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Price Dynamics and Volatility of Virtual Items in Online Games: Evidence from CS:GO Weapon Balance Updates and Case Releases

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Abstract. Virtual-item prices can react to game updates, but these responses are difficult to separate from trends already under way. Based on Buff.163 daily minimum listing price data from July 2021 to January 2024, this paper examines five CS:GO events—two weapon balance adjustments (M4A1-S magazine capacity reduction, combined AWP and M4A1-S nerf) and three weapon case releases (Dreams & Nightmares, Recoil, Revolution)—using event study methodology, a two-way fixed-effects DID model, and volatility analysis. The results show that treatment-group skins exhibit a significant pre-trend reversal before and after the updates; their outperformance relative to the AK-47 control group disappears immediately and turns sharply negative post-update. M4A4 skin prices exhibit a positive abnormal performance as a substitute weapon. All three cases show negative price dynamics relative to the benchmark over their observable periods. The study demonstrates that virtual asset pricing is highly sensitive to game balance decisions, while also revealing that pre-trends and data gaps impose serious constraints on causal inference.

Keywords: virtual goods, event study, price dynamics, CS:GO, secondary market

1. Introduction

CS:GO developed a large secondary market for weapon skins and cases, with third-party platforms such as Buff.163 making prices visible on a daily basis. Earlier studies on virtual goods have shown that item demand depends on design, scarcity, social value, and player motivations [1-5]. Research on skins and loot boxes also shows that these items can carry economic value beyond their in-game function [6, 7]. This makes game updates economically relevant. A weapon nerf can change how often a weapon is used, while a new case changes the supply of tradable items. Both mechanisms can be reflected in market prices, although the response may be confounded by trends that were already present before the update.Most studies of virtual goods focus on why players buy items or on the behavioural effects of loot-box systems [1-7]. Much less is known about how balance changes within a game are reflected in secondary-market prices. CS:GO offers a useful setting because Valve changes weapon parameters and item supply while the affected skins continue to trade. The main difficulty is identification: an update may occur after a weapon has already become more popular, so a simple before-and-after comparison can overstate the effect of the update itself.

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This paper addresses three research questions. First, how do prices and volatility of skins linked to nerfed weapons change around major balance updates? Second, how do recently released cases perform relative to other active cases during the period that can be observed in the Buff archive? Third, is there evidence that demand moves toward a close substitute, such as the M4A4, when the M4A1-S is weakened?

2. Empirical methodology

The analysis uses an event-study framework together with a two-way fixed-effects DID specification for the two weapon-balance events. Event studies are well suited to tracing short-run price responses around a dated shock [8]. Because the Buff archive does not include the initial listing period for the three case releases, those events are treated separately as descriptive benchmark-adjusted price dynamics rather than as DID estimates.

2.1. Event study

For the two demand-side events, daily item returns are calculated from log differences in minimum listing prices:

$$R_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) \tag{1}$$

where P_i,t denotes the daily minimum listing price of item i on day t. The estimation window is [-60, -10]. Market-wide movements are removed using the equal-weighted return of the AK-47 control group: $R_{i,t}^{excess} = R_{i,t} - R_{m,t}$. Expected excess return is the item-specific mean over the estimation window. Abnormal return is $AR_{i,t} = R_{i,t}^{excess} - \overline{R_i^{excess}}$ and $CAR_i\left[0,\tau\right] = \sum_{s=0}^{\tau} AR_{i,s}$.

$$CAAR_\tau = \frac{1}{N}\sum_i CAR_i[0,\tau] \tag{2}$$

CAAR is used to summarize the average accumulated abnormal return across affected skins. Statistical inference follows standard event-study practice [8]. Because skins linked to the same weapon are exposed to a common underlying shock, the Patell test is reported with the Kolari-Pynnönen correction for cross-sectional dependence [9].

2.2. Difference-in-differences analysis

For D01 and D02, post-event relative price changes are also summarized using a two-way fixed-effects DID specification:

$$\ln(P_{i,t}) = \alpha_i + \gamma_t + \beta(Treat_i \times Post_t) + \varepsilon_{i,t} \tag{3}$$

where Treat_i equals one for affected skins and zero for AK-47 control skins. $Post_t$ equals one from the event date onward. Item fixed effects α_i absorb time-invariant differences across items, while date fixed effects γ_t absorb shocks common to all items on a given day. Standard errors are clustered by item. Because the dependent variable is in logs, the coefficient is converted to an exact percentage change using $100 \times [\exp(\beta) - 1]\%$

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2.3. Volatility analysis

Price volatility is measured using the absolute daily log return:

$$VOL_{i,t} = |R_{i,t}| \tag{4}$$

The main volatility measure is the absolute log return. Squared returns and rolling standard deviations are used as robustness checks. For D01 and D02, volatility is estimated with the same two-way fixed-effects structure. For S01-S03, volatility is reported descriptively over the observable Buff period rather than through a launch-date DID.

2.4. Parallel-trends test and dynamic effects

The event-time specification is used to inspect the path of the treatment-control gap before and after each weapon update. In a standard DID design, the pre-event coefficients should be jointly close to zero. Here they are tested jointly rather than judged only from individual coefficients. When that condition fails, the DID coefficient is retained as a descriptive post-event gap rather than a clean causal treatment effect, consistent with recent work on sensitivity to non-parallel trends [10].

$$Y_{i,t} = \alpha_i + \gamma_t + \sum_{k \neq -1} \beta_k D_{i,t}^k + \varepsilon_{i,t} \tag{5}$$

where $D_{i,t}^k$ is an indicator for treated item i at event time k. The period $k = -1$ is omitted. The lead coefficients describe pre-event differences in trends, while the lag coefficients show how the relative price gap evolves after the update.

3. Data sources and sample construction

3.1. Data source

The main dataset is the public Buff.163 price-history archive [11]. It contains 21,954 item series and covers July 26, 2021 to about January 19, 2024. Prices are denominated in Chinese Yuan (¥). The analysis uses the daily minimum listing price; this is a posted market price, not a transaction price.

3.2. Events

Five events fall within the archive period. Dates and update details are taken from Valve's official CS:GO release notes and blog posts [12-16].

Demand-side events (weapon balance reductions):

• D01 (2022-06-15): M4A1-S magazine capacity reduced from 25 to 20 rounds [12]

• D02 (2022-11-18): AWP magazine capacity reduced from 10 to 5 rounds; M4A1-S range modifier reduced from 0.99 to 0.94 [13]

Supply-side events (case releases):

• S01 (2022-01-20): Dreams & Nightmares Case released [14]

• S02 (2022-07-01): Recoil Case released [15]

• S03 (2023-02-09): Revolution Case released [16]

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3.3. Treatment and control groups

For the two weapon-balance events, the groups are defined as follows:

- Treatment group: skins linked directly to the weapon affected by the update
- Main control group: AK-47 skins
- Substitution group: M4A4 skins, analysed separately because the M4A4 is a close in-game substitute for the M4A1-S

Table 1 summarizes the composition of treatment, control, and substitution groups for the two demand-side events (D01 and D02).

Table 1. Sample composition of treatment, control, and substitution groups by event

Event	Treatment	Control	Substitution
D01	125 M4A1-S skins	176 AK-47 skins	153 M4A4 skins
D02	295 AWP + M4A1-S skins	201 AK-47 skins	176 M4A4 skins

For S01-S03, the three focal cases are compared with an equal-weighted benchmark of 38 active weapon cases. The first Buff observations for Dreams & Nightmares, Recoil, and Revolution occur 233, 254, and 54 days after their official release dates, respectively. For this part of the analysis, $\tau = 0$ therefore means the first Buff observation, not the release date.

3.4. Data cleaning

Items are retained only when at least 80% of the required price observations are available in the relevant estimation and event windows. Souvenir items are excluded because they enter the market through a different supply process. No trading-volume filter is used, because reliable listing-count data in the archive are not available for most of the sample period.

4. Results

4.1. Demand-side weapon balance events

4.1.1. M4A1-S magazine reduction (D01)

The M4A1-S update shows a large change in relative pricing. The two-way fixed-effects coefficient is $\beta = -0.1176$ ($p < 0.001$), equivalent to an average post-event gap of −11.10% relative to AK-47 skins. A separate weapon-level price index gives −11.51%, which is very close to the panel estimate.

Table 2 summarizes the key estimation results for D01, including the DID coefficient, relative price changes, cumulative abnormal returns, and diagnostic statistics.

Table 2. D01 summary: M4A1-S magazine reduction

Metric	Estimate
TWFE DID coefficient (β)	−0.1176 ($p < 0.001$)
Relative price change	−11.10%
Aggregated index gap change	−11.51%
CAAR [0, +20]	−16.93% ($p < 0.001$)
KP-adjusted Patell z [0, +20]	−8.43 ($p < 0.001$)

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Table 2. (continued)

Joint pre-trend F-test	7.01 ($p < 10^{-6}$)
Observations	27,387
Items (treat / control)	125 / 176

The dynamic estimates are more informative than the single DID coefficient. M4A1-S skins were already outperforming AK-47 skins before the update: the gap is about +3.7% at day −10 and +4.9% at day −5. It remains positive on the event day (+4.0%), then falls to roughly zero by day +1. The gap is −5.3% by day +5, −11.3% by day +10, and −11.7% by day +20. The pattern is therefore a reversal rather than a simple level drop from a flat pre-event baseline.

The lead coefficients are jointly significant ($F = 7.01$, $p < 10^{-6}$), so the standard parallel-trends assumption is rejected. For that reason, −11.10% is not treated as a clean causal estimate of the nerf. It is better read as the average post-event relative gap after a period in which M4A1-S skins had already been gaining on the control group.

Volatility also rises after D01. The coefficient for absolute daily log return is 0.0089 ($p < 0.01$), equivalent to an increase of about 0.89 percentage points in the absolute-return measure relative to AK-47 skins.

M4A4 skins move in the opposite direction. Their CAAR over [0, +20] is +13.01% ($p < 0.001$) relative to the AK-47 benchmark. A separate post-event comparison is also positive (+6.95%, $p < 0.001$). The sign is consistent with a substitution response, although the data do not directly observe players switching weapons.

4.1.2. AWP and M4A1-S combined nerf (D02)

The November 18 update reduced the AWP magazine size and also weakened the M4A1-S at range. The same treatment-control design is used, with AWP and M4A1-S skins in the affected group and AK-47 skins as the main control.

Table 3 lists the main estimates and test statistics for the combined AWP and M4A1-S nerf event.

Table 3. D02 summary: AWP and M4A1-S combined nerf

Metric	Estimate
TWFE DID coefficient (β)	−0.0643 ($p < 0.001$)
Relative price change	−6.22%
Aggregated index gap change	−6.66%
CAAR [0, +20]	−9.28% ($p < 0.001$)
KP-adjusted Patell z [0, +20]	−5.93 ($p < 0.001$)
Joint pre-trend F-test	5.02 ($p < 10^{-6}$)
Observations	44,987
Items (treat / control)	295 / 201

D02 shows the same broad reversal. Before the update, affected skins are above the AK-47 benchmark ($\beta_{-5} = +2.3\%$ and $\beta_{-2} = +3.2\%$). After the update, the gap turns negative, reaching -4.5% by day +5 and -6.1% by day +10. The two-way fixed-effects estimate is -6.22%, while the aggregate weapon-level index gives -6.66%.

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M4A4 again performs positively over the same window. Its CAAR [0, +20] is +21.75% ($p < 0.001$), and the post-event DID-style gap is +30.03% ($p < 0.001$). As with D01, these estimates are consistent with substitution but should not be read as direct evidence of individual player switching.

The volatility response is smaller than in D01. The absolute-return coefficient is 0.0054 ($p < 0.05$), or about 0.54 percentage points on the volatility measure.

4.2. Supply-side case releases

The case results require a different interpretation because the archive starts observing each case after its official launch. The first available dates are September 10, 2022 for Dreams & Nightmares, March 12, 2023 for Recoil, and April 4, 2023 for Revolution. These are 233, 254, and 54 days after release. Table 3 therefore reports benchmark-adjusted price changes from the first Buff observation, not launch effects.

Table 4 presents the benchmark-adjusted cumulative returns of S01–S03 over the observable Buff window.

Table 4. Benchmark-adjusted price dynamics during the observable Buff period

Days since first Buff observation	Dreams & Nightmares (S01)	Recoil (S02)	Revolution (S03)
+5	−4.88%	+1.08%	−3.79%
+10	−8.24%	−6.97%	−4.24%
+20	−12.09%	−17.18%	−7.08%
+30	−11.11%	−14.39%	−24.28%
+60	−12.46%	−34.66%	−54.08%

All three cases underperform the active-case benchmark over the longer observable horizons. Dreams & Nightmares is down 12.46% by day +60 from its first Buff observation. Recoil falls 34.66%, while Revolution falls 54.08%. These numbers describe later price paths and cannot be used to infer what happened during the first weeks after release.

For S03, the absolute-return measure is elevated by 0.012 relative to the benchmark during the first 20 observable days ($p < 0.05$). Because Buff begins observing Revolution 54 days after release, this result is not labelled an immediate post-release volatility effect.

4.3. Cross-event comparison

Table 5 compares the price and volatility responses across all five events, highlighting differences between demand-side weapon-balance shocks and supply-side case releases.

Table 5. Cross-event summary

Event	Type	Price Change	Volatility Change	Persistence	Key Pattern
D01	Demand shock	−11.10%	+0.89 pp (absolute return)	Sustained (20 days)	Pre-trend reversal
D02	Demand shock	−6.22%	+0.54 pp (absolute return)	Sustained (20 days)	Pre-trend reversal
S01	Case series	−12.46% (60-day)	Moderate	Observed 60 days	Observed-period decline
S02	Case series	−34.66% (60-day)	Moderate	Observed 60 days	Observed-period decline
S03	Case series	−54.08% (60-day)	Elevated	Observed 60 days	Observed-period decline

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The demand-side events show a sharp break around a known balance-update date: an earlier positive relative trend is followed by a negative post-event gap and higher short-run volatility. The case series look different, with gradual benchmark-adjusted declines during the periods visible in Buff. The two sets of results should not be compared as if they used the same event timing, because the initial launch period is missing for S01-S03.

5. Discussion

Three points stand out from the results.

The first is the reversal around weapon-balance updates. Prices of skins linked to the affected weapons were rising relative to AK-47 skins before both nerfs, and the gap changed sign shortly afterward. This pre-event movement matters because it shows why a standard causal DID interpretation is too strong. The data are consistent with rising demand for the affected weapons before Valve intervened, but price data alone cannot identify whether players anticipated the update or why Valve chose that timing.

The M4A4 results add a second piece of evidence. M4A4 skins earned positive abnormal returns around both M4A1-S nerfs, and the response was larger in D02 than in D01. That pattern is consistent with demand shifting toward a close substitute. It is suggestive rather than direct proof, since the dataset records item prices rather than individual weapon choices.

Volatility rises around both demand-side events, especially D01. For the cases, the observable-period evidence is weaker and less directly tied to release because the archive begins late. The safer conclusion is therefore that weapon-balance updates coincide with a clear short-run increase in price uncertainty, while the supply-side volatility results are more limited by data coverage.

The rejected pre-trend tests are not treated as a minor technical issue. They change what can be claimed from the DID estimates. The coefficients still summarize the size of the post-event treatment-control gap, and they line up closely with the aggregate weapon indices, but they do not by themselves identify the causal effect of the update. The Kolari-Pynnönen adjustment addresses cross-sectional dependence in the event-study tests [9]; it does not restore the parallel-trends assumption.

6. Conclusion

Using daily Buff.163 listing prices, this paper examines two CS:GO weapon nerfs and three case releases. The clearest result comes from the demand-side events. Skins linked to the affected weapons were outperforming AK-47 skins before the updates, but that advantage disappeared and turned negative afterward. The average post-event gaps are −11.10% for D01 and −6.22% for D02, and aggregate weapon-level indices give almost the same changes.

The event-study tests remain significant after adjusting for cross-sectional dependence, while M4A4 skins show positive abnormal returns around both M4A1-S nerfs. This is consistent with a substitution response. Volatility also increases around the two balance updates.

The supply-side evidence is more limited. Buff begins observing the three cases well after their official release dates, so those results describe later benchmark-adjusted price movements rather than launch effects. Taken together, the findings show that virtual-item prices can move substantially around changes in game balance, but they also show why pre-trends and data coverage need to be handled carefully when interpreting these markets. The analysis has four main limitations. First, the demand-side DID estimates are descriptive because the pre-event trends are not parallel. Second, Buff records minimum listing prices rather than completed transaction prices. Third, the archive

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misses the initial listing period for all three focal cases, which prevents a clean study of launch effects. Finally, the data come from one third-party marketplace. Steam Community Market data or other platform records would help test whether the same patterns appear across venues and over a longer period.

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