be highlighted.) :

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Table 3. Actual and Expected Return of Gallery Case

Buff Actual Return	Buff Expected Return	Steam Actual Return	Steam Expected Return
-	-	-	-
-0.001405	-	-0.075770	-
-0.024279	-	0.009719	-
-0.035050	-	-0.030899	-
-0.030152	-	-0.047447	-
0.042136	-	0.083115	-
0.008801	-	-0.009756	-
0.045993	-	-0.017619	-
0.011128	-	-0.005568	-
-0.001382	-	-0.008960	-
-0.008313	-	0.008960	-
0.004179	-	-0.008960	-
0.031527	-	0.008960	-
0.017218	-	0.013330	-
0.077444	0.012308	0.142068	0.010184
-0.003677	0.016878	0.020866	0.014123
0.031527	0.019136	-0.062866	0.016023
-0.024279	0.010158	-0.007021	0.008434
-0.016000	0.013265	-0.006036	0.011798
-0.015189	0.022278	0.005044	0.019016
0.012531	0.005537	0.029986	0.004319
0.009901	0.007230	0.021373	0.005955
0.164023	0.007158	0.141067	0.005779
0.227271	0.022928	0.145068	0.020262
-0.065306	0.004687	-0.001440	0.003532
0.008960	0.027934	-0.007203	0.023463
-0.000893	0.006478	0.007203	0.005054
-0.010758	0.003052	-0.008645	0.002418
-0.024575	0.038236	-0.006530	0.032400

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Table 4. Actual and Expected Return of Fracture Case

Buff Actual Return	Buff Expected Return	Steam Actual Return	Steam Expected Return
-	-	-	-
0.044635	-	0.000000	-
-0.040107	-	0.040936	-
0.040094	-	0.019867	-
0.000000	-	-0.019867	-
0.000000	-	0.019867	-
-0.004376	-	0.000000	-
0.004376	-	-0.019867	-
0.087833	-	0.019867	-
-0.004016	-	0.019487	-
-0.004024	-	0.019110	-
-0.036967	-	0.000000	-
0.000000	-	0.000000	-
0.036967	-	0.018756	-
0.285320	0.020801	0.436162	0.014093
0.184712	0.019326	0.195874	0.012938
-0.073193	0.023255	-0.173617	0.016016
-0.067277	0.013632	-0.022013	0.008476
-0.044452	0.009283	-0.024304	0.005068
0.038638	0.005252	-0.078536	0.001912
-0.072570	0.005761	-0.070887	0.002309
0.000000	0.017228	-0.043788	0.011294
0.000000	0.013037	0.002128	0.008010
0.030845	0.022980	-0.014969	0.015801
0.003034	0.018604	0.017133	0.012372
0.026906	0.010925	-0.014969	0.006355
0.000000	0.022029	-0.015225	0.015055
-0.029958	0.009864	-0.019867	0.005524
0.024024	0.011893	-0.015723	0.007113

In order to specifically study the effect the event brought, further calculation of the abnormal return of each day(AR, started from t=0, to t=14) and total abnormal return(CAR) generated after the days from the event will be done according to the defined function of AR. The results is represented in table 5 and 6.

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Table 5. Abnormal Return of Gallery Case and Fracture Case each day

Gallery Case BuffAR	Gallery Case Steam AR	Facture Case BuffAR	Facture Case Steam AR
0.065136	0.131884	0.264519	0.422069
-0.020555	0.006743	0.165386	0.182936
0.012391	-0.078889	-0.096448	-0.189633
-0.034437	-0.015455	-0.080909	-0.030489
-0.029265	-0.017834	-0.053735	-0.029372
-0.037467	-0.013972	0.033386	-0.080448
0.006994	0.025667	-0.078331	-0.073196
0.002671	0.015418	-0.017228	-0.055082
0.156865	0.135288	-0.013037	-0.005882
0.204343	0.124806	0.007865	-0.030770
-0.069993	-0.004972	-0.015570	0.004761
-0.018974	-0.030666	0.015981	-0.021324
-0.007371	0.002149	-0.022029	-0.030280
-0.013810	-0.011063	-0.039822	-0.025391
-0.062811	-0.038930	0.012131	-0.022836

Table 6. Cumulative Abnormal Returns

Case	Platform	Cumulative Abnormal Return (CAR)
Gallery Case	Buff	0.153717
Gallery Case	Steam	0.230174
Fracture Case	Buff	0.082159
Fracture Case	Steam	0.015063

Finally, data of AR calculated will be utilized into the function of t-test, make it possible to obtain the p-value, which reflects the significance of the cases removal events.

Table 7. One-sample t-test Results for Abnormal Returns (15 days: t = 0 to t = 14, df = 14)

Case	Platform	t-value	Two-tailed p-value	Significance
Gallery Case	Buff	0.517	0.613	Not significant
Gallery Case	Steam	0.921	0.372	Not significant
Fracture Case	Buff	0.223	0.826	Not significant
Fracture Case	Steam	0.028	0.978	Not significant

With comparing the actual p-value against the p=0.05 threshold, like table 7 suggests, meaning we failed to reject the null hypothesis (mean AR=0) for all case-platform combinations.

3.3. Effect of Extend the Trading Cycle on Third-party Platform

Throughout CS:GO and CS2 trade market, significant adjustments on trading policies would seriously affect the price fluctuation of skins, especially the adjustments that will extend the trading cycle. In order to measure the effect of this kind of adjustments, we have chosen an important adjustment occurred in 2025, July, 16, following the initial introduction of the seven-day trade hold in 2018, the second change of policies were implemented. The new rule allows

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users to reverse or cancel private trades that are not on Steam Community Market within seven days after completion. At the same time, since all the trades on third-party platform are based on private offer, this modification further tightened control over item circulation, aimed to reduce the risks of fraud and accidental trades. This adjustment will be be abbreviated as E-Return in the study.

Because the implement of trading policy will not further extend the trading cycle of Steam Community Mar- ket(Trades on Steam Community Market can not be canceled), the data from the platform will no longer included in this section of research.

Additionally, in order to apparently represent the actual impact the event brought, the study will chose the skins that remained a relatively stable price trend before the event took place. According to the choosing standard, three Representative skins of each price range are selected. That are Desert Eagle | Printstream (Field-Tested), Stiletto Knife | Tiger Tooth (Factory New) and Butterfly Knife | Tiger Tooth (Factory New).

The following table 8 shows their price data around the selected event window:

Table 8. Daily Prices of Three Items on Buff(CNY)

Day from Event	Desert Eagle | Printstream	Stiletto Knife | Tiger Tooth	Butterfly Knife | Tiger Tooth
-14	226.00	3949.00	16783.50
-13	224.00	3948.50	16666.00
-12	220.00	3928.49	16750.00
-11	223.94	3935.00	16779.99
-10	220.00	3930.00	16780.00
-9	222.00	3899.50	16500.00
-8	217.00	3935.00	16599.50
-7	210.00	3924.50	16566.00
-6	216.00	3929.40	16500.00
-5	214.00	3928.90	16649.00
-4	217.66	3928.90	16664.00
-3	217.00	3917.50	16666.00
-2	213.00	3910.00	16664.50
-1	217.00	3918.00	16738.00
0	209.49	3845.00	16499.50
1	206.50	3770.00	16298.50
2	214.00	3769.50	16000.00
3	209.00	3750.00	16200.00
4	203.49	3670.00	15750.00
5	199.50	3450.00	14945.00
6	209.00	3500.00	15450.00
7	208.00	3650.00	15300.00
8	209.30	3635.00	15449.50
9	209.24	3595.00	15500.00
10	208.00	3620.00	15985.00
11	202.00	3648.00	15777.00
12	205.00	3660.00	15690.00
13	206.89	3650.00	15280.00
14	210.00	3640.00	15490.00

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Meanwhile, the Daily Benchmark Market Return is showed as below in table 9:

Table 9. Daily Benchmark Market Return

Day from	Event	Benchmark Market	Return
-14		-0.003615	
-13		0.001334	
-12		0.002773	
-11		-0.001584	
-10		-0.004099	
-9		-0.001641	
-8		-0.002825	
-7		-0.010161	
-6		0.010072	
-5		0.005115	
-4		0.006324	
-3		0.002074	
-2		0.010875	
-1		0.002739	
0		-0.029375	
1		-0.017491	
2		0.002037	
3		-0.017701	
4		-0.027135	
5		-0.055678	
6		0.053594	
7		-0.006480	
8		0.013897	
9		0.006838	
10		0.009182	
11		-0.002246	
12		0.000343	
13		-0.002479	
14		-0.005866	

According to the price data, we can calculate the actual daily log return of each item.

Meanwhile, with using the data of daily price of each item and the benchmark market return of the day, we can conduct further calculation to obtain the expected daily log return of each item. Table 10 to 12 represent the calculated result.

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Table 10. Daily Log Returns and Expected Log Return of Desert Eagle | Printstream

Day from Event	Actual Log Return	Expected Log Return
-14	-	-
-13	-0.008921	_
-12	-0.018029	_
-11	0.017749	_
-10	-0.017789	_
-9	0.009047	_
-8	-0.022857	_
-7	-0.032718	_
-6	0.028158	_
-5	-0.009298	_
-4	0.016957	_
-3	-0.003030	_
-2	-0.018598	_
-1	0.018609	_
0	-0.035237	-0.037054
1	-0.014358	-0.024879
2	0.035618	0.000588
3	-0.023679	-0.037804
4	-0.026728	-0.074243
5	-0.019839	0.067271
6	0.046618	-0.010126
7	-0.004789	0.016325
8	0.006229	0.007176
9	-0.000289	0.010244
10	-0.006039	-0.004654
11	-0.029289	-0.001201
12	0.014739	-0.004977
13	0.009179	-0.009323
14	0.014919	-0.009323

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Table 11. Daily Log Returns and Expected Log Return of Stiletto Knife | Tiger Tooth

Day from Event	Actual Log Return	Expected Log Return
-14	-	-
-13	-0.000129	_
-12	-0.005089	_
-11	0.001659	_
-10	-0.001269	_
-9	-0.007809	_
-8	0.008809	_
-7	-0.002669	_
-6	0.001249	_
-5	-0.000129	_
-4	0.000000	_
-3	-0.003109	_
-2	-0.001909	_
-1	0.002049	_
0	-0.018839	-0.022451
1	-0.019749	-0.018824
2	-0.000129	-0.011426
3	-0.005189	-0.028730
4	-0.021549	-0.057993
5	-0.061819	0.049468
6	0.014389	-0.007431
7	0.041999	0.012042
8	-0.004119	0.005242
9	-0.011059	0.007470
10	0.006929	0.007757
11	0.007699	-0.000876
12	0.003279	-0.000262
13	-0.002729	-0.003045
14	-0.002739	-0.003045

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Table 12. Daily Log Returns and Expected Log Return of Butterfly Knife | Tiger Tooth

Day from Event	Actual Log Return	Expected Log Return
-14	-	-
-13	-0.007049	_
-12	0.004999	_
-11	0.001789	_
-10	0.000000	_
-9	-0.016859	_
-8	0.005999	_
-7	-0.002009	_
-6	-0.004009	_
-5	0.009009	_
-4	0.000900	_
-3	0.000120	_
-2	-0.000090	_
-1	0.004400	_
0	-0.014359	-0.026145
1	-0.012069	-0.022541
2	-0.018479	-0.013796
3	0.012419	-0.030235
4	-0.028239	-0.060193
5	-0.052539	0.055744
6	0.033229	-0.008031
7	-0.010009	0.013347
8	0.009909	0.006288
9	0.003259	0.008290
10	0.030819	0.008677
11	-0.013099	-0.001006
12	-0.005529	-0.000362
13	-0.026559	-0.003245
14	0.013649	-0.003245

Start from the date the event happened, we can compute the abnormal return of each day(AR) and total abnor- mal return(CAR) generated after the days from the event day according to the defined function of AR and CAR. Which finally in returns the data of table 13 and 14.

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Table 13. Daily Abnormal Returns (ARs)

Day from Event	Desert Eagle | Printstream	Stiletto Knife | Tiger Tooth	Butterfly Knife | Tiger Tooth
0	0.001817	0.003612	0.011786
1	0.010521	-0.000925	0.010472
2	0.035030	0.011297	-0.004683
3	0.014125	0.023541	0.042654
4	0.047515	0.036444	0.031954
5	-0.087110	-0.111287	-0.108283
6	0.056744	0.021820	0.041260
7	-0.021114	0.029957	-0.023356
8	-0.000947	-0.009361	0.003621
9	-0.010533	-0.018529	-0.005031
10	-0.001385	-0.000828	0.022142
11	-0.028088	0.008575	-0.012093
12	0.019716	0.003541	-0.005167
13	0.018502	0.000316	-0.023314
14	0.024242	0.000306	0.016894

Table 14. Cumulative Abnormal Returns (CARs)

Item	CAR
Desert Eagle Printstream	0.079035
Stiletto Knife Tiger Tooth	-0.001521
Butterfly Knife Tiger Tooth	-0.001144

In the end, the last step to get conclusion is to apply the calculated ARs data into t-test, and further reveal the significant of the effect the adjustment in policies brought on specific single item.

Table 15. Statistical Test Results of AR for Each Item

Item name	t-value	Two-tailed p-value	Significance
Desert Eagle | Printstream Stiletto Knife | Tiger Tooth Butterfly Knife | Tiger Tooth	0.588	0.565	Not significant
	-0.0115	0.991	Not significant
	-0.0081	0.994	Not significant

Consequently, from table 15, we failed to reject the null hypothesis (mean AR=0) for three items that separately represents different price range.

4. Conclusion

In the research, two types of events, which are in-game content update event and adjustments event on trade policies that extend trading cycle, are conducted research based on actual data.

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Regarding in-game content update event, the study have chosen two representative events happened recently. Both events are the removal of weapon case of CS2(Gallery Case and Fracture Case). And in order to study the trade policy adjustments that extend the trading cycle on third-party platform, the recently published policy is selected as the event.

In first type of event,the calculated result failed to suggest that the price of the removed cases are significantly affected by their removal events. Therefore, collectively, these findings imply that the event of their removal did not exert a statistically significant impact (neither increase nor decrease) on the prices of the Gallery Case or Fracture Case on either the Buff or Steam platform in a short term. The fluctuation of the price of the removed cases did not have statically significant differences compare with the overall market trend.

However, descriptive analysis of raw prices reveals notable price dynamics due to the event. For instance, the price of Fracture Case on Buff, as the table shows, remain the tendency of slightly increasing and decreasing around 2.19 to 2.5 CNY before the day of event. However, as the event happened, the price jumped to 3.3 CNY, and have never fell back to the pre-event level of 2.5. This kind of instances may suggest that while the event's impact did not reach the threshold of statistical significance (might due to factors such as small sample size or residual volatility in ARs), it may have triggered a short-term price surge that was sustained in the post-event period, reflecting the potential market recognition of the event's value correlation, although the specific removal of the case may not brings the statically expected significant effect to the price of the corresponding case. Hence, for those profit-seeking indicators, though it might unable to provide the huge returns imagined, by hoarding some case that is determined to be removed, it still engenders considerable profits as selling after the event happened in a short term.

For the second type of event, three items from different price ranges that are chosen. However, the result also failed to prove if significant effect on single item due to the event existed, according to the comparison with overall market trend at the same time.

Nevertheless, by observing the table shows the Daily Benchmark Market Return and the collected price data of three items, we can discover that in the first few days of the event occurred, the prices of all of the three items and the benchmark market return have sharply declined for more than 5 percent, and generally reflect a downward trend in a short term. From this, it can be inferred that such fluctuation might be an signal shows the effect of policies adjustments carried out did not targeted at a single or specific item, but eventually acted on the hole market. Since all of the prices of three studied items got violently drop after the event occurred, that generates the illusion that AR=0 for specific item due to the event. However, the overall market shows a sharply downward trend and even the skins used to maintained a stable price trend cannot remain indifferent.

But as the price data reflects, although the prices of each item has dropped sharply, one should not sell items at a low point out of fear of price fluctuations. Just as the theory of Behavioral Finance suggested, such Herd Behaviors and Loss Aversion in turn leads to market prices deviating further from expectations, resulting in explainable irrational fluctuations. Which ultimately provide investment opportunities for other investors to get long term return through bottom-fishing.

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