Master Thesis
Major in Quantitative Methods

Esports, Football and Economics: An Econometric Analysis of a $1.4bn In-Game Market

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Abstract

The combination of football, video games and economics in FIFA Ultimate Team is a huge financial success for Electronic Arts. In this paper I gathered data for the in-game markets of said game mode and performed an econometric analysis on the player prices. I find that gamers pay large premiums for special versions of cards even when controlling for their better in-game stats. The successful business model incentivises gamers to regularly buy the in-game currency for a chance of receiving one of the desired special cards or to rapidly accumulate coins which can be used to buy a specific card on the in-game market. From a business perspective it's certainly interesting to push FIFA esports to advertise the more expensive cards which are usually used by competitors.

Keywords: Video Game Economics, FIFA, Panel Data Analysis, Esports.
JEL: Z21, L83

Contents

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Plagiatserklärung

Ich bezeuge mit meiner Unterschrift, dass meine Angaben über die bei der Abfassung meiner Arbeit benutzten Hilfsmittel sowie über die mir zuteil gewordene Hilfe in jeder Hinsicht der Wahrheit entsprechen und vollständig sind. Ich habe das Merkblatt zu Plagiat und Betrug vom 22. Februar 2011 gelesen und bin mir der Konsequenzen eines solchen Handelns bewusst.

Mitchell Goldberg

Acknowledgements

I would like to thank Prof. Dr. Fabian Schär for his advice and support throughout the thesis work and for giving me the opportunity to research this quite exotic, but very interesting topic. I would also like to thank Rune Mentzoni from the University of Bergen for his Ultimate Team pack opening data.

1 Introduction

This paper explores the relationship between several player characteristics and prices of FIFA Ultimate Team player cards. Section 2 will be a brief introduction to the Ultimate Team game mode and give the reader an overview of important aspects for the following econometric analysis. In Section 3 and 4 I describe the most important variables of the dataset and their relationship before I move on to Section 5 where I run a simple random draw experiment to analyse the probability distribution of the FIFA Ultimate Team loot boxes. The main econometric analysis in Section 6 explores the price effects of different player characteristics and discusses econometric problems like the high multicollinearity in the data. Last but not least, I develop a simple inflation model for the FUT economy which gives an interesting insight in regards to the coin spending by gamers.

2 FIFA 19

Electronic Arts' (EA) football franchise "FIFA" is one of the most popular video game series in the world and sells millions of copies every year. FIFA 19 even became the best-selling console game in Europe in 2018, despite its relatively late launch at the end of September. (Electronic Arts Inc., 2019, p. 1)
In FIFA, gamers can play with their favourite teams against one another or against the AI in a number of game modes. Through its licensing agreement with the international football association "Fédération Internationale de Football Association" (FIFA), EA has the exclusive rights to release FIFA branded action and management games (Electronic Arts Inc., 2013). This is one of the reasons why EA dominates the global football video game market and outsells its biggest competitor Konami by a large number (e.g. vgchartz.com, 2019). For years, the latest version of FIFA has featured many different game modes: e.g. a career mode where you manage your favourite club and compete against the AI

to win domestic and international titles, "The Journey" – a story mode where gamers get to play as an English up-and-coming prospect and the most popular game mode "FIFA Ultimate Team".

2.1 FIFA 19's Ultimate Team (FUT 19)

FIFA Ultimate Team was first introduced in FIFA 09. In this game mode, gamers collect virtual cards of current and former professional football players and build their own personalised squad with them to play against the AI or other gamers online. EA have also implemented the game mode in their other sports games like "Madden", "NHL" and "NBA Live". The Ultimate Team game mode is a financially successful service and represents a large share of EA's total net revenue (see Figure 1).

Total Net Revenue Earned per Year

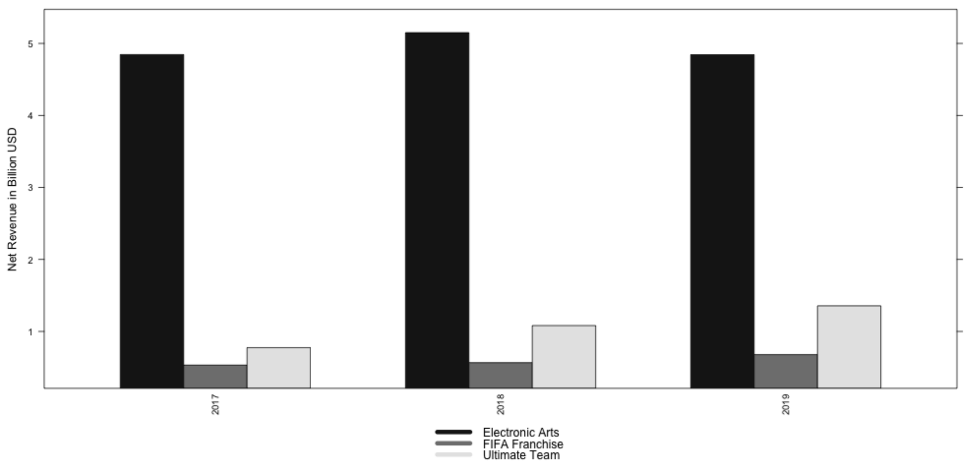

Figure 1: Both the absolute and relative net revenue from Ultimate Team has increased over the last three years. This graph uses the total net revenue measured under the old reporting standard before the 2019 fiscal year. Source: Electronic Arts Inc. (2019)

Note that a "substantial portion" of the Ultimate Team revenue comes from the FIFA series. EA acknowledges that any events or circumstances which limit their ability to provide the FIFA Ultimate Team service would have a large, disproportionate effect on their financial result.(Electronic Arts Inc., 2019, p. 9) Thus, FIFA Ultimate Team is one of the key components for EA's financial success.

2.1.1 The Club

In FIFA Ultimate Team, gamers collect virtual Panini sticker-like cards of former and current professional football players, combine them with each other to compete against other players online. The club stores a gamer's collection of cards and the two in-game currencies.

2.1.2 Currencies

Gamers earn coins by playing matches, discarding cards, selling a card on the in-game market or as a component of different rewards. Sales on the in-game market are transactions from one gamer to another and don't create new coins. Instead they are taxed at 5% and reduce the total coin supply. On the other hand, playing matches, discarding a card or earning coins through rewards increase the FUT economy's total coin supply.

Coins can be used to either buy a specific card on the in-game market or to buy packs which contain a random set of cards. By buying packs gamers burn coins and decrease the total coin supply.

In contrary to the coins, FIFA Points can only be bought in exchange for fiat money and are mainly used to open packs. Gamers try their luck at packing[1] the best players in the game, but instead often end up with a lot of other cards which they discard or sell on the in-game market. Big spenders will eventually accumulate enough coins to buy any desired card. In the 2019 fiscal year EA sold roughly $1.4bn worth of in-game currency in all Ultimate Team modes combined (Electronic Arts Inc., 2019).

[1] The term is often used in the FIFA community for receiving a card from a pack.

2.1.3 Cards

Player cards in Ultimate Team are based on real professional football players and have 13 distinctive properties (see Figure 2). The player's name, position, nationality, club, chemistry style, Overall Rating (OVR) and six card stats (CS) are represented on a specific card version.

Card Example: Lionel Messi

Figure 2: FUT cards have 13 distinctive properties. This card represents Lionel Messi with an OVR of 94. His CS are indicated at the bottom. Underneath the OVR, the card also shows his main position (CF), his nationality (Argentina) and his club (FC Barcelona). The boot at the bottom of the card is an indicator for the "Basic" chemistry style. This is Lionel Messi's regular card – i.e. it is a rare gold card which has Messi's base stats. Source: futbin.com

Volunteers(Murphy, 2019) and EA judge professional football players in real life based on the same set of abilities. For this paper I focus on field players only – i.e. I'm interested in 29 different "In-Game Stats" (IGS). These stats include e.g. a player's acceleration, his shooting accuracy and his jumping ability. It is said (e.g. Lopes, 2019) the player's OVR is a summary of important IGS which are relevant for his position. I.e. Lionel

Messi's OVR depends on his attacking skills whereas Sergio Ramos' OVR is based on his defending abilities.
The 29 IGS can be grouped into six categories: pace, shooting, passing, dribbling, defending and physicality (PAC, SHO, PAS, DRI, DEF, PHY). The six CS are said to be weighted averages of the same underlying IGS for all players. Figure 3 summarises the 29 IGS and their affiliation to the six card stats for all field players. A short description for all IGS can be found in Table 3 in Appendix A.

IGS, CS and OVR

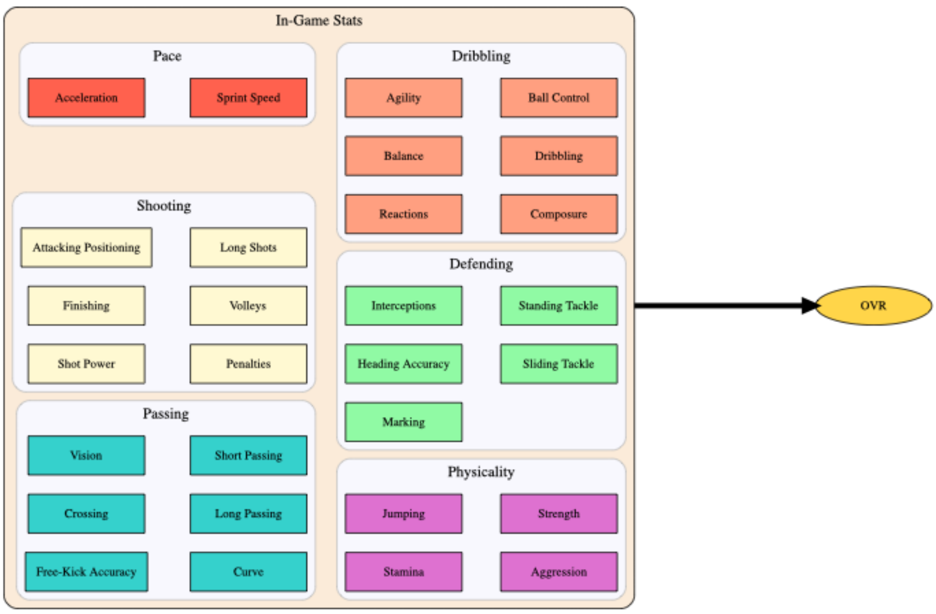

Figure 3: Each of the 29 IGS contributes to one of the 6 card stats. The OVR is based on relevant IGS for the player's position.

Each player is defined by his 29 IGS, but also a number of other characteristics, e.g. a player's nationality, league, club, work rates, skill moves and weak foot ability. These variables will be explained in short when needed.

Throughout the FIFA year[2], EA releases special cards on a regular basis. These special cards are either based on a real life event or an in-game promotion. E.g. every Wednesday EA releases the Team of the Week (TOTW) – a team consisting of 23 players who performed extraordinarily well during the last week for the club or international team in real life. These cards are upgraded versions of the regular or earlier released TOTW cards of the same player. Most special cards are obtainable from packs and can be traded on the in-game market. However, there are some cards that are only obtainable through Squad Building Challenges (SBCs) or objectives. Gamers who want to receive a special card through SBCs are asked to create a squad which a meets a number of specific requirements, e.g. at least 5 Brazilian players, at least a chemistry rating of 60 and an OVR of 75 or higher. The built squad's cards are destroyed and exchanged for a reward like a special player card, a special kit, packs or coins. A simplified summary for all special cards in FUT 19 can be found in Appendix A (Table 4).

2.1.4 Chemistry

Gamers can build any squad with their collected cards, but they are rewarded during matches if they combine players from the same nation, league or club. When creating a squad, the gamer chooses his preferred formation and can pick one of his collected player cards per position. Each card has a chemistry rating ranging between 0 and 10 based on the correct position and the links to the surrounding positions. Players from the same nation, league or club have better links between them and their chemistry ratings increase. Players with a higher chemistry rating receive a boost for some of their IGS. Therefore, it's favourable for all gamers to maximise each player's chemistry rating. Icon cards – special cards of former professional football players – link well with any other player card and are very valuable when creating a squad. A chemistry

[2]New FIFA games usually launch in September and gamers move on to the newest version.

example for a full squad can be seen in Figure 4.

Chemistry Example

Figure 4: All players play on their main position indicated on the player card. The links between players are either red, orange or green depending on matching nationalities, leagues or clubs. Although some players have red links between them – like Messi and Mbappé – all of the player cards have at least a chemistry rating of 9. Icon cards have at least an orange link with all other player cards and thus are very valuable in FUT squads. It is desirable to combine the player cards in a way that they all reach their maximum chemistry rating to get the highest boost possible for each player. The easiest way to reach maximum chemistry is to only use players from one league or nation, but as shown with Messi and Mbappé this is not necessary. Their red link is compensated by other green links and they will receive a loyalty bonus of +1 chemistry after 10 matches for the gamer's club. Source: futbin.com

2.1.5 Other Cards in FUT

There are not only player cards in FUT, but also club items, consumables and staff cards. Club items include kits, stadiums and badges and help personalise the FUT gaming experience. Consumables are cards which can be used once on a specific player card, manager card or a whole squad. They include contracts, position changes, chemistry styles, healing, fitness, player training and manager league cards. Every player card has an individual contract value, main position, chemistry style and fitness value assigned to it. After every match, the contract value decreases by one. Player cards with a contract value of 0 cannot be used in a squad, i.e. gamers have to add contracts to the card before starting a match. Contract cards add a pre-determined number of games to the contract value of a card. Whenever a player card was used during a match, its fitness level also decreases depending on how tiring the game was for the player. The fitness level can be increased by using a fitness card. Furthermore, gamers can use special fitness cards for a whole squad including players on the bench and the reserves. As mentioned before, players with a high chemistry rating receive a boost for some of their IGS. Applying a chemistry style to a player card changes the IGS which are boosted during a match. E.g. the "Hunter" chemistry style only boosts a player's pace and shooting and is the preferred chemistry style for most attacking players. In order to maximise every player's chemistry rating, gamers want to use them on their main position. Depending on the formation chosen, this is not always possible. E.g. a gamer wants to play with a 4-2-3-1(2) formation – which requires a right midfielder – but he also wants to use Raheem Sterling. Sterling's regular card is a right winger (RW), not a right midfielder (RM). Using a "RW to RM" position change card, the gamer can change the player card's position permanently, although with some limitations. E.g. it's not possible to change a right winger to a left back. Player cards which had their position changed can be traded on the in-game market. Therefore, it's possible to buy a RM Raheem Sterling on the in-game market, but any newly packed Sterling card is a RW. Player training cards have an effect

on one specific or all CS for a limited amount of games only. These cards are banned from the Weekend League and the FIFA Global Series. Staff cards are collectibles which give a bonus when applying a consumable card. E.g. a regular fitness card may increase a player's fitness by 10 points. Having multiple fitness coach cards at the club gives up to a 50% bonus, i.e. the player's fitness increases by 15 instead of 10.
Some cards have a glistening effect on them and are considered to be "rare". Depending on which pack a gamer opens, he receives a specific amount of rare cards. E.g. a "Premium Gold Pack" includes 12 cards of which 3 are rare.

2.1.6 Packs

Gamers can buy regular packs on the FUT Store at any time for either coins or FUT Points. Throughout the FIFA year, EA release promotional packs which are only available for a limited time or in limited quantities. These packs are usually more expensive, but in general consist of more valuable cards, e.g. only rare gold player cards.
Rune Mentzoni at the University of Bergen has studied FIFA 18's loot box system by opening packs worth around €3800. His data is publicly available and summarised in Table 1.

Pack Opening Experiment FIFA 18

OVR Range	Number of Players	Relative Frequency (%)
75-79	2647	58.12
80-84	1807	39.68
85-89	89	1.95
$\geqslant$90	11	0.24
Total:	4554	

Table 1: The table summarises the absolute and relative packing frequencies for rare gold players of different OVR ranges and includes all special cards with an OVR of 75 or higher. The packs were opened between 18th of February 2018 and 25th of May 2018. The summary statistics suggest that high rated players are packed less often. Data: Rune Mentzoni, University of Bergen

The summary statistics of the data suggest that high rated players have

a lower probability of being packed. Of course this could happen because of the lower number of high rated players in the total population of cards or simply by chance. A simple experiment in Section 5 will test if all players can be packed with the same probability.
From Mentzoni's data I also calculated the simple return R for each pack using the following formula:

$$R = \frac{V - C}{C}, \tag{1}$$

where V is the value[3] of the packed cards and C is the cost of the pack measured in coins. Opening FIFA Ultimate Team packs is like playing the lottery: on average, players lose coins, but they may pack a very valuable player and earn a lot of coins with a little bit of luck (see Figure 5).

FUTEconomist, an active community member, has also studied the profitability of FUT packs and has found that packs are in general not profitable for gamers, but there are exceptions. E.g. the "Standard Bronze Pack" costs 400 coins and its cards sell for 450 coins on average. This seemingly free lunch is usually referred to as the "Bronze Pack Method" (BPM) by gamers. Keep in mind that the method requires a lot of effort. Gamers need to open a lot of packs, list the cards on the in-game market and wait for them to be sold – which may take a while for undesired bronze cards.
Although EA doesn't believe that its products and services violate gambling laws, it has discontinued the sale of FIFA Points in Belgium (Electronic Arts Inc., 2019, p. 106). Loot box systems in games are critiqued in many countries and often linked to gambling addiction (e.g. Zendle and Cairns, 2018).

[3] The value of a card is $max(p, d)$, i.e. whichever is greater: the price on the in-game market or the discard value.

Simple Returns for FIFA Ultimate Team Packs

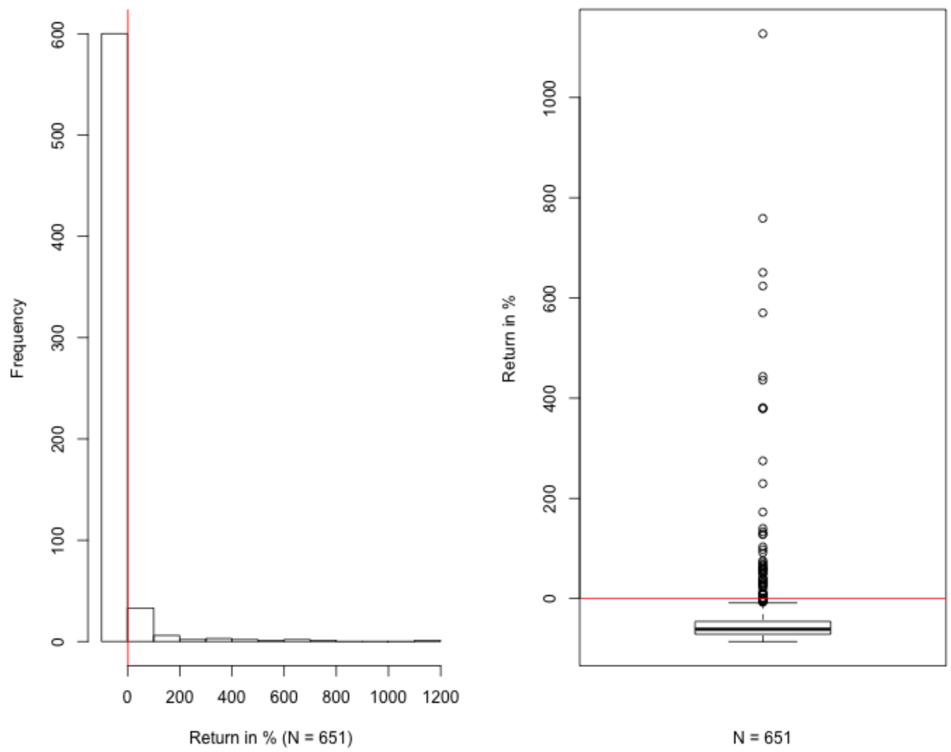

Figure 5: This Figure summarises the distribution for all pack returns in Mentzoni's data. The red line indicates the gamer's breakeven point, where the value of all cards is the same as the cost of the pack. Note that players usually lose coins when they open packs, but if they're very lucky they may earn a lot of them. Data: Rune Mentzoni, University of Bergen

2.1.7 Game Modes: Squad Battles, FUT Rivals and FUT Champions

There are several game modes within FIFA Ultimate Team. The most important ones are: Squad Battles (SB), FUT Rivals and the Weekend League (WL). SB are a weekly competition where gamers play against AI controlled teams and receive points to climb the weekly ladder. Every Monday gamers receive their SB rewards in the form of coins and packs.

FUT Rivals is another weekly competition with a ladder system, but gamers directly compete against one another online. The matchmaking system matches gamers of a similar skill level to ensure a fair competition. Gamers can pick one of three rewards which are based on their performance during the last week: either coins only, packs only or even more packs, but the cards aren't tradable.
After Rivals matches, gamers earn FUT Champions Points which can be redeemed to compete in the WL. For 72 hours – starting on Friday – gamers can play up to 30 WL matches against other players. The more matches they win, the better rewards they'll receive the following week. WL rewards include coins, tradable packs and untradable players from the current TOTW.
There is no general goal for FUT, but most players are usually in an infinite circle of playing matches to earn coins, improving their squads with new player cards in order to have a better chance of winning matches and earn even more coins. The most talented players have a chance to compete in the FIFA Global Series.

2.1.8 Esports

EA believe that the interest and enthusiasm surrounding esports will drive gamer's engagement and monetisation of their own live services. Thus, esports is an important long-term investment opportunity for them. (Electronic Arts Inc., 2019, p. 88)
In earlier FIFA titles, EA tried to develop a competitive game mode with an even playing field for all competitors, but they eventually employed a ladder system for FIFA Ultimate Team. Gamers can earn "FGS Points" during the WL and different live events to earn their ticket to the final event at the end of the season where the top 16 PS4 and top 16 Xbox One players compete for a total prize pool of $500,000. Last season "Mo Auba" – who competes for SV Werder Bremen's esports team – won the grand finals against Rogue's "Msdossary". Although competitors in FIFA esports usually compete on their own, they also represent an esports organisation which could be either a gaming brand like "FaZe

Clan" or the esports branch of a real football club like PSG.
During the WL, competitors are only able to use player cards from their own club, i.e. there is a competitive advantage for players who spend a lot of money on FIFA Points. When Mentzoni opened packs worth €3,800 in FIFA 18, he wanted to build a team of players which cost 40.5M coins, but he only earned 12.4M coins from the packs (Forum for Gaming Trends, 2018, p. 21).
This is certainly enough to buy a very competitive team, but it pronounces how expensive the most valuable players are and how much money gamers must spend in order to buy some of the top-tier players. Earning them through rewards or by playing a lot of matches is possible, but only for the absolutely best players and it certainly takes a lot of time.
At the FGS live events, competitors have the opportunity to use any available card in FUT to ensure a fair competition, but also to promote the most valuable cards to the viewers.

3 The Data

In this section I describe several variables in the dataset to give the reader an overview of possible relationships between player stats or characteristics and player prices. The data was collected from futbin.com – a third-party website which lists several stats, characteristics and prices for all FUT player cards. The raw data only consists of player stats on the 17th of September 2019, i.e. some stats had to be corrected first. Although most cards have constant stats, some of them also upgrade over time. OTW and Headliner cards were corrected according to the stats of the highest rated TOTW card of the same player on each day.

In February 2019, some players with good performances in real life received a "Winter Upgrade" card which replaced their regular card in packs. This means the old cards were still available on the in-game market, but could no longer be packed. Instead, a new upgraded version of the same player was packable. This had an effect on the stats of TOTW

The OVR Distribution

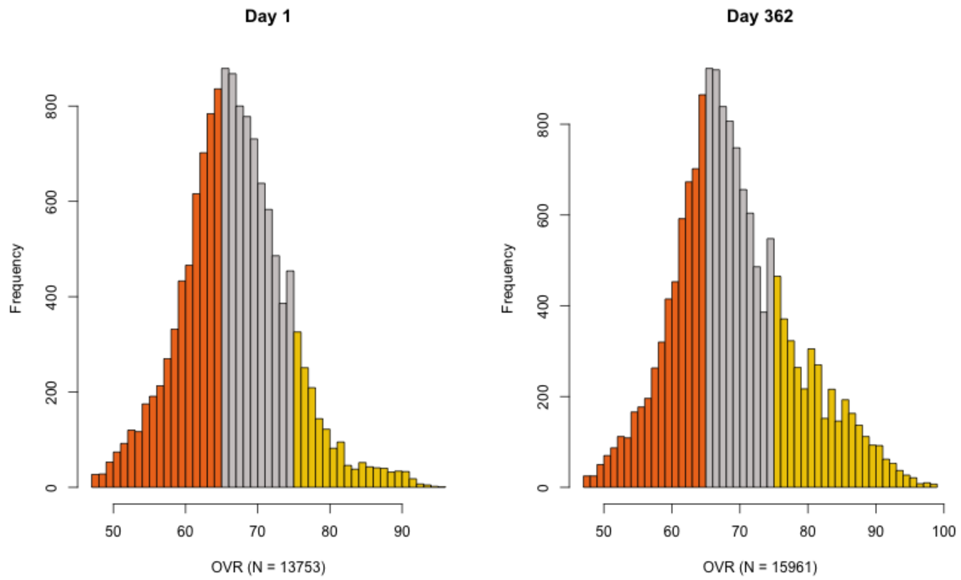

Figure 6: The histograms compare all available player cards at the start and at the end of the FIFA 19 year and pronounce the high rating of cards which were added to the game after launch. There are a lot more 80+ OVR players at the end of the game.

cards of the same player. E.g. Juventus' right-back Joao Cancelo had a regular 81 OVR card at the start of the game. In February 2019 his regular gold card was replaced by an 83 OVR Winter Upgrade for the rest of the season. In order to prevent his already released TOTW cards from losing value, they were upgraded from 84, 86 and 87 to 86, 88 and 89 OVR. Thus, I downgraded the stats of TOTW cards which were released before the Winter Upgrade. Unfortunately, I couldn't find reliable data for the IGS and CS of UCL Live and UEL Live cards. These cards upgraded according to the club's advancement in the European competitions – e.g. Fabinho's card received an upgrade when Liverpool went to the round of 16 of the UEFA Champions League. Thus, I excluded these cards from the sample.

Gamers on Xbox One, PS4 and PC can only play and trade with other gamers on the same platform. Therefore there are also three separate

The CS Distributions

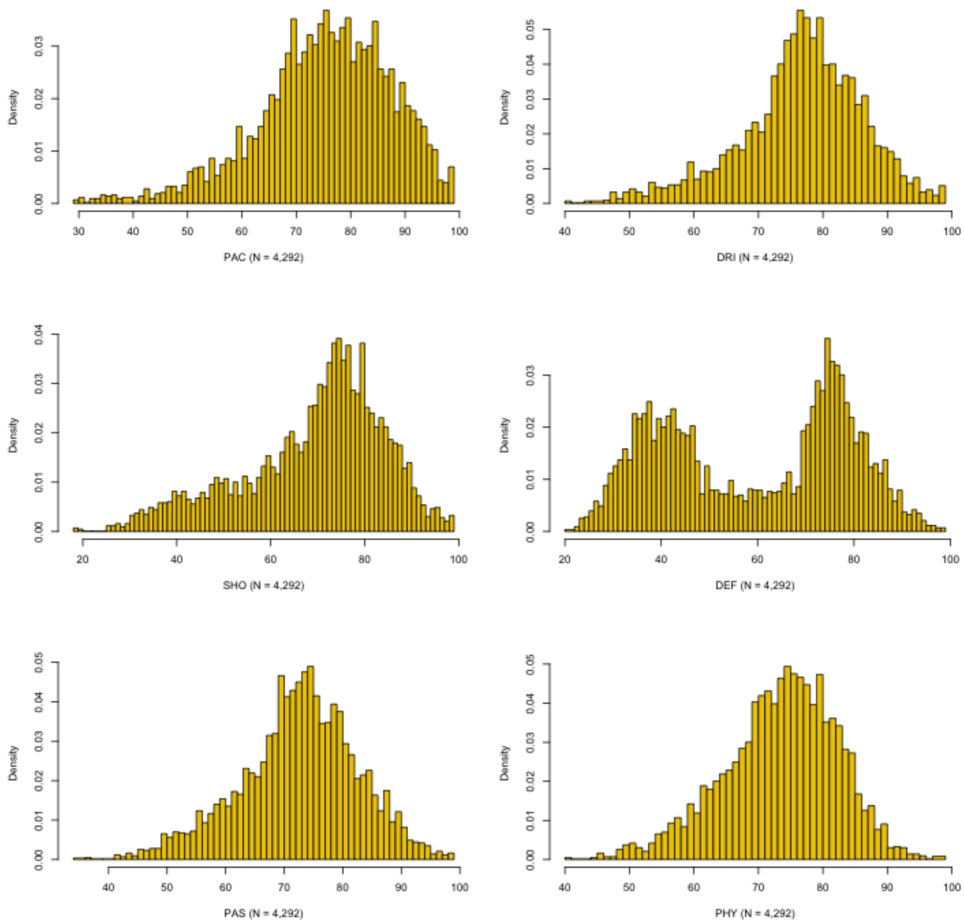

Figure 7: This figure shows the distribution of all card stats for the gold field player dataset. Interestingly, 5 stats follow some sort of bell-shaped curve while the DEF stat follows a bimodal distribution. Strikers and other forwards usually have a very low DEF stat, whereas defenders also have reasonably good SHO, PAS, etc.

markets and three different prices per player and day. Futbin regularly scans these markets for each player's lowest BIN[4]. The price data is a daily average of these scans. Although these aren't actual trading prices, they should still be a good indicator for the value of each card formed

[4]"Buy it now" - this price is set by the seller. If the buyer is willing to pay the BIN the auction automatically stops and the buyer receives the card immediately.

by supply and demand.
One very important characteristic of the dataset is the constant addition of new special cards. Figure 6 compares the OVR distribution of all cards released at the launch of FIFA 19 and all available cards at the end of the year. The main interest of this paper are price effects of different characteristics. In order to have a more comparable sample, I exclude goalkeepers, bronze, silver cards as well as very cheap players from the analysis. Goalkeepers are judged on different abilities than field players and the irrelevant players may bias the price estimates. Figure 7 shows the distributions for all six card stats of all players in the final dataset. Interestingly, DEF follows a bimodal distribution while the other five CS distributions are more or less bell-shaped. This suggests that attackers probably have very low defending stats. Table 5, Table 6 and Table 7 in Appendix A list descriptive statistics for several player stats and compare the players at the the launch of FIFA 19 with the players at the end of the FIFA 19 year. Most FUT players trade at a couple thousand coins, but the most expensive players trade at up to 15 million. The price data is very skewed. For the stat-price relationships I'm mainly interested in percentage changes and therefore transformed all prices to Log-Prices (see Figure 8).

Log-Prices in FUT

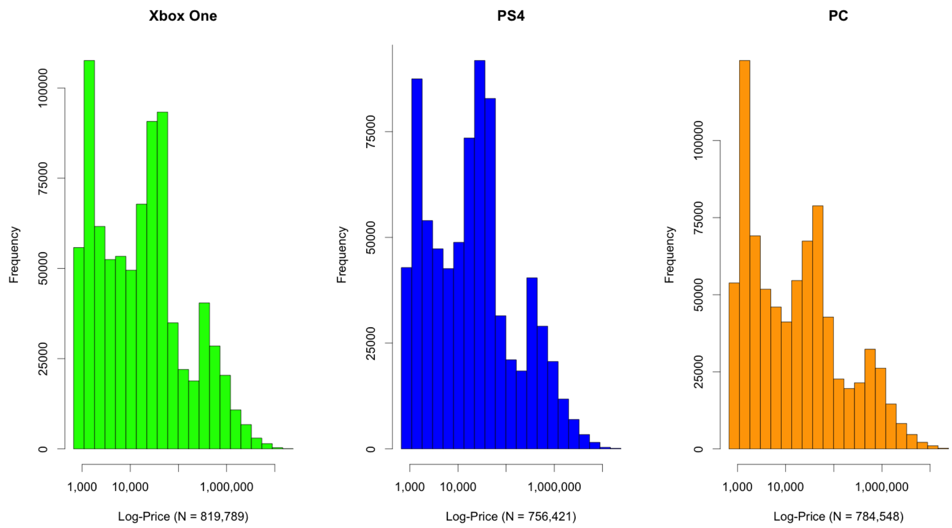

Figure 8: These prices exclude player prices of 950 coins or less. The coefficients for very cheap player cards is assumed to be different than for more expensive player cards.

4 The IGS-CS-OVR Relationship

In order to estimate different regression models with IGS, CS or OVR as explanatory variables, the relationship between these stats have to be clear. It is said that CS are weighted averages of their underlying IGS and that the weights are the same for all player cards. To get the correct weights, solve the following equation system:

$$\begin{aligned}
\tilde{y_1} &= \omega' x_1 \\
&\dots \\
\tilde{y_i} &= \omega' x_i \\
&\dots \\
\tilde{y_N} &= \omega' x_N
\end{aligned}$$

where $\tilde{y}_i$ is player i's observed CS, ω' is a row vector which consists of K weights and x_i are player i's K underlying IGS for the corresponding CS. Although there are N equations available, you only need K equations to solve for all the weights ω'. The problem is that the observed CS $\tilde{y}_i$ is a mathematically rounded integer and not the exact weighted average of the underlying IGS. In order to find the correct weights, I used OLS for all six CS:

$$\tilde{Y} = Y + v = X\omega + e, \tag{2}$$

where $\tilde{Y}$ is a vector which consists of all regular players'[5] CS, Y is a vector of all unobserved weighted averages, v is a vector of uncorrelated, uniformly distributed measurement errors of range $[-0.5, 0.5)$, X is a matrix of size $N \times K$ and consists of each player's underlying IGS and e is a vector of additive error terms. Note that the OLS estimates for noisy dependent variables are unbiased.
I also applied a second approach to find the correct weights. Instead of using OLS, I defined the CS as censored data on the interval $[\tilde{Y} - 0.5, \tilde{Y} + 0.5)$ and treated the observed CS as a grouped dependent variable (see e.g. Stewart, 1983). After sensible rounding both approaches lead to the same results which are shown in Figure 9 and correspond to the weights of other sources (e.g Lopes, 2019).

To control if these weights are correct, I apply them to all regular gold player cards, correctly round the found weighted averages and compare the found CS to the actual CS for each player card (see Figure 9.2). I find that the fitted CS match all CS as stated on the regular players' cards.

Interestingly, applying the same weights to other card types doesn't lead to the same results. Some player cards have a higher CS than the fitted value based on their IGS. Assuming players during matches have the abilities of their IGS (and not their CS) this means that some special cards

[5] In order to find the correct weights, I used all regular player cards including bronze and silver cards.

IGS Weights for Each Card Stat

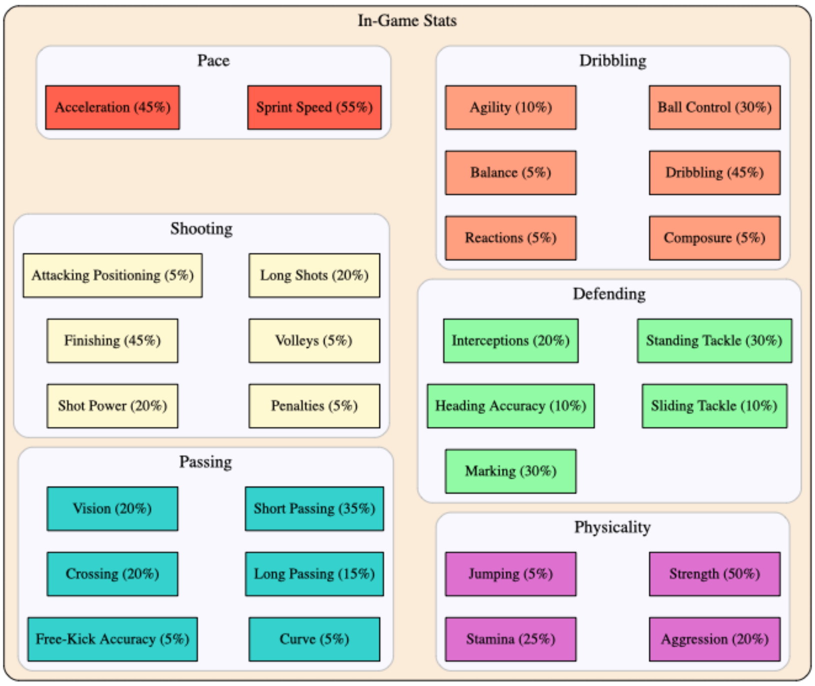

Figure 9: These are the found weights for both the OLS and censored regression approach. Note that these are in line with other sources.

are advertised to better than they actually are (see e.g. Figure 9.1 or Appendix B for more details). Lopes (2019) mentions that special cards' CS are determined differently than they are for regular cards. Nonetheless, this means comparing CS of different card types is like comparing apples and oranges.

A player's OVR is said to be a weighted average of relevant IGS for his position and an additional term which is based on the player's international reputation, i.e. Lionel Messi's OVR is based on his attacking skills whereas Sergio Ramos' OVR is based on his defending abilities and they both have a higher OVR than a hypothetical unknown player with the same IGS. The following equation defines the player's OVR:

$$\tilde{y_{i,p}} = y_{i,p} + r_i + v_i = v_p' x_{i,p} + r_i, \tag{3}$$

Applying the IGS Weights to All Regular Cards

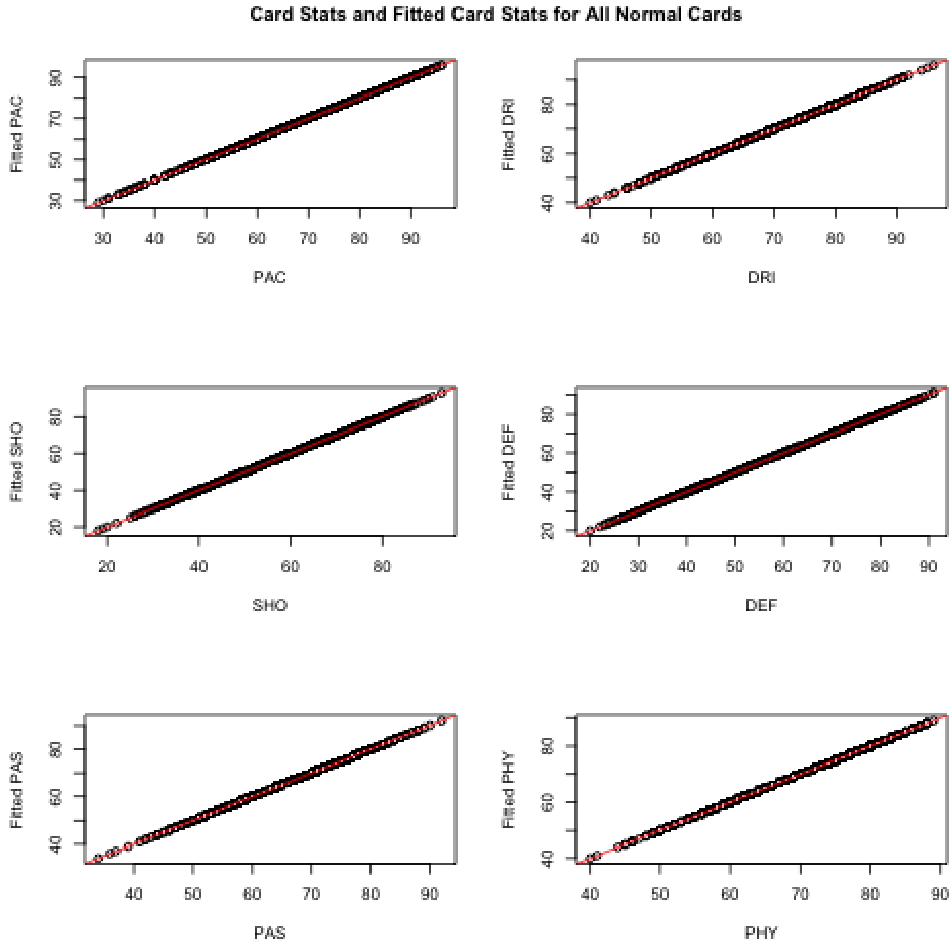

Figure 10: I find the correct CS by applying the found weights to all regular player cards.

where $\tilde{y_{i,p}}$ is the player's observed OVR, $y_{i,p}$ is the weighted average of the his relevant IGS, r_i is an additive term based on the player's reputation, v_i is an uncorrelated, uniformly distributed measurement error, υ'_p is a row vector which consists of K weights for position p and $x_{i,p}$ is a column vector which consists of K relevant IGS for player i's position. It's unknown if r_i depends on the player's international reputation stat or is "random", i.e. that in contrary to online sources (e.g. Lopes, 2019) the r_i term is either determined by other factors – like the player's na-

Applying the IGS Weights to TOTY Cards

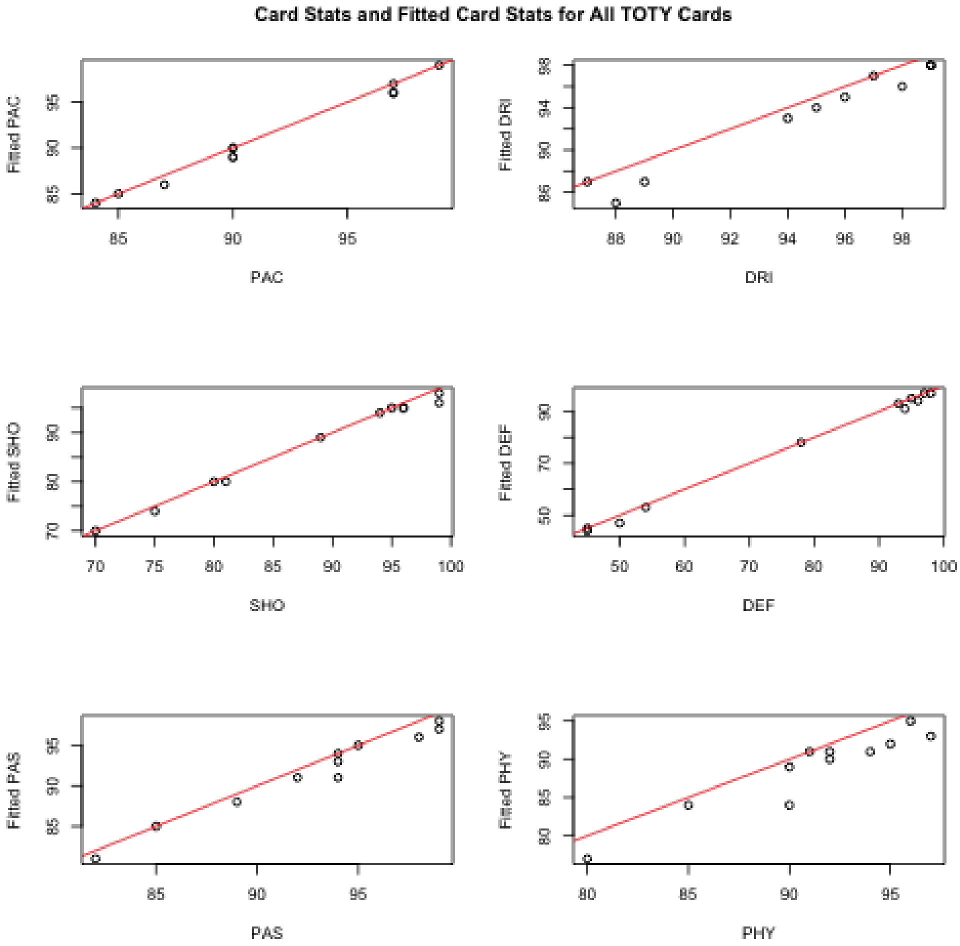

Figure 11: I find that some TOTY cards have higher CS indicated on their cards than the weighted average of the underlying IGS.

tionality, league or club – or given by EA and doesn't rely on any player characteristics. The main goal of the following calculations is to find out if the OVR is a linear combination of position-relevant IGS and the international reputation stat. I use the censored regression approach from the CS calculations.

I calculate the IGS weights for all regular strikers using four different sets of assumptions: (I) $r_i = 0$ and OVR is a linear combination of all IGS only, (II) $r_i = 0$ and OVR is a linear combination of proposed IGS (see

Lopes (2019)), (III) r_i = "International Reputation" and OVR is a linear combination of proposed IGS and (IV) OVR is a linear combination of proposed IGS and r_i. The results can be found in Table 8 in Appendix B.

Under the four different sets of assumptions I can't replicate the correct striker OVRs. Thus, I try one last approach proposed by Lopes (2019) where r_i follows a specific rule based on $y_{i,p}$ and the player's international reputation value. The result is the same: a lot of calculated OVRs deviate from their actual OVRs as indicated on the player's card.

The key takeaways from this section are: regular cards' CS are weighted averages of their underlying IGS. Applying the same weights to special cards sometimes underestimates the CS. This could be an indication that special cards are advertised to be better than their IGS really are. Also, using CS and the underlying IGS as explanatory variables in the same regression model could be an issue. OVR on the other hand is not a linear combination of IGS and may be appropriate to use in a regression model together with all IGS. The exact determination for the OVR couldn't be cleared up and may need further research.

5 Loot Boxes: Random Draw Experiments

The $1.4bn revenue from Ultimate Team was exclusively made with the sale of in-game currencies which are mainly used to open packs. In order to analyse if gamers have an equal chance of packing every player, I perform two very simple random draw experiments and compare them to Rune Mentzoni's data.

I use player names and OVRs of all rare gold cards from FIFA 18 excl. special cards. The first experiment limits the random draw sample to the lowest rated card per player – i.e. for players with two different cards (e.g. a Winter Upgrade) the sample only includes the regular card of the player at the launch of FIFA 18. The second experiment does the opposite, it gives priority to the highest rated card of the same player and excludes lower rated cards from the sample.

For both experiments I draw 4,554 random cards (like Rune Mentzoni did) from the sample, calculate the OVR mean and repeat it 10,000 times. Then I test if the random draw OVR mean is equal to Rune Mentzoni's OVR mean ($H_0 : \mu_{RD} = \mu_{RM}$) by calculating the t-statistic:

$$t = \frac{\mu_{RD} - \mu_{RM}}{SE(\mu_{RD})}. \tag{4}$$

10,000 Experiments of 4,554 Random Draws

	μ_{RM}	μ_{RD}	SE_{RD}	t
Min Rating	79.03	79.93	0.05	16.68
Max Rating	79.03	80.15	0.06	20.04

Table 2: Although Mentzoni was able to pack special cards which are higher rated than each player's regular card, his mean OVR was lower than all 20,000 draws of 4,554 draws each. Under the null hypothesis $H_0 : \mu_{RD} = \mu_{RM}$ his mean OVR is very unlikely to happen. I reject the null hypothesis and conclude that players with higher OVR ratings are drawn with a lower probability than lower rated players.

In conclusion, I reject the null hypothesis that the random draw OVR mean is equal to Rune Mentzoni's OVR mean. Although he was able to pack players with even higher ratings (e.g. special cards) the OVR mean from his data is a lot smaller than the OVR mean in both experiments. It's extremely unlikely you end up with such low rated players if players are drawn randomly with the same probabilities. The supply of high rated players on the in-game market is not only restricted due to the lower amount of high rated players in general, but they are additionally drawn with a lower probability than other cards. The OVR effect on prices is probably quite substantial.

6 A Series of Mincer Regressions

This section consists of the main analysis: developing and estimating player price models based on their OVR, CS, IGS and other characteristics. In order to explore different price components, I run a series of

Mincer-like regressions. Usually these regressions are used to examine the inequality in wages between different groups, but the approach may also be appropriate for FIFA Ultimate Team prices. E.g. gamers may prefer players from the Premier League because of its popularity or because of the chemistry system. There may be confounding factors like the player's OVR: higher rated player tend to be more expensive, but at the same time a lot of high rated players play in the Premier League.

6.1 Estimation Method

The standard econometric model for panel data looks like this:

$$y_{it} = \alpha + x_{it}'\beta + z_i'\gamma + c_i + u_{it}, \tag{5}$$

where y_{it} is the dependent variable for individual i at time t, x_{it}' is a K-dimensional row vector of time-varying variables and z_i' is a M-dimensional row vector of time-invariant explanatory variables excluding the constant, α is the intercept, β and γ are K-/M-dimensional column vectors of parameters, c_i is an individual-specific effect and u_{it} is an idiosyncratic error term.

For most cards the Futbin data consists of time-invariant variables z_i only. Upgradable cards – like OTW and Headliners – have time-variant stats, but the changes are very small. Price changes over time may be driven by other economic forces, like inflation or the introduction of substitutes (special cards).

In general, the main goal of these Mincer regressions is to decompose the individual-specific effect. I believe players are priced according to their IGS, CS and OVR, but there are also premiums for players of certain nationalities, leagues or for special cards. I use the RE model to control for other random unobserved individual-specific effects and report cluster-robust standard errors. Estimating the coefficients for time-invariant variables is a problem for the FE estimator. Under the within-transformation all the explanatory variables vanish. Plümper and

Troeger (2007) note that a RE estimator "trades the unbiased estimation of time-varying variables for the ability to compute estimates of time-invariant variables. Thus, they may be a second-best solution if researchers are solely interested in coefficients of the time-invariant variables."
Given other time-varying variables Plümper and Troeger (2007) propose an estimator for the time-invariant or rarely changing variables and Hausman and Taylor (1981) develop an IV like estimator. These aren't applicable to the Futbin dataset.

6.2 General Models

I want to estimate the premiums for several player characteristics and start with a very simple model which only includes OVR and a linear trend as explanatory variables. All estimations of this section can be found in Appendix C and generally use Xbox One prices.
The first simple model in Table 9 suggests a significant relationship between OVR and player prices. Players with higher OVRs are rarer in general and the supplied quantity on the in-game market is lower than for other players. At the same time, players with higher OVRs have better stats for their position and are more desirable for gamers. The demanded quantity is higher. Both of these forces explain the increase in price per OVR unit, but there are certainly confounding factors which have to be treated.
Although a player may have a high OVR, they are not always very popular among gamers and don't have the same price as other players with the same OVR. Gamers care about specific abilities for each position, e.g. a striker's pace and shooting ability, but not his defending. The OVR accounts for that and weighs the important IGS for the player's position, but these weights may be set arbitrarily and don't necessarily reflect what gamers are willing to pay for. Thus, I want to integrate the CS in the model and summarise the estimates in Table 10.
However, the CS coefficients aren't very meaningful and are driven by strong multicollinearity in the data. Most attackers have very low DEF

stats, yet they may still be quite expensive. I will estimate position-based regressions later in Section 6.3. For now, I keep OVR in the model as an explanatory variable for a player's performance related stats.

The chemistry system in FIFA Ultimate Team is quite important and gamers usually build squads with full chemistry ratings. Therefore Icons and players from the "best" nations, leagues and clubs are preferred by gamers. I use dummy variables for the top 5 leagues and top 10 nations as well as a dummy variable for Icons. Note that these are confounding factors of the OVR: a part of the OVR effect may be due to Icons being highly rated on average, but Icons may also be more expensive themselves because they are extremely rare and popular among gamers. I could technically also include a dummy variable for the most popular clubs, but I don't want to overcomplicate the model.

In general, special cards may be more expensive due to their rarity – remember that special cards are only obtainable for a limited time – or their popularity among gamers. Therefore, I include a dummy for special cards in general, a dummy for TOTY cards and a dummy for TOTS cards. Note that the total price effects of icon, TOTS or TOTY cards are the sum of their respective coefficients and the special card coefficient.

The last general model I want to estimate also controls for the player's position. Like in real life, attackers may be both more expensive and have higher OVRs. I create dummy variables for all position groups and use the central midfielder as e reference point. Note that I don't distinguish between left and right wingers, left or right backs and instead am only interested in the vertical position on the field. The results for all three general models can be found in Table 11.

The estimates suggest that player's are 6% more expensive per OVR unit, players from the top 5 leagues are significantly more expensive than players from other leagues and special cards are a lot more expensive than regular cards. In general attacking players are also more expensive than defenders or midfielders.

These results may be driven by the sample selection. Comparing 75 OVR players which are barely used in games to the high-end players which are too expensive for most gamers to buy was probably not a good idea. I re-run the three models with three different samples: (A) is the same model as before and is a reference point, (B) are all players with an OVR of 83 or higher and (C) only includes observations with a price per OVR unit of 1,000 or more. For fullbacks I allow players with a price of 500 or more. This very restricted sample only includes META[6] players which are used by esports competitors.

The results in Table 12 show that the model fits the META sample very nicely. The OVR coefficient increased which is comprehensible, considering the sample now only includes players where performance related stats are very important. From the top 5 leagues only Premier League and LaLiga Santander players are significantly more expensive than the rest. Some coefficients are quite similar for all three samples, e.g. French players have a 20 to 27% premium. Once again, special cards, Icon cards, TOTY cards and TOTS cards are a lot more expensive than other items even in the META sample where the OVR should be more important. It's reasonable to assume that esports competitors prioritise the performance related stats like OVR and care less about the exclusivity of a card. Yet, it's also possible that these Icons and other special cards are the very best players for each position and the coefficients so far are driven by the "top 1%" of players. I re-estimate the same model with a fourth sample (D) which is the former sample (C) but excludes price observations of 2,000,000 coins or more.

The coefficients for Icon and other special cards are quite robust to these outliers and are still extremely large. Also the OVR effect and the premiums for Premier League and French players don't change a lot and and remain statistically significant. Note that the goodness-of-fit for the C and D samples is around 70 to 75%.

[6] "Most effective tactic available"

6.3 Position-Based Models

From an esports competitor's perspective OVR may not be the most important performance indicator. Instead gamers often prefer specific CS/IGS. Including all of these variables in the same model should be done with caution due to the multicollinearity in the data. I find spurious relationships, e.g. strikers who are good at defending are cheaper. In general, all CS/IGS coefficients should be non-negative because increasing a stat by one unit and keeping all other stats the same shouldn't decrease a player's price. Even increasing an irrelevant stat for the player's position should have a positive or non-significant price effect.
The model specification was quite tricky and a tradeoff had to be made: including a lot of variables results in biased and non-sense coefficients, but the goal is to find reasonable CS-IGS-based models which fit the data better than the OVR model. Thus, I followed a stepwise procedure which treated the multicollinearity issue and tried to include as many relevant stats as possible: I estimated a model with all IGS as explanatory variables and then calculated the variance inflation factor (VIF) for all regressors. VIFs greater than 5 were treated by using the CS as a linear combination of its underlying IGS. E.g. Acceleration and Sprint Speed both had a VIF of 5 or greater and were replaced by PAC in the model. Then I re-estimated the new model and treated VIFs greater than 5 again. This time, I excluded the least important IGS/CS for the player's position from the model. I repeated these steps until all VIFs of the explanatory variables were smaller than 5.
For all positions I estimated three different models (I) OVR, (II) relevant CS/IGS, (III) relevant CS/IGS and other relevant characteristics, like a player's ability to shoot with his weaker foot or his work rates[7], using the META players sample (C). I controlled for all confounding factors of the previous model.

[7]Keep in mind that gamers only actively control one player at a time. The higher the work rates of a player are the more he runs when he is controlled by the AI.

6.3.1 Attackers

There are two different attacker positions in FIFA Ultimate Team. A striker's main job is to score goals. Thus, he should be fast enough to outrun defenders and have good shooting skills. Forward usually play right behind the main striker and set their teammate up for goal scoring opportunities. Table 13 and 14 show the estimated coefficients for strikers and forwards.

For strikers the OVR model performs just as well as the CS/IGS models. Faster strikers with better shooting stats tend to be more expensive. Strikers which can perform special dribbling moves ("Skill Moves") and are better at shooting the ball with their weak foot are around 20% more expensive per unit. Premier League, LaLiga Santander, Brazilian and Portuguese strikers are significantly more expensive. Icons, TOTS and special cards are a lot more expensive, too. The TOTY coefficient is roughly 50%, but not significantly different from zero. This is because there is only one TOTY striker in the game and the standard error is rather large.

The estimations of the model for forwards is more problematic due to the very small sample size. There are only 26 unique cards in the sample. I don't discuss the estimated coefficients in detail.

6.3.2 Wide Positions

Wingers, right and left midfielders need to be good passers, dribblers and quite fast to get past their opponents and set their teammates up for goal scoring opportunities. Gamers often use wingers or wide midfielders interchangeably, i.e. they use position change cards to use their desired player in a wide position. Thus, the coefficients for wingers and wide midfielders may be quite similar. I specified the model for wingers and estimated the same model for right and left midfielders.

For wingers the OVR model performs pretty much as well as the CS/IGS based models. I find that faster wingers with good shooting stats are more expensive, but dribbling doesn't have significant effect on player

prices. Players from the major leagues tend to be more expensive as well as players from Argentina, Belgium and England. Interestingly, with all other variables in the model, the ability to perform certain skill moves and get past a defender easily seems to have no effect on prices. Special cards are once again a lot more expensive than regular cards.
In comparison, the performance specific coefficients are quite different for wide midfielders. The OVR model once again performs quite well. Note that the number of unique cards in the wide midfielder sample is quite small and coefficients may be driven by outliers.

6.3.3 Central Midfielders

There are three different types of central midfielders in FIFA Ultimate Team. Attacking midfielders are usually natural playmakers and rely on good passing and dribbling skills, central midfielders need to be good at pretty much everything – controlling the game, winning the ball back or even scoring goals while defensive central midfielders are usually busy winning back the ball and passing it to more creative players.
For CAM players the OVR model fits the data better than the CS/IGS and I find a negative coefficient for DRI which means the model specification procedure couldn't fix the multicollinearity issue. In general, CAMs from the top 5 leagues tend to be a lot more expensive than other players.
The position based model for CMs fits the data just as well as the OVR model. Once again, faster players tend to be more expensive and gamers also spend more coins on good passers. French CMs are a lot more expensive than CMs from other nations.
For CDMs the position-based models outperform the OVR model and fit the data a lot better. Fast, good passers with good stats to win the ball back are significantly more expensive. Interestingly, a player's physicality doesn't seem to have a significant effect on prices. For all three positions Icon cards and TOTY cards tend to be a lot more expensive than regular players. Also, the negative linear time trend seems to be persistent in all position-based models.

6.3.4 Defenders

Defenders need to be able to win the ball back easily and should be able to keep up with fast attackers. Central defenders are usually taller and physically strong while fullbacks often dribble up the field and set up plays for their teammates.
The CS/IGS models for fullbacks fit the data not as well as the OVR model. But I find small significant positive coefficients for pace, passing, defending and physicality.
Fast centre-backs with good defending skills, high stamina and strength tend to be more expensive. Players from the Premier League and almost all major nations are significantly more expensive than other centre-backs. The CS/IGS model outperforms the goodness-of-fit of the OVR model.
Also, among defenders Icon and other special cards are more expensive.

6.3.5 Do Gamers Pay for Falsely Advertised CS?

In Sectino 4 I found that some special cards have higher CS than they should have based on their IGS. All of the models so far found that special cards are a lot more expensive than regular cards. Thus, I want to examine if gamers pay more for special cards which have a higher CS on their card than the usual weighted average of the underlying IGS.
I split the CS into two components: the correct weighted average and an artificial part which is the difference between the correct weighted average and the CS indicated on the card. For all regular cards and some special cards the artificial component is zero, but for some special cards it's 1 or even higher.
When I discovered that CS are higher for certain special cards, I tried to find a pattern. Among Icon cards I found that only "Icon Moments" – special cards released towards the end of the FIFA year – have artificially higher CS and other Icon cards aren't generally affected by this problem. To control for the possible status premium of having a "Icon Moments" card I added a dummy in the regression model.

Although not all of these coefficients are significant, I find that some of them are. E.g. fullbacks are more expensive per artificial PAC, PAS, DEF and PHY unit. It should also be noted that I find two negative coefficients; one for centre-backs and one for wide midfielders. Since the FIFA 20 launch, gamers have been quite vocal about the smaller upgrades for special cards. It would be interesting to check if the special cards in FIFA 20 in fact receive similar upgrades for their IGS and the CS is instead calculated the same way for all cards.
The high special card coefficients, including TOTY, TOTS and Icon cards are in general not substantially smaller when the artificial CS and Moments dummy are included in the model.

6.4 The Final Models & Discussion

So far I have assumed that there are unrelated unobserved individual-specific effects and the main goal of the analysis was to decompose this effect by controlling for relevant characteristics. If the remaining individual-specific effect truly is random, RE should be unbiased and RE is only unbiased if OLS is, too.
Therefore, I re-estimate the general model for all cards in sample (C) using both the RE estimator and pooled OLS and find different coefficients. Depending on the regressor, the difference is very small or quite large and the estimates don't even agree on the direction of the price effect. Remember that prices are based on supply and demand. Thus, players which are packed at lower probabilities can't be supplied in the same quantities as other cards on the in-game market. I found with Rune Mentzoni's data that high rated players are not only rare in the population, but their pack weight is additionally small. Gamers prefer high rated players because of higher stats, but also because they're popular. The demand for a player like Lionel Messi is probably driven by his popularity and not because he's Argentinian. In fact, other lower rated Argentinian players may be more expensive because they link well to Messi. Therefore, the RE model assumptions may be true for lower rated players which aren't very popular, but not the used sample.

Nonetheless, some coefficients are very similar under the assumptions that there are random effects or no individual-specific effects at all. Players from the Premier League as well as Brazilian, French, Dutch and Portuguese cards are significantly more expensive than other META players. Also, the main finding that Icon and other special cards are substantially more expensive persists under both assumptions. It's not hard to believe that Icon cards are more expensive because their pack weights are extremely low. E.g. Rune Mentzoni spent €3,800 and didn't pack a single Icon card. Of course these players are also individually very popular and the demand may be driven by the individual-specific price effect of each and every card. From an econometric perspective it would be interesting to estimate the effects with an estimator which accounts for the fixed effects.

I also estimated a second model in Table 22 which accounts for the top 2.5% of players per position and day measured by the OVR. RE finds a negative coefficient which is certainly very questionable while OLS finds 39% price effect. This dummy was included to control for the possibility that Icon and TOTY estimates were driven by the absolutely best players for each position. Esports competitors may be willing to pay large premiums for the best players to have competitive advantage or at least not be at a disadvantage. Nonetheless, even when accounting for the best of the best, the Icon and TOTY coefficients remain extremely large. This hints once again at the extremely low packing weights.

7 Inflation

In all model I only included a linear time trend, but I didn't discuss price movements for specific players. Due to the constant stats for most player cards its quite reasonable to assume player prices only change because of substitutes and complements or the general price level shifts because of changes in the coin supply or other factors.

When FIFA 19 launched at the end of September 2018, all gamers started the new Ultimate Team year with a coin balance of 0. Their clubs only contained a small number of lower rated cards and a few free packs. Although it was possible to sell cards on the in-game market, even the richest gamers usually can't offer millions of coins on day 1. Throughout the FIFA year, gamers accumulate new coins by playing matches, discarding cards or receiving rewards, but they also destroy coins when buying packs with them or when they buy a player on the in-game market.

I want to model the total coin supply in the FUT Economy and see if there are specific patterns. Therefore I use the Equation of Exchange:

$$M \times V = P \times Q \tag{6}$$

where M is the total coin supply, V is the velocity of coins, P is the average price per card and Q is the number of traded cards. Usually Q is the GDP which could be interpreted as either the number of produced goods, but also the number of goods which were sold and switched hands. Assuming a fixed percentage of all listings are actual trades, then the number of listings on the market are closely related to the actual number of trades per day. From Futbin I gathered the average number of daily listings[8] on the FIFA 20[9] Xbox One market for the first 85 days after launch. Figure 12 summarises the model variables, including the implied M.

In general it's very difficult to infer anything about this relationship because the data comes from two different video games, but its quite reasonable to assume that the economic forces that drive the coin supply were quite similar after the launch of both games. Gamers played a lot of games, opened a lot of packs and accumulated a lot of coins rapidly. Some force decreased the coin supply at the end of October. This could be because gamers spent a lot of coins on the "Halloween" in-game promotion. A closer look at the log-differenced time series M also hints at a weekly pattern (See Figure 13).

[8] Once again, Futbin regularly scans the market for the number of listings and publishes the daily average of these scans.

[9] Unfortunately, it wasn't possible to get the data for the FIFA 19 markets.

The Implied Coin Supply

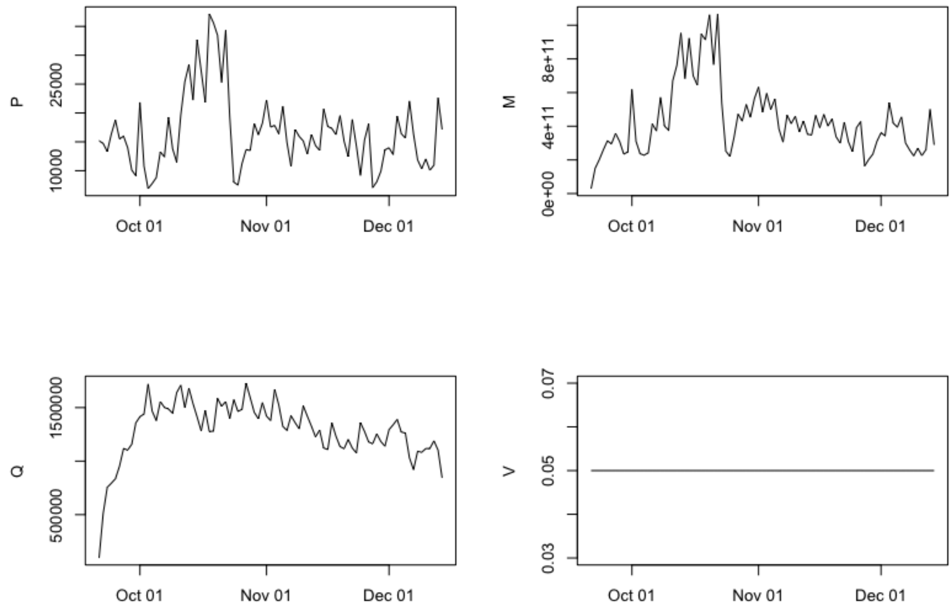

Figure 12: This figure shows the implied coin supply M based on a constant velocity of coins, the number of listings on the FIFA 20 market and the average price of FIFA 19 gold cards.

The differenced series hints at EA's control of the coin supply through weekly scheduled rewards and in-game promotions. It would certainly be interesting to analyse the average prices over time and maybe find possible trading strategies for gamers. For the main analysis I assume that the inclusion of a linear time trend is enough to control for the time variation in prices. Note that the META players decrease in price over time which may be due to new special cards which are substitutes.

8 Conclusion

In this paper I present the reader with the stats, characteristics and prices of FIFA Ultimate Team prices and examine the probabilities of

Log-Differenced Coin Supply M

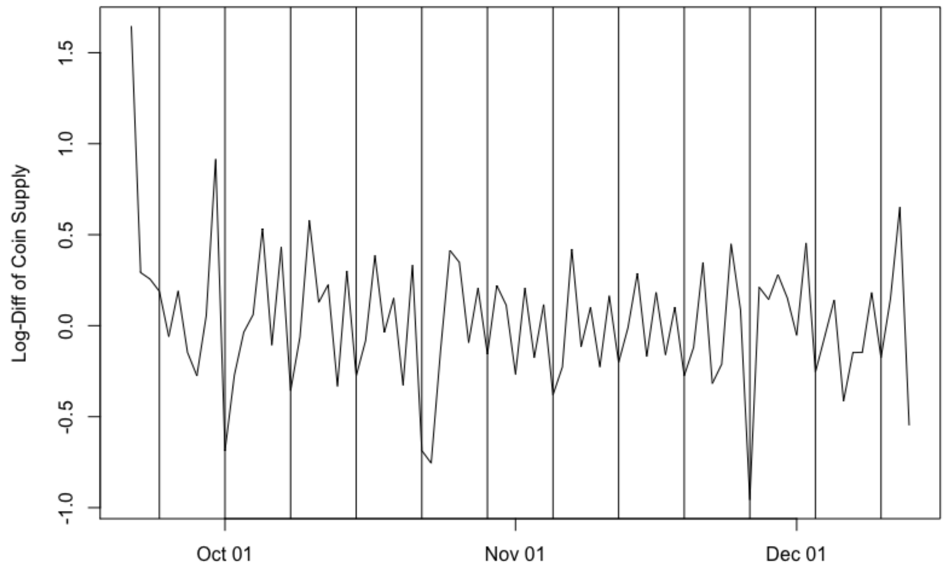

Figure 13: The vertical lines indicate the start of a new week and shows the weekly pattern of rewards and TOTW releases.

packing high rated players, explore the relationship between certain stats or characteristics and prices and develop a simple inflation model for the FUT economy. I find that players with higher ratings have a lower chance of being packed. This is not surprising for a business model which is built around the sale of an in-game currency for loot boxes. Under the assumption that players perform in games like their IGS, some special cards are advertised to be better through their CS and there is a hint that gamers pay for these falsely advertised stats. The main finding of the Mincer regressions are that gamers pay large premiums for special cards, especially Icon and TOTY cards, even when adjusting for their relevant performance stats and the top 2.5% of players per position. This may also not be surprising: throughout the year Electronic Arts releases a large number of special cards which incentivise gamers to buy the in-game currency and open packs. Even if gamers don't end up with their desired cards they may accumulate coins by opening packs and eventually will be able to buy their dream player cards. From a business perspective Electronic Arts may use esports as an advertising platform for higher rated players – competitors often use the rare Icon cards and other gamers may wish to do so, too.

From an econometric point of view, the estimation was tricky due to a multicollinearity issue for CS and IGS, but also because estimating time-invariant variables only doesn't allow to control for fixed effects. I had to make the assumption that prices for star players are the combination of all relevant player stats, characteristics and a random effect, but the demand for these players certainly varies with their individual popularity which may be related to the regressors.

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9 Appendix

9.1 Appendix A

In-Game Stats Descriptions

Stat Name	Description
Acceleration	How fast a player reaches his top speed
Sprint Speed	The player's top speed while sprinting
Attacking Positioning	Ability to position himself in an open spot when attacking
Finishing	Accuracy when shooting from inside the box
Shot Power	How powerful the ball can be shot by the player
Long Shots	Accuracy when shooting from outside the box
Volleys	Technique and accuracy of shots taken while the ball is in the air
Penalties	Accuracy when shooting a penalty
Vision	How far a player can "see" to accurately pass the ball to his teammate
Crossing	Accuracy when crossing the ball
FK Accuracy	Accuracy when shooting a free-kick
Short Passing	Accuracy and speed of passes over a short distance
Long Passing	Accuracy and speed of passes over a long distance
Curve	Ability to curl shots, crosses and passes
Agility	Has an effect on the controlled player's responsiveness
Balance	Also has an effect on a controlled player's responsiveness
Reactions	A player's ability to adapt to contextual changes
Ball Control	Initial ball control and ability to keep control of the ball
Dribbling	Ability to keep possession of the ball while running
Composure	Ability to shoot, pass or cross under pressure from an opponent
Interceptions	Ability to read opponent's passes (AI)
Heading Accuracy	Accuracy when heading the ball; also ability to get the head to the ball

Marking	For AI controlled players: ability to track and defend against opposing players; for player controlled players: ability to hold important defending position
Standing Tackle	Ability to win the ball while staying on your feet
Sliding Tackle	Accuracy of sliding tackle and chance of succeeding
Jumping	How high a player can jump
Stamina	Has an effect on the player's fatigue during the game
Strength	Ability to win a physical battle
Aggression	Has an effect on the chance of winning the ball back; also increases risk of fouling an opposing player

Table 3: The table summarises the most important IGS according to Cross (2016).

Simplified Table of Special Cards

Card Type	Description	Basis	Obtainability	Duration
Normal	Regular player card	RL	Packs	All year
TOTW	Team of the Week	RL	Packs	One week
OTW	Ones to Watch – upgrades based on TOTW – Summer and Winter version	RL	Summer: 23 in packs, 1 SBC, 1 OBJ – Winter: 18 in packs	One week
Icons	Former professional footballers	RL	Packs, SBCs	All Year
TOTS	Team of the Season (league based)	RL	Packs, SBCs, OBJs	One week
TOTY	Team of the Year (global)	RL	12 in packs, 3 SBCs	Five days
TOTGS	Team of the Group-Stage (CL or EL)	RL	21 in packs, 3 SBCs, 1 OBJ	One week
TOTT	Team of the Tournament (CL or EL)	RL	18 in packs, 4 SBCs, 3 OBJ	One week
Award Winner	Player of the Month or Year (league based)	RL	SBCs	One to four weeks
MOTM	Man of the Match (cup games, CL or EL)	RL	Packs	Three to five days
Record Breaker	For breaking a meaningful record	RL	Packs, 1 OBJ	24 hours or one week
Hero	Helped team achieve something historical	RL	Packs – part of TOTW	One week
CL	Upgraded player cards for all CL competitors – different design	RL	Packs	During UCL Group Stage
UEL LIVE	Selected players in EL – upgrade based on team's current stage in the tournament	RL	Packs	One Week
UCL LIVE	Selected players in CL – upgrade based on team's current stage in the tournament	RL	Packs	One Week
Headliners	22 selected players with good form this season – upgradeable based on TOTW	RL	19 in packs, 2 SBCs, 1 OBJ	One week
Futties	12 community voted SBCs	IGP	SBCs	One week
Halloween	24 selected players – boosted stats which change on 5 different dates throughout the FIFA year	IGP	21 in packs, 2 SBCs, 1 OBJ	Two weeks
FUTmas	3 SBCs for 10 days to celebrate Christmas	IGP	30 SBCs	One day
FUT Birthday	32 selected players who had their position changed	IGP	21 in packs, 5 SBCs, 6 OBJs	One week
Flashback	5 selected players who used to be great in earlier FIFA years	IGP	SBCs	3 days
FUT Future Stars	28 selected young players with great potential	IGP	21 in packs, 6 SBCs, 1 OBJ	One week
Carniball	26 selected players from major carnival host nations	IGP	14 in packs, 8SBCs, 4 OBJs	One week

Table 4: This table is a simplified overview for all special cards in FIFA 19. The "Basis" describes if the special cards are based on a real life event – like the TOTW – or on an in-game promotion by EA.

Descriptive Statistics of Numeric Variables on Day 1

Statistic	N	Mean	St. Dev.	Min	Max
OVR	13,753	67.370	7.258	47	96
PAC	13,753	68.267	11.712	24	97
SHO	13,753	53.137	14.475	15	95
PAS	13,753	58.094	10.776	24	92
DRI	13,753	63.159	10.299	24	96
DEF	13,753	52.479	16.292	15	95
PHY	13,753	66.064	9.496	30	91
Skill Moves	13,753	2.590	0.646	2	5
Weak Foot	13,753	3.045	0.650	1	5
Intl. Reputation	13,453	1.138	0.433	1	5
Height	13,753	180.528	6.449	155	204
Weight	13,753	74.658	6.712	50	110
Age	13,550	26.621	4.406	18	42
Log-Price (Xbox One)	13,568	6.459	1.377	5.298	16.524
Log-Price (PS4)	13,669	6.056	1.178	5.298	16.067
Log-Price (PC)	981	7.867	1.937	5.991	15.297

Table 5: This table lists the mean, standard deviation, minimum and maximum value for all tradable field player cards on 21st September 2018. Note that the OVR, CS (and IGS), weight and height are documented for all 13,753 cards. Some lesser known players and the icon cards didn't have a value for their 'Intl. Reputation' or age on Futbin. The three stats at the bottom are log-prices for the player cards on the three platforms Xbox One, PS4 and PC. The number of observations deviates because of Futbin's ability to scan the prices varies for each platform.

Table 6: Descriptive Statistics of Numeric Stats on Day 362

Statistic	N	Mean	St. Dev.	Min	Max
OVR	15,961	69.723	8.860	47	99
PAC	15,961	69.905	12.170	24	99
SHO	15,961	56.113	16.102	15	99
PAS	15,961	60.559	12.243	24	99
DRI	15,961	65.595	11.622	24	99
DEF	15,961	53.359	17.094	15	99
PHY	15,961	67.461	9.957	30	99
Skill Moves	15,961	2.692	0.715	2	5
Weak Foot	15,961	3.097	0.673	1	5
Intl. Reputation	15,588	1.261	0.625	1	5
Height	15,961	180.605	6.504	155	204
Weight	15,961	74.833	6.800	50	110
Age	15,711	26.695	4.310	18	42
Log-Price (Xbox One)	13,921	7.548	1.804	5.298	16.402
Log-Price (PS4)	12,994	7.386	1.944	5.298	16.160
Log-Price (PC)	507	8.365	1.877	5.298	13.952

Table 6: This table lists the mean, standard deviation, minimum and maximum value for all tradable field player cards on 17th September 2019 and is a comparison to Table 5. Note that the number of cards increased by 2,208 over 362 days and that all means increased: higher OVR, CS, skills, weak foot ability, reputation – even height, weight and age.

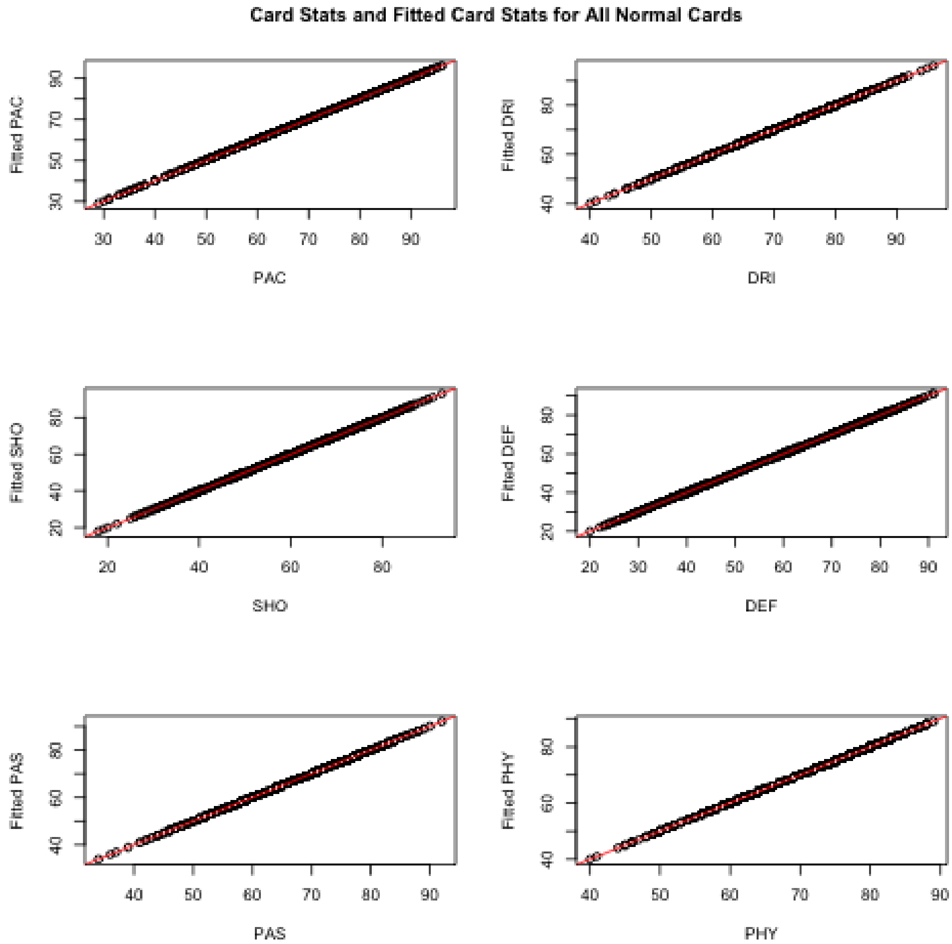
Descriptive Statistics of Numeric Stats for Gold Field Players

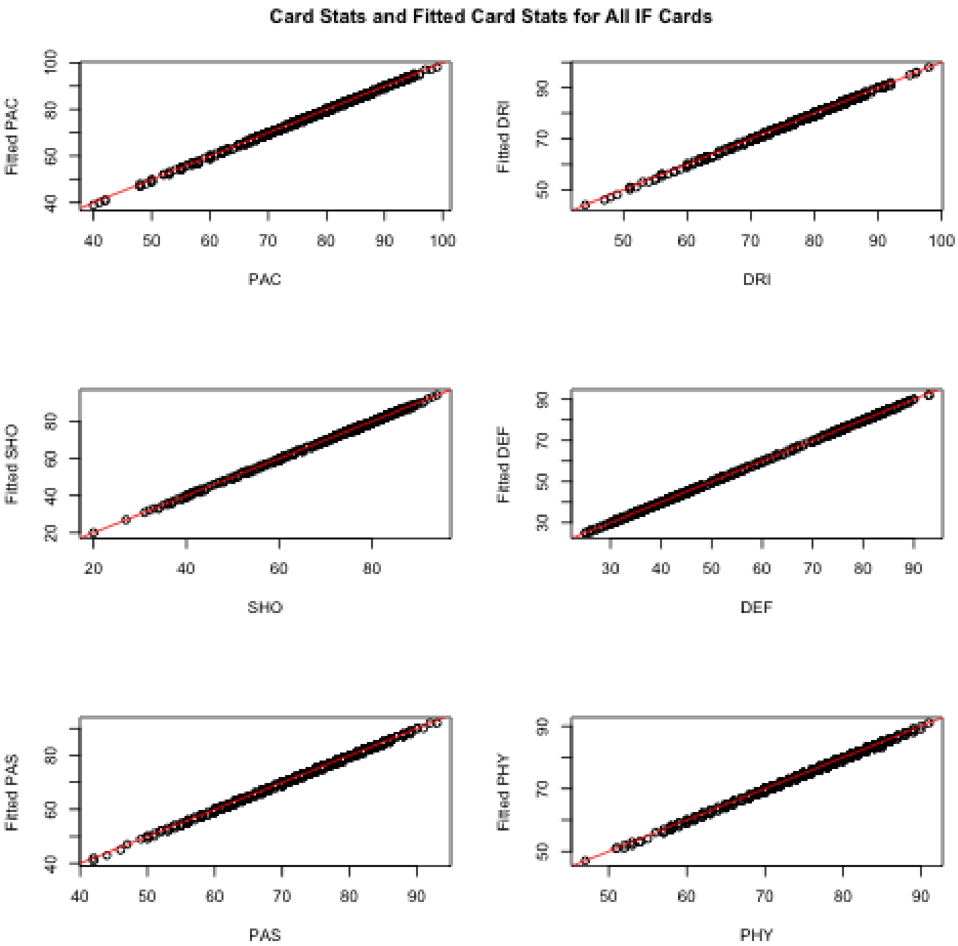
Statistic	N	Mean	St. Dev.	Min	Max
OVR	1,260,130	80.645	5.088	75	99
PAC	1,260,130	74.624	12.147	29	99
SHO	1,260,130	68.210	14.873	18	99
PAS	1,260,130	72.054	9.743	34	99
DRI	1,260,130	76.170	9.415	40	99
DEF	1,260,130	60.113	19.093	20	99
PHY	1,260,130	73.209	8.684	40	99
Skill Moves	1,260,130	3.212	0.807	2	5
Weak Foot	1,260,130	3.337	0.735	1	5
Intl. Reputation	1,173,238	1.910	0.892	1	5
Height	1,260,130	181.157	6.540	158	201
Weight	1,260,130	76.045	6.938	56	101
Age	1,175,551	27.976	3.822	18	42
Log-Price (Xbox One)	1,255,092	8.600	2.289	5.858	16.524
Log-Price (PS4)	1,259,284	8.495	2.348	5.313	16.524
Log-Price (PC)	1,136,504	8.706	2.357	5.858	16.524

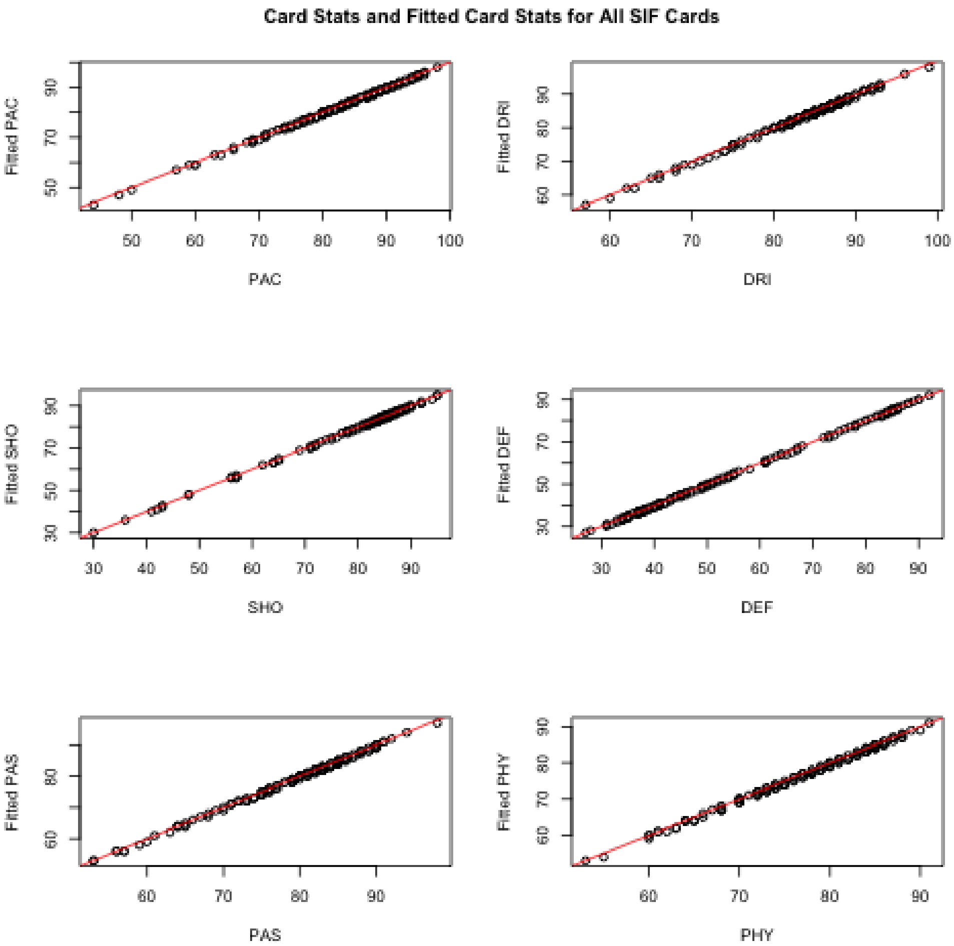
Table 7: Note that the mean OVR for all gold field players is at 80.645 while all CS are below 80. The standard deviation for defending is the highest due to its bimodal distribution. The number of price observations is different for all platforms, but moves in the 1.1M to 1.3M range, or about 3,000 to 3,600 observations per day.

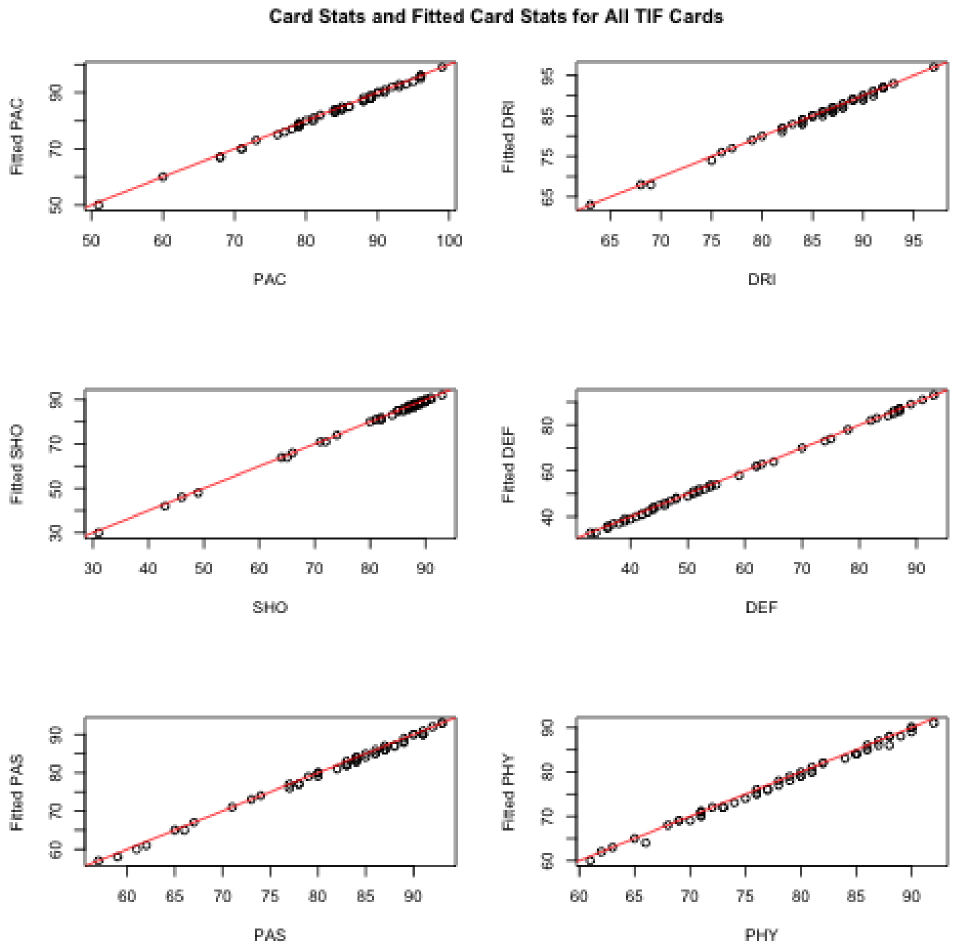
9.2 Appendix B

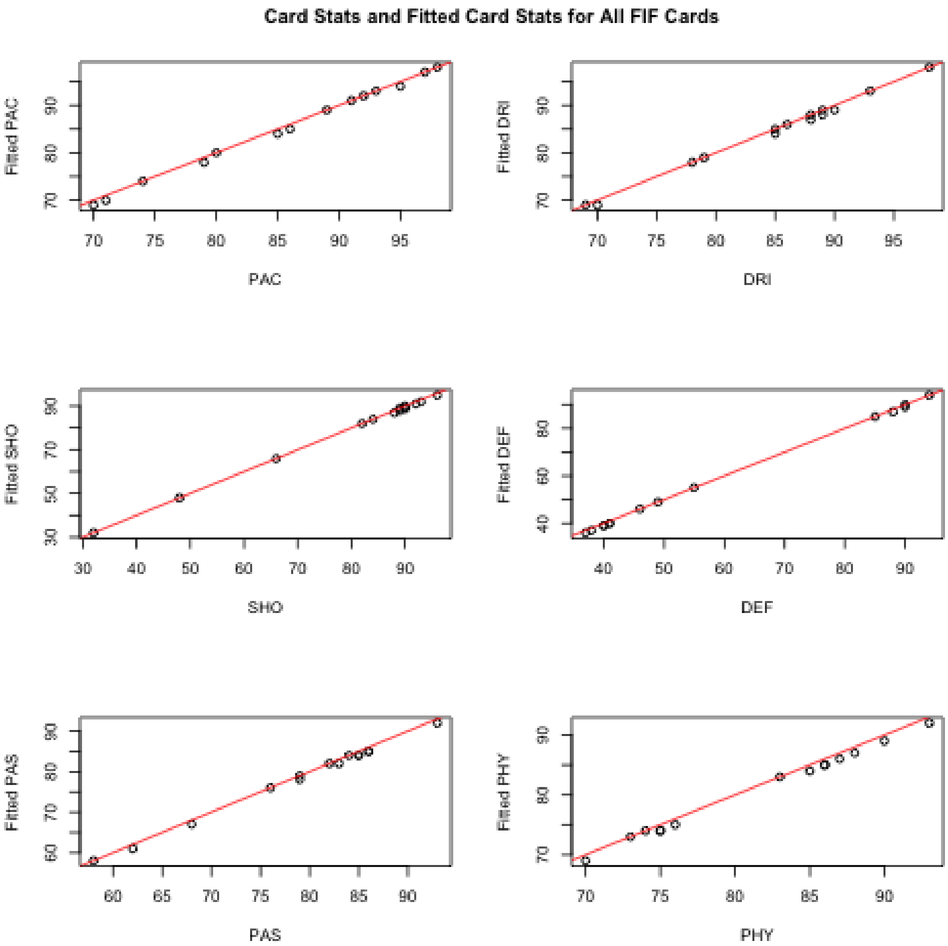
In this part of the appendix, I illustrate the difference in CS for different special cards and find that special cards may have higher CS than the weighted average of their IGS.




Card Stats and Fitted Card Stats for All IF Cards
Fitted PAC
PAC
Fitted DRI
DRI
Fitted SHO
SHO
Fitted DEF
DEF
Fitted PAS
PAS
Fitted PHY
PHY


Card Stats and Fitted Card Stats for All SIF Cards
Fitted PAC
PAC
Fitted DRI
DRI
Fitted SHO
SHO
Fitted DEF
DEF
Fitted PAS
PAS
Fitted PHY
PHY


Card Stats and Fitted Card Stats for All TIF Cards
Fitted PAC
PAC
Fitted DRI
DRI
Fitted SHO
SHO
Fitted DEF
DEF
Fitted PAS
PAS
Fitted PHY
PHY



Card Stats and Fitted Card Stats for All FIF Cards
Fitted PAC
PAC
Fitted DRI
DRI
Fitted SHO
SHO
Fitted DEF
DEF
Fitted PAS
PAS
Fitted PHY
PHY

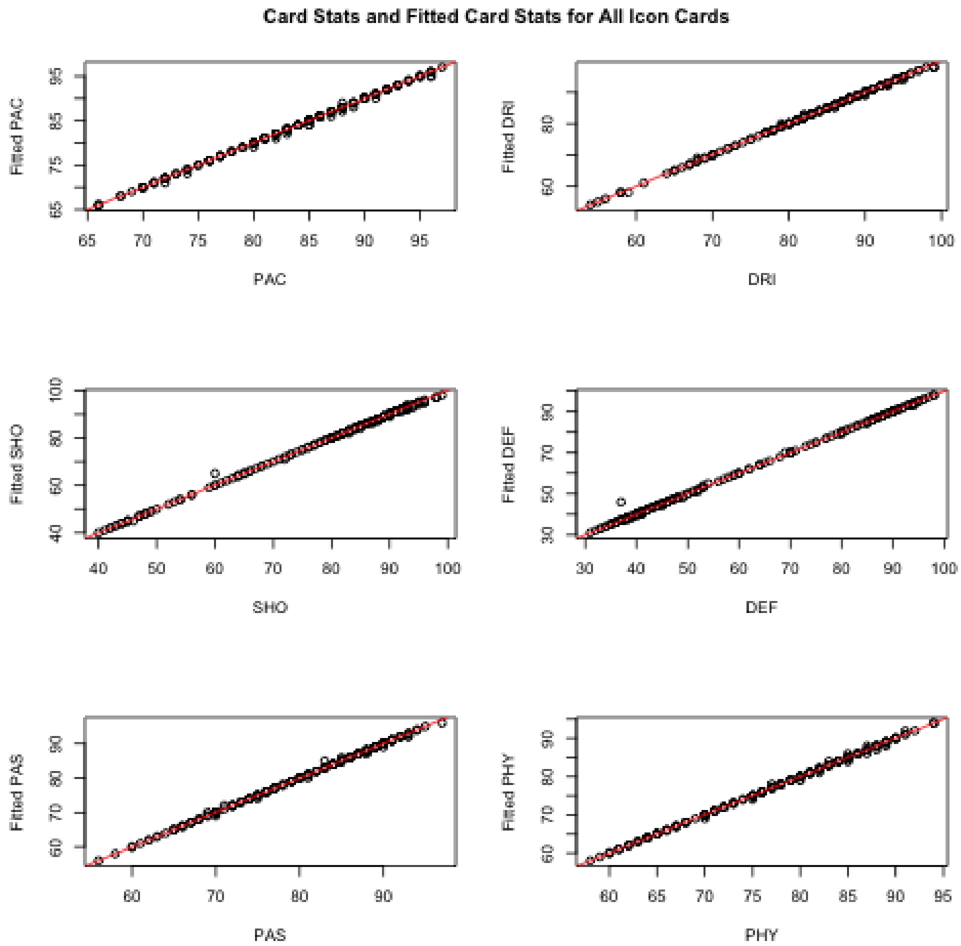
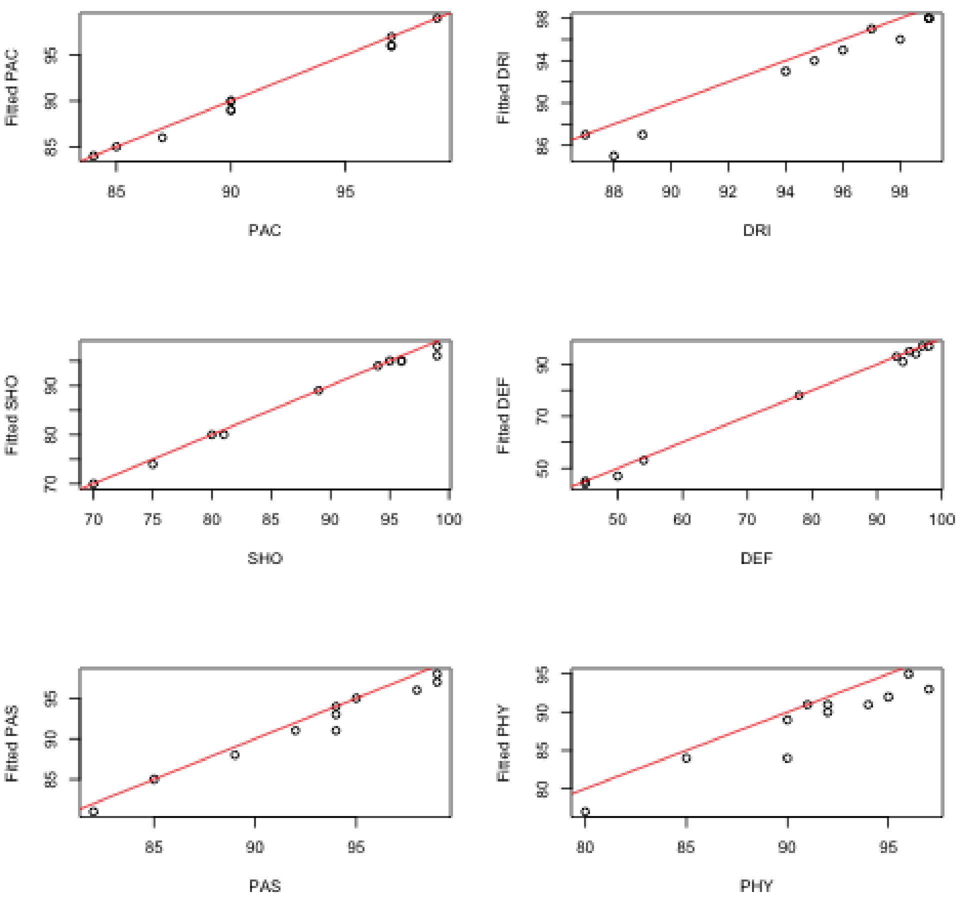
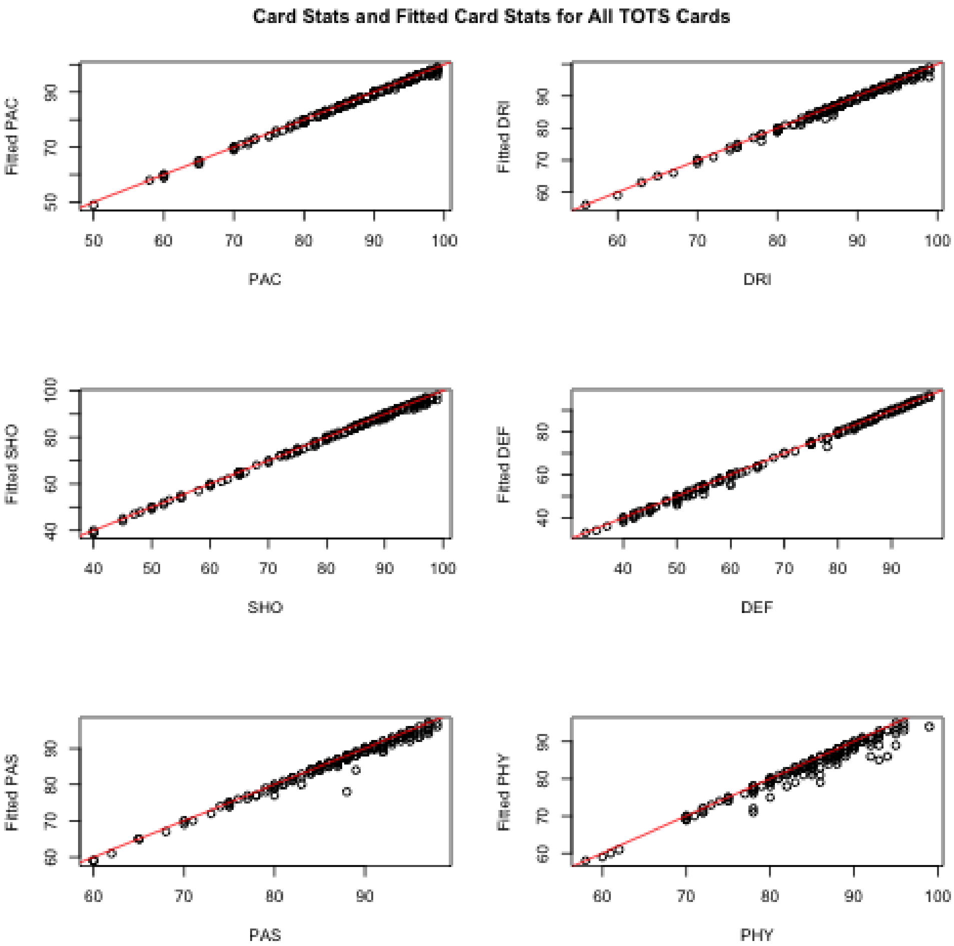


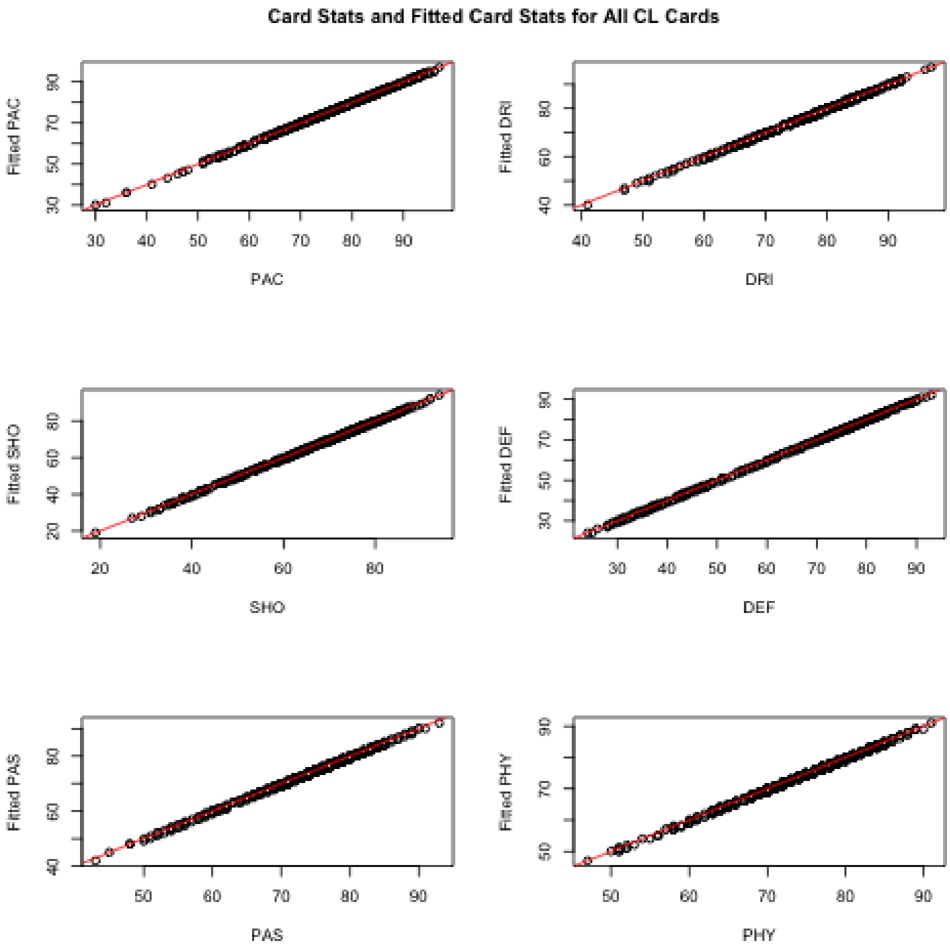
Figure 14: *
Note that some Icons have lower CS than they should have.

Card Stats and Fitted Card Stats for All TOTY Cards





Card Stats and Fitted Card Stats for All TOTS Cards
Fitted PAC
PAC
Fitted DRI
DRI
Fitted SHO
SHO
Fitted DEF
DEF
Fitted PAS
PAS
Fitted PHY
PHY


Card Stats and Fitted Card Stats for All CL Cards
Fitted PAC
PAC
Fitted DRI
DRI
Fitted SHO
SHO
Fitted DEF
DEF
Fitted PAS
PAS
Fitted PHY
PHY

Is OVR a Linear Combination of IGS and IR?

	Dependent variable:			
	OVR_{ST}		$OVR_{ST} - IR$	OVR_{ST}
	I	II	III	IV
Acceleration2	0.03	0.01	0.02	0.01
Sprint Speed	0.06	0.07	0.06	0.07
Attacking Positioning	0.14	0.15	0.12	0.13
Finishing	0.19	0.17	0.20	0.18
Shot Power	0.07	0.08	0.10	0.09
Long Shots	0.03	0.04	0.03	0.04
Volleys	0.02	0.04	−0.01	0.02
Penalties	0.01			
Vision	0.001			
Crossing	0.005			
Free-Kick Accuracy	0.004			
Short Passing	0.07			
Long Passing	−0.004			
Curve	0.005			
Agility	−0.01			
Balance	−0.02			
Reactions	0.10	0.12	0.11	0.12
Ball Control	0.09	0.10	0.10	0.10
Dribbling	0.06	0.09	0.09	0.09
Composure	0.01			
Interceptions	−0.004			
Heading Accuracy	0.09	0.10	0.11	0.10
Marking	−0.001			
Standing Tackle	0.003			
Sliding Tackle	−0.001			
Jumping	0.005			
Stamina	0.0003			
Strength	0.04	0.05	0.05	0.05
Aggression	0.003			
Intl. Reputation				0.41
Sum	1.02	1.01	0.99	1.41
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 8: Under four different sets of assumptions I don't find that OVR is an exact linear combination of proposed IGS and a player's international reputation.

9.3 Appendix C

The Relationship Between OVR and Player Prices

	Dependent variable:		
	Log-Price (Xbox One)	Log-Price (PS4)	Log-Price (PC)
OVR	0.103***	0.108***	0.136***
	(0.002)	(0.002)	(0.002)
Time	0.0002***	−0.0002***	0.0001***
	(0.00001)	(0.00001)	(0.00001)
Constant	0.789***	0.434***	−1.819***
	(0.150)	(0.153)	(0.152)
Observations	819,789	756,421	784,548
R^2	0.031	0.037	0.034
Adjusted R^2	0.031	0.037	0.034
F Statistic	24,862***	26,978***	26,579***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: This first regression model suggests that players are roughly 10% more expensive per OVR unit, but the constants are quite different for each platform. Also, depending on the platform, player prices may become increase or decrease over time. There are certainly a lot more variables to consider. The adjusted R^2 is quite low at just 3%.

The Relationship Between CS and Player Prices

	Dependent variable:	
	Log-Price (Xbox One)	
	(1)	(2)
OVR	0.176***	
	(0.004)	
PAC	0.016***	0.029***
	(0.002)	(0.002)
SHO	0.005**	0.013***
	(0.002)	(0.002)
PAS	−0.053***	−0.046***
	(0.003)	(0.003)
DRI	0.017***	0.068***
	(0.004)	(0.004)
DEF	−0.001	0.017***
	(0.001)	(0.002)
PHY	−0.052***	−0.033***
	(0.002)	(0.002)
Time	0.0002***	0.0002***
	(0.00001)	(0.00001)
Constant	−0.281*	5.569***
	(0.159)	(0.163)
Observations	819,789	819,789
R^2	0.036	0.018
Adjusted R^2	0.036	0.018
F Statistic	29,304***	14,180***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 10: Including CS in the model increases both the OVR coefficient and adjusted R^2, but the coefficients aren't very meaningful. A negative coefficient suggests players become cheaper with better stats. Two things have to be considered: missing variables and multicollinearity.

OVR and Other Confounding Factors

	Dependent variable:		
	Log-Price (Xbox One)		
	(1)	(2)	(3)
OVR	0.100***	0.061***	0.059***
	(0.002)	(0.002)	(0.002)
Premier League	0.424***	0.580***	0.592***
	(0.047)	(0.037)	(0.037)
Bundesliga	0.001	0.137***	0.169***
	(0.055)	(0.043)	(0.043)
LaLiga Santander	0.239***	0.406***	0.423***
	(0.052)	(0.041)	(0.041)
Ligue 1 Conforama	0.115*	0.196***	0.223***
	(0.059)	(0.046)	(0.046)
Serie A TIM	0.238***	0.358***	0.377***
	(0.052)	(0.041)	(0.041)
Argentina	−0.119*	0.156***	0.127***
	(0.063)	(0.049)	(0.049)
Belgium	0.556***	0.386***	0.377***
	(0.092)	(0.071)	(0.071)
Brazil	0.244***	0.288***	0.310***
	(0.056)	(0.044)	(0.043)
England	−0.053	−0.164***	−0.143***
	(0.067)	(0.052)	(0.052)
France	0.176***	0.184***	0.204***
	(0.057)	(0.044)	(0.044)
Germany	0.113*	0.141***	0.151***
	(0.069)	(0.053)	(0.053)
Italy	−0.248***	−0.166***	−0.165***
	(0.069)	(0.054)	(0.054)
Holland	0.089	0.044	0.039
	(0.075)	(0.058)	(0.058)
Portugal	0.019	0.108*	0.109*
	(0.073)	(0.057)	(0.056)
Spain	−0.231***	−0.063	−0.044
	(0.056)	(0.044)	(0.043)
Icon	3.839***	3.104***	3.069***
	(0.069)	(0.056)	(0.056)
TOTS		0.762***	0.796***
		(0.057)	(0.056)
TOTY		3.320***	3.306***
		(0.222)	(0.220)
Special Card		2.331***	2.302***
		(0.025)	(0.025)
Striker			0.264***
			(0.039)
Forward			0.599***
			(0.087)
Winger			0.418***
			(0.052)
Wide Midfielder			0.126***
			(0.044)
Central Attacking Midfielder			0.211***
			(0.050)
Central Defensive Midfielder			−0.097*
			(0.051)
Fullback			−0.034
			(0.044)
Centreback			0.028
			(0.041)
Time	0.0002***	0.0002***	0.0002***
	(0.00001)	(0.00001)	(0.00001)
Constant	0.580***	2.513***	2.520***
	(0.144)	(0.142)	(0.145)
Observations	819,789	819,789	819,789

R^2	0.047	0.084	0.085
Adjusted R^2	0.047	0.084	0.085
F Statistic	39,425***	74,682***	76,101***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 11: The three models include dummy variables for the top leagues, nations, special cards and positions. Note that the total effect for Icon, TOTS and TOTY cