# Consumer preferences in a virtual barter market: A study of Counter Strike 2's item economy

*By* Anthony Vo*

*The size of virtual economies, especially as tied to video games, has exploded in the last two decades. Users spend countless hours of playtime accruing valuable items and selling them for real-word money, but it is unclear what determines the value of items. With data from Counter-Strike 2's various item markets, this paper uses regression analysis to discover features that contribute the most to the pricing of items. The analysis reveals that all of the features of an item are statistically significant in determining its price, a phenomenon explained by characterizing a feature as either indicating utility or scarcity. We apply these conclusions to other, similar economies (e.g. Team Fortress 2 and Rust) and use them to make inferences about consumer preferences in larger markets.*

Markets involving real-world currency derived from video games have garnered much attention in the last two decades. European lawmakers have enforced policies forcing developers to be transparent with item drop rates; American lawmakers have outlawed gambling symbolism in children's games; celebrities have become famous for owning expensive collections of virtual items. Despite the attention that these virtual economies attract, little is known about how they relate to real world economies. Intuition assumes that virtual markets behave similarly to real world markets, but there exists little evidence to back this assumption up. This paper aims to bridge the gap between our assumptions on virtual markets and what currently occurs in virtual markets, providing evidence that consumer preferences are unaffected by the fact that goods are immaterial. To accomplish this goal, we analyze the market of Counter-Strike 2 (herein referred to as CS2), discovering the determinants of value in this smaller market.

Virtual markets contained within virtual worlds are nothing new. Perhaps the most famous early example is the Second Life Marketplace available in Second Life. Ke (2012) showed that agents in the Second Life Marketplace exhibit similar traits as agents in real-world economy when faced with issues such as piracy and online sharing, providing a foundation for this paper to build off of. One key difference between Second Life and CS2 is that the Second LIfe Marketplace hosts items that users create whereas CS2 does not allow users to create and sell their own items. As a result, this study differentiates itself from past work by deriving a framework for virtual economies similar to CS2's (e.g. Rust, Team Fortress 2).

CS2 is a first-person shooter game where players can acquire cosmetics for their in-game

* Acknowledgements. Chen: Primary Advisor, jiaweic@uci.edu. Richardson, Advisor, garyr@uci.edu. Milani, Advisor, fmilani@uci.edu.

weapons. These cosmetics, colloquially referred to as “skins”, have different appearances than the original weapons. Obtaining cosmetics costs money; players must first earn cases which contain skins through playing the game, and then they can open them with keys bought from the in-game store for \$2.50. Cases produce a random skin with random attributes once opened. A table of these attributes and what they mean is provided in Table A1.

Each case is a part of a collection. A collection is a subset of skins, and the case belonging to a collection will only give players skins belonging to their respective collection. When a player obtains a case, the collection of the case will also be random. The vast randomness in obtaining skins derives the value of the skins themselves; players have varying utility for skins, and they are willing to trade lower utility skins for higher utility ones.

Once a player owns an item, it is linked to their account until they either trade it to another player or sell it on the Steam Community Market, a dedicated platform created by Valve for the purchase and sale of items. The Steam Community Market is the canonical price-setter for items because it is the most accessible for players; however, Valve takes a cut of all sales in order to make a profit. Third-party marketplaces exist to circumvent the cut that Valve takes and offer lower prices to players. To sell items, players use online wallets to first transfer money before trading the sold item away to an account associated with the marketplace. Buying items follows a similar procedure. Though there is less security in this type of transaction for both players and firms, the cut that Valve takes is significant enough for agents to engage in third-party markets.

Due to the size and data available of CS2’s item prices, this paper uses the market as a case study to understand more about consumer preferences in these virtual markets. The CS2 item market shares many traits with real-world markets. For example, there exist macroeconomic shocks that come from events relevant to the game world, such as a positive shock upon the announcement of a large update or negative shocks to prices when certain weapons are made weaker. Additionally, the various features allocated to each item allows consumers to differentiate between items and identify their individual utilities through purchasing items.

In order to predict the effect of different features on weapon pricing, we use OLS linear regression and analyze the magnitude and sign of the coefficients. We find that rarer qualities (such as Covert vs. Classified) have positive effects on price alongside qualities that influence the usage rate of a skin (such as the type of weapon it belongs to). These findings suggest that consumers have high preferences for scarcity and in-game utility (i.e. how often you can actually use an item inside of the virtual world). However, our findings are limited by the extent of data available to us, specifically due to the small time scale we examined.

The conclusions derived from studying CS2 can naturally be applied to other games with Steam Community Market support. Understanding these smaller virtual economies will further our understanding of economies with larger consequences, progressing the literature on consumer preferences.

The rest of the paper is organized as follows. We discuss previous literature relating to this topic, highlighting methods used by other economists to determine significant features for pricing. We then describe the data used for our analysis, followed by the regression model. Next, we analyze the results of our regression, touching on interesting results. We end with practical use cases of our findings, limitations of our research, and future ways to build upon our discussion

## I. Literature Review

Other scholars have analyzed CS2 as an economy before but not under an econometric lens. Yamamoto and McArthur (2015) discuss unique aspects of CS2's item economy as a virtual market but did not go into quantitative depth. Xenopoulos, Coelho, and Silva (2021) analyze CS2's in-game economy, as opposed to its cosmetic item economy, using game theory and machine learning to optimize winning matches, but this analysis has nothing to do with weapon skins.

There exist many other studies focused on quantitative analysis of virtual good pricing. Yang, Dimitrov, and Mantin (2014) used the chess Elo system, as formulated in Elo (1978), to determine the price of collectible virtual goods after a batch release. The system proposed is relevant for firms who own virtual worlds and want to maximize profits, as it dynamically changes the prices of goods based on demand. Also, the paper provides insight into deriving consumer preferences, but this system is less useful for modeling pricing strategies of sellers who don't have the same market power as large firms.

Ke (2012) used linear regression to analyze the ways users set permissions on user-generated content in the virtual world Second Life. The paper details data collection from Second Life's online marketplace, linear regression techniques to determine correlation between permissions setting, and inference of the results to form conclusions about how creators choose to price and distribute their products.

Wang, Mayer-Schönberger, and Yang (2012) also used linear regression in their paper in order to determine what factors lead to real-world monetary value in MMORPGs. Features such as in-game social networking time, number of servers, and size of development team were analyzed to see what affected the price of virtual goods. Their fixed effects model was effective in finding these factors, and this paper incorporates the same methodologies to create its model.

## II. Data

We collected data from the CSGOSKINS.GG API which records prices from different third-party markets. The reason why we used this data source was because of its comprehensiveness. The API supports queries for the histories of prices over a variety of different markets, and there were no other options that provided that level of robustness.

This API had two separate endpoints for prices and item data. The prices endpoint provided the prices from different markets on different dates, and the item data provided different aspects of the items for sale. As such, the script we wrote to collect data consolidated these two pieces of information based on the unique names for each item, as determined by the Steam Marketplace.

One downside of the API was that it only supported queries for prices up to ninety days ago. As such, a full survey of all historical prices was not possible. However, further analysis showed that the prices were not stationary with respect to time. This meant that a cross-sectional approach was appropriate for the data, eliminating the need to get more data points across a longer time period.

An issue with the data is that there are many outliers. There are some very expensive skins in the game, such as the coveted AWP Dragon Lore. This skin is extremely rare, and it is well-established as one of the most expensive skins in the game. As a result, the coefficients recovered from OLS become inflated, and the analysis becomes less informative. Therefore, removing outliers is necessary for a good regression, even if it comes at the cost of removing data from some of the most well-known items.

Another issue with the data is that it contains a slew of categorical variables, leading to an extremely sparse dataset with many columns. To combat this, we turned these categorical features into dummy columns and dropped one of the columns to prevent multicollinearity, using built-in implementations of sparse matrices to reduce the memory usage of the dataset. The columns dropped to prevent multicollinearity match the columns corresponding to a Field-Tested AK 47 | Blue Laminate; as such, coefficients will be interpreted relative to the features of this item.

Some items were missing the "collections" feature; specifically, gloves and knives do not belong to any specific one collection, as they can be dropped from any case. Two new collections were created for them titled "Gloves" and "Knife", respectively.

Figure 1. Field-Tested AK-47 | Blue Laminate.

*Source:* Steam Community Market.

## III. Methodology

We propose the following linear model for the prices of skins:

$$p_{ij} = \alpha_i + \Theta_j + \beta_1 X_i + \beta_2 Z_j + \varepsilon_{ij}$$

In this model, $i$ is the skin of interest and $j$ is the market that the skin comes from. $\alpha_i$ represents the fixed effect of the skin. $\Theta_j$ represents the fixed effect of the market. $\beta_1 X_i$ represents the effect that an item's attributes have on price, where $\beta_1$ is a matrix representing the coefficients of attributes and $X_i$ is a matrix representing the values of attributes. $\beta_2 Z_j$ represents the effect that a market's attributes have on price, where $\beta_2$ and $Z_j$ are analogous to $\beta_1$ and $X_i$ but with respect to markets.

After obtaining and cleaning the data, we performed an OLS regression on the data using Mackinnon and White's (1985) correction for heteroskedasticity robust standard errors, as the variance in price for more expensive items is greater than the variance for cheaper items.

## IV. Results

The coefficients (shown in Tables A2-A8) derived from the OLS regression match many of our initial assumptions about the pricing of skins. From Table A2, we find that items that are either StatTrak or Souvenir are more expensive, likely due to the fact that having the StatTrak or Souvenir qualifier is uncommon. Additionally, StatTrak provides utility to the player in the form of tracking the number of kills that the player gets with the item, making it more valuable at large. This fact establishes one of the determinants of value in this market: rarity. Items that are more rare are more valuable, as scarcity drives prices up.

The signs and magnitudes of the wear coefficients (Table A2) are expected: Factory New items are the most expensive, followed by Minimal Wear items, with battle-Scarred items being the least expensive. Interestingly, Well-Worn items appear to be worth a little bit more than Field-Tested items. One intuitive reason is that more worn skins can have hidden patterns not immediately visible on less worn skins. Consider the Glock-18 | Ramese's Reach. The Factory New version depicts the Nile on the barrel along with the Eye of Anubis on the grip. However, once the skin becomes more worn, more details become visible; the Eye of Anubis becomes darker, and a body appears on the desert horizon. Generally, this means that extreme wears can be more valuable than middling wears, hinting at why Field-Tested items are worth less on average compared to Well-Worn items. Note that wears are uniformly distributed, so they do not provide evidence for rarity being a main determinant of value. As such, the coefficients of wears represents general consumer tastes for what they find aesthetically pleasing.

The signs and magnitudes of the item rarities (Table A2) are mostly expected. The order of rarities from least to most valuable are Consumer Grade, Industrial Grade, Mil-Spec Grade, Restricted, Classified, Extraordinary, and Covert; the order of rarities from least to most rare are Consumer Grade, Industrial Grade, Mil-Spec Grade, Restricted, Classified, Covert, and Extraordinary. The Extraordinary rarity was added to CS2 relatively recently, meaning that there are fewer items that are Extraordinary. This factor can drive down

Figure 2. Glock-18 | Ramese's Reach.

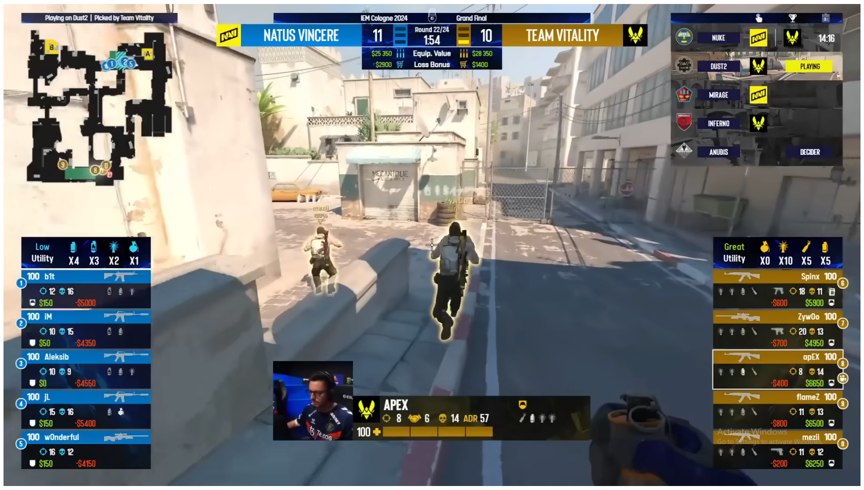
*Note:* Two Glock-18 | Ramese's Reach, with a Factory New variant on the left and a Battle-Scarred variant on the right. Note the emergence of a figure lying down in the Battle-Scarred version.
*Source:* Steam Community Market.

the price, especially since people who obtain Extraordinary items can be less willing to sell them unless other qualities of the Extraordinary item are poor (i.e. a collector would want to hold onto a Factory New Extraordinary item but may want to sell a Battle-Scarred one). This observation provides more evidence for the fact that consumers value scarcity in virtual markets.

Weapon categories provide a broad overview of which weapons have more valuable items. Our analysis (Table A3) shows that Gloves and Knives have the most valuable skins. Since Glove skins and Knife skins are rarer than other types of skins, it makes sense for them to be more valuable. Rifles are the third most valuable out of the weapon types. They are the most-used weapons in the game – professional teams designate four players out of their five to be "riflers" – and their skins would be seen the most often. Herein lies another determinant of value: in-game utility. The more useful an item is in game, the more utility it provides and the more expensive it becomes. The coefficients for the other weapon types provide further proof for this observation. Pistols, SMGs, and shotguns are some of the least purchased items in the game, and as a result, their skins are priced much lower compared to the other weapon types. Their low usage rate deteriorates the monetary value of their skins.

Our regression also suggests that this virtual market faces market segmentation, just like real-world economies do. The coefficients for the market an item is sold (Table A6) on are all significant, meaning that each market charges prices that are markedly different from the Steam Marketplace. For many of these markets, the coefficient is negative, meaning that it is cheaper to purchase from them compared to purchasing on the Steam Marketplace. Third-party marketplaces are able to do this because they take a lower cut, but consumers also have to be wary of the risk incurred from purchasing from these alternative websites, as they are not officially supported by the game developers. Interestingly, some markets

FIGURE 3. IEM COLOGNE 2024 GRAND FINALS.




*Note:* A round from the second map of IEM Cologne 2024 Grand Finals, a notable eSports event. All players have purchased a Rifle.
*Source:* ESL Counter-Strike Highlights Channel on YouTube.

have a positive coefficient for prices. Upon closer inspection, these markets with positive coefficients offer prices for high-end skins; as such, their prices will be more expensive on average. This means that third-party marketplaces cater to different types of consumers: some will target demand-elastic consumers looking for a discount, while others will target demand-inelastic consumers looking to purchase high-end goods.

The last set of coefficients to analyze is the set of coefficients relating to the collection an item belongs to (Table A7-A8). Most of them are statistically significant. Many of the most expensive collections are ones that have cases that are harder to obtain, as many of the older cases rarely drop for players anymore. For example, the Operation Bravo case, which was the second case to be released, has a large, positive coefficient. In contrast, the Recoil case, which was released in 2022 and can still be easily obtained, has a large, negative coefficient. Therefore, these coefficients also support the hypothesis that rarity is a large determinant of price.

## V. Conclusions

This paper studies the determinants of value in CS2's virtual item economy. Our analysis concludes that agents do not buy and sell items at random; instead, agents exhibit many of the same behaviors that they would in real-world economies. Specifically, scarcity in the CS2 economy drives up prices, and items that have a higher utility are more expensive. The observation that higher utility items are more expensive is consistent with the findings in Yang, Dmitrov, and Mantin (2014), thus providing evidence for previous literature in virtual goods pricing.

The results found in this paper can be further expanded upon. CS2's profit model is also shared with Team Fortress 2 (TF2), another Valve title. In TF2, there are cosmetics that players can receive through opening loot boxes for real world currency, similar to CS2. However, TF2's economy is less refined than CS2. As such, it more closely resembles a barter market which may be cause for further economic research. Despite the differences in these markets, the methodology in this study can be applied to TF2's economy in order to understand more about it at a precursory level, especially since TF2 items can also be bought and sold on the Steam Community Market.

Another game that has Steam Community Market support is Rust. Rust items are also cosmetic, but the method of obtaining them is different than in CS2 or TF2. Instead of using a loot box system, Rust allows players to purchase items for a limited time inside of their in-game store, and these items can be relisted on the Steam Community Market for sale. The main reason why players would purchase items on the Steam Community Market is that limited-time items only go on sale in the in-game store for short periods of time. As a result, some items are only available on outside marketplaces. The methods in this paper can be extended to Rust's economy, providing evidence for or against our hypotheses.

Figure 4. "Blue Gem" AK-47 | Case Hardened.

*Source:* Steam Community Forums.

Our study's findings are limited by the data available to us. One issue is that the time period that we could analyze was short. Though a ninety-day window revealed that prices were non-stationary, an analysis on a longer time period could provide deeper insights into pricing. For example, do the prices of CS2 items follow inflation and/or traditional macroeconomic shocks such as tax increases or wars? Additionally, our data missed some of the nuances that items can have. Many items have special patterns that are randomly generated, and some of these patterns can provide immense value. A well-known example is the Case Hardened line of skins. Some patterns of this skin have a top which is completely blue, and these community-dubbed "blue gems" can go for thousands of dollars. On the other hand, normal patterns are less blue and worth significantly less.

The results of this paper can be best utilized by developers wishing to create their own virtual economies. The foundation for the CS2 economy is the Steam Community Market, and since third-party marketplaces closely follow the prices available on the Steam

Community Market, the best practice to found a virtual economy is to establish a canonical price-setter of virtual goods. The pricing of these virtual goods will first and foremost rely on the quality of the virtual world in which they inhabit, so an engaging virtual world is a must to create a virtual economy. Goods should have both random and inherent differentiation, as scarcity and utility are the biggest determinants of price for the virtual goods in the CS2 economy. Finally, a laissez-faire approach to governing is recommended for virtual economies. Policing third-party marketplaces will lead to less overall interest in the game, as these marketplaces combined handle thousands of transactions each day, and most players will rely on the canonical price-setter regardless of other options.

## VI. Bibliography

Geng, Wei, and Zuguang Chen. "Optimal pricing of virtual goods with conspicuous features in a freemium model." International Journal of Electronic Commerce 23.3 (2019): 427-449.

Glaser, Tim. "Steam and the Platformization of Virtual Goods: An Analysis of the Weapon Skin Economy in Counter Strike: Global Offensive." Spiel Formen (2022): 139-162.

Ke, Dan, et al. "An empirical analysis of virtual goods permission rights and pricing strategies." Decision Sciences 43.6 (2012): 1039-1061.

MacKinnon, James G., and Halbert White. "Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties." Journal of econometrics 29.3 (1985): 305-325.

Ren, Qun, et al. "Value-informed pricing for virtual digital products: Evidence from Chinese MMORPG industry." International Journal of Market Research 62.3 (2020): 350-368.

Xenopoulos, Peter, Bruno Coelho, and Claudio Silva. "Optimal team economic decisions in counter-strike." arXiv preprint arXiv:2109.12990 (2021).

Yamamoto, Kei'Ichiro, and Victoria McArthur. "Digital economies and trading in counter strike global offensive: How virtual items are valued to real world currencies in an online barter-free market." 2015 IEEE Games Entertainment Media Conference (GEM). IEEE, 2015.

Yang, Lin, Stanko Dimitrov, and Benny Mantin. "Forecasting sales of new virtual goods with the Elo rating system." Journal of Revenue and Pricing Management 13 (2014): 457-469.

## Appendix of Tables

Table A1—Descriptions of Item Attributes

| Attribute | Possible Values | Description |
|---|---|---|
| StatTrak | StatTrak, not StatTrak | Determines whether or not the skin will track player kills. |
| Souvenir | Souvenir, not Souvenir | Exclusive to Souvenir Packages, which are a special type of case. If a skin is Souvenir, it will be adorned with the signature of a professional CS2 player and the logos of their team. |
| Wear | Battle-Scarred, Well-Worn, Field-Tested, Minimal Wear, Factory New | Affects how worn an item looks. A Battle-Scarred item will have lots of scratches and paint taken off; a Factory New item will have very few scratches. |
| Rarity | Consumer Grade, Industrial Grade, Mil-Spec, Restricted, Classified, Covert, Contraband, Extraordinary | Determines how often a skin will come from a case. Consumer grade skins are the most common and will appear from cases the most often, while Extraordinary skins are extremely rare. |

Table A2—Base Weapon Quality Coefficients

| Variable | Coefficient | Standard Error | p-value |
|---|---|---|---|
| StatTrak | 896.9615 | 14.148 | 0.000*** |
| Souvenir | 613.3876 | 34.494 | 0.000*** |
| Battle-Scarred | -156.9764 | 18.405 | 0.000*** |
| Factory New | 1386.1381 | 21.438 | 0.000*** |
| Minimal Wear | 586.0092 | 18.392 | 0.000*** |
| Well-Worn | 46.6546 | 18.491 | 0.012** |
| Classified | 1726.5367 | 23.983 | 0.000*** |
| Consumer Grade | -3208.6069 | 40.902 | 0.000*** |
| Covert | 3960.1211 | 43.398 | 0.000*** |
| Extraordinary | 2927.5116 | 43.601 | 0.000*** |
| Industrial Grade | -2681.0369 | 41.140 | 0.000*** |
| Mil-Spec Grade | -571.6495 | 13.418 | 0.000*** |

*Note:* *: $p<0.05$, **: $p<0.025$, ***: $p<0.01$

Table A3—Weapon Type Coefficients

| Variable | Coefficient | Standard Error | p-value |
|---|---|---|---|
| Gloves | 2927.5116 | 43.601 | 0.000*** |
| Knife | 4691.7580 | 66.667 | 0.000*** |
| Machinegun | -1301.9687 | 39.469 | 0.000*** |
| Pistol | -1740.9565 | 53.406 | 0.000*** |
| SMG | -1732.7700 | 50.365 | 0.000*** |
| Shotgun | -1674.6214 | 46.468 | 0.000*** |
| Sniper Rifle | -1324.8907 | 48.048 | 0.000*** |

Table A4—Weapon Coefficients (1)

| Variable | Coefficient | Standard Error | p-value |
|---|---|---|---|
| AUG | -2335.5071 | 64.964 | 0.000*** |
| AWP | 555.2712 | 46.818 | 0.000*** |
| Bayonet | 4718.7973 | 90.057 | 0.000*** |
| Bloodhound Gloves | -1469.7708 | 185.332 | 0.000*** |
| Bowie Knife | -1267.6582 | 94.645 | 0.000*** |
| Broken Fang Gloves | -1862.0332 | 159.504 | 0.000*** |
| CZ75-Auto | -352.2516 | 30.951 | 0.000*** |
| Classic Knife | -351.8012 | 119.929 | 0.003** |
| Desert Eagle | 625.2123 | 46.315 | 0.000*** |
| Driver Gloves | 238.8362 | 179.562 | 0.183 |
| Dual Berettas | -427.6511 | 30.876 | 0.000*** |
| FAMAS | -2302.5503 | 65.851 | 0.000*** |
| Falchion Knife | -1314.8999 | 91.214 | 0.000*** |
| Five-SeveN | -3.6573 | 34.098 | 0.915 |
| Flip Knife | 2461.9462 | 95.373 | 0.000*** |
| G3SG1 | -699.9177 | 31.231 | 0.000*** |
| Galil AR | -1826.8604 | 65.943 | 0.000*** |
| Glock-18 | -158.8617 | 29.861 | 0.000*** |
| Gut Knife | -2669.8076 | 83.533 | 0.000*** |
| Hand Wraps | -444.9065 | 84.095 | 0.000*** |
| Huntsman Knife | -743.9690 | 97.471 | 0.000*** |
| Hydra Gloves | -3105.4163 | 184.308 | 0.000*** |
| Kukri Knife | 1372.8843 | 124.638 | 0.000*** |
| M249 | -904.9592 | 30.499 | 0.000*** |
| M4A1-S | -750.5803 | 78.990 | 0.000*** |
| M4A4 | -1983.4613 | 72.644 | 0.000*** |
| MAC-10 | -7.1288 | 27.321 | 0.794 |
| MAG-7 | -471.6816 | 27.589 | 0.000*** |
| MP5-SD | -371.6284 | 31.473 | 0.000*** |

Table A5—Weapon Coefficients (2)

| Variable | Coefficient | Standard Error | p-value |
|---|---|---|---|
| MP7 | -534.8279 | 28.396 | 0.000*** |
| MP9 | 46.3155 | 34.986 | 0.186 |
| Moto Gloves | 782.9545 | 146.358 | 0.000*** |
| Navaja Knife | -4037.9905 | 85.299 | 0.000*** |
| Negev | -397.0095 | 28.217 | 0.000*** |
| Nomad Knife | -71.9452 | 123.967 | 0.562 |
| Nova | -319.4322 | 27.838 | 0.000*** |
| P2000 | -261.2704 | 36.032 | 0.000*** |
| P250 | -427.4185 | 26.548 | 0.000*** |
| P90 | -358.1775 | 32.414 | 0.000*** |
| PP-Bizon | -386.9119 | 27.699 | 0.000*** |
| Paracord Knife | -2611.6322 | 117.089 | 0.000*** |
| R8 Revolver | -76.7146 | 29.429 | 0.009** |
| SCAR-20 | -495.1553 | 32.705 | 0.000*** |
| SG 553 | -1861.1403 | 68.348 | 0.000*** |
| SSG 08 | -685.0889 | 32.501 | 0.000*** |
| Sawed-Off | -621.1897 | 28.053 | 0.000*** |
| Shadow Daggers | -3774.1145 | 75.924 | 0.000*** |
| Skeleton Knife | 5602.6236 | 84.180 | 0.000*** |
| Specialist Gloves | 2898.9492 | 197.056 | 0.000*** |
| Sport Gloves | 5888.8985 | 299.213 | 0.000*** |
| Stiletto Knife | 3725.3931 | 101.264 | 0.000*** |
| Survival Knife | -2558.7785 | 116.744 | 0.000*** |
| Talon Knife | 7310.6841 | 84.654 | 0.000*** |
| Tec-9 | -261.2157 | 30.007 | 0.000*** |
| UMP-45 | -120.4109 | 27.778 | 0.000*** |
| USP-S | 428.5161 | 40.502 | 0.000*** |
| Ursus Knife | -1097.9738 | 103.840 | 0.000*** |
| XM1014 | -262.3178 | 30.129 | 0.000*** |
| Zeus x27 | -825.6441 | 85.997 | 0.000*** |

Table A6—Market Feature Coefficients

| Variable | Coefficient | Standard Error | p-value |
|---|---|---|---|
| Quantity | 0.0016 | 0.002 | 0.388 |
| avanmarket | -1162.8278 | 41.931 | 0.000*** |
| bitskins | -369.4808 | 39.413 | 0.000*** |
| buff163 | -746.5390 | 37.074 | 0.000*** |
| buffmarket | -368.2973 | 39.770 | 0.000*** |
| cs_deals | -327.9070 | 48.697 | 0.000*** |
| cs_money | -402.5403 | 37.805 | 0.000*** |
| csfloat | -463.5737 | 39.194 | 0.000*** |
| dmarket | -658.3553 | 37.327 | 0.000*** |
| gamerpay | -490.3412 | 41.970 | 0.000*** |
| haloskins | -536.5233 | 37.132 | 0.000*** |
| lis_skins | -1081.5551 | 42.165 | 0.000*** |
| mannco_store | -301.6182 | 38.051 | 0.000*** |
| marketcsgo | -477.9398 | 36.609 | 0.000*** |
| shadowpay | -438.8164 | 37.654 | 0.000*** |
| skinbaron | -298.6942 | 38.818 | 0.000*** |
| skinbid | 421.6665 | 60.411 | 0.000*** |
| skinport | -460.3557 | 37.010 | 0.000*** |
| skinswap | -1075.5900 | 56.838 | 0.000*** |
| tradeit_gg | -554.1320 | 37.486 | 0.000*** |
| waxpeer | -488.5621 | 37.923 | 0.000*** |

Table A7—Collection Coefficients (1)

| Variable | Coefficient | Std. Error | p-value |
|---|---|---|---|
| Gloves | 3372.4181 | 72.432 | 0.000*** |
| Knife | 4246.8515 | 61.350 | 0.000*** |
| 2018 Inferno | 442.2483 | 89.336 | 0.000*** |
| 2018 Nuke | 408.1148 | 86.611 | 0.000*** |
| 2021 Dust 2 | 1787.0781 | 96.700 | 0.000*** |
| 2021 Mirage | 1394.1074 | 100.151 | 0.000*** |
| 2021 Train | -389.4573 | 95.291 | 0.000*** |
| 2021 Vertigo | 1630.8978 | 104.620 | 0.000*** |
| Alpha | 3522.4277 | 148.184 | 0.000*** |
| Ancient | 1823.6934 | 110.806 | 0.000*** |
| Anubis | 829.1087 | 94.463 | 0.000*** |
| Arms Deal 2 | 515.2621 | 114.723 | 0.000*** |
| Arms Deal 3 | -286.5690 | 95.626 | 0.003** |
| Arms Deal | 5545.9122 | 209.843 | 0.000*** |
| Assault | 6999.6884 | 341.099 | 0.000*** |
| Aztec | 2848.6754 | 197.384 | 0.000*** |
| Baggage | 4202.9193 | 144.147 | 0.000*** |
| Bank | 402.1685 | 99.789 | 0.000*** |
| Blacksite | -1919.9814 | 130.487 | 0.000*** |
| Bravo | 2319.5406 | 131.707 | 0.000*** |
| Breakout | -1554.3007 | 84.588 | 0.000*** |
| CS20 | -1224.7305 | 80.493 | 0.000*** |
| Cache | 1261.6652 | 91.399 | 0.000*** |
| Canals | 3229.1938 | 121.426 | 0.000*** |
| Chop Shop | 4739.5475 | 185.641 | 0.000*** |
| Chroma 2 | -1698.2736 | 82.693 | 0.000*** |
| Chroma 3 | -1541.0476 | 80.251 | 0.000*** |
| Chroma | -1253.0383 | 82.622 | 0.000*** |
| Clutch | -2006.4658 | 79.777 | 0.000*** |
| Cobblestone | 3079.4714 | 130.098 | 0.000*** |
| Control | 3540.3472 | 128.914 | 0.000*** |
| Danger Zone | -1598.9442 | 80.916 | 0.000*** |
| Dreams & Nightmares | -1964.6304 | 79.855 | 0.000*** |
| Dust 2 | 1178.6265 | 94.915 | 0.000*** |
| Dust | 4995.8557 | 246.188 | 0.000*** |
| Falchion | -1129.2068 | 84.389 | 0.000*** |
| Fracture | -1708.0512 | 81.756 | 0.000*** |
| Gamma 2 | -1702.2527 | 80.589 | 0.000*** |
| Gamma | -1511.8130 | 80.152 | 0.000*** |

Table A8—Collection Coefficients (2)

| Variable | Coefficient | Std. Error | p-value |
|---|---|---|---|
| Glove | -1680.5795 | 78.854 | 0.000*** |
| Gods and Monsters | 4374.5031 | 176.089 | 0.000*** |
| Havoc | 3026.5536 | 136.904 | 0.000*** |
| Horizon | -1202.3394 | 81.144 | 0.000*** |
| Huntsman | 323.3356 | 95.797 | 0.001** |
| Inferno | 2528.8754 | 140.227 | 0.000*** |
| Italy | 2391.3525 | 125.645 | 0.000*** |
| Kilowatt | -878.4688 | 84.941 | 0.000*** |
| Lake | 2151.4668 | 124.536 | 0.000*** |
| Militia | 3082.4324 | 177.756 | 0.000*** |
| Mirage | 2663.5022 | 109.705 | 0.000*** |
| Norse | 5127.0232 | 165.374 | 0.000*** |
| Nuke | 3850.3125 | 143.473 | 0.000*** |
| Office | 4101.9516 | 233.705 | 0.000*** |
| Broken Fang | -505.8055 | 88.816 | 0.000*** |
| Hydra | 724.1256 | 99.850 | 0.000*** |
| Riptide | -1039.0534 | 81.833 | 0.000*** |
| Overpass | 1998.7309 | 104.130 | 0.000*** |
| Phoenix | -732.1349 | 106.574 | 0.000*** |
| Prisma 2 | -1690.2274 | 82.407 | 0.000*** |
| Prisma | -1695.6289 | 80.660 | 0.000*** |
| Recoil | -1662.4264 | 80.378 | 0.000*** |
| Revolution | -1748.9109 | 83.505 | 0.000*** |
| Revolver Case | -1455.7741 | 82.210 | 0.000*** |
| Rising Sun | 4921.3517 | 206.881 | 0.000*** |
| Safehouse | 2435.2543 | 130.106 | 0.000*** |
| Shadow | -585.6515 | 86.207 | 0.000*** |
| Shattered Web | -726.0933 | 85.063 | 0.000*** |
| Snakebite | -1799.0134 | 80.624 | 0.000*** |
| Spectrum 2 | -1655.8472 | 80.148 | 0.000*** |
| Spectrum | -1064.7621 | 87.265 | 0.000*** |
| St. Marc | 4992.0785 | 159.403 | 0.000*** |
| Train | 1235.9549 | 91.255 | 0.000*** |
| Vanguard | -962.7086 | 92.566 | 0.000*** |
| Vertigo | 1550.5839 | 132.364 | 0.000*** |
| Wildfire | -721.9754 | 90.706 | 0.000*** |
| Winter Offensive | -109.2252 | 105.706 | 0.301 |
| X-Ray | -1551.5929 | 103.180 | 0.000*** |
| eSports 2013 | 2231.5916 | 159.063 | 0.000*** |
| eSports 2014 Summer | -305.4968 | 96.554 | 0.002** |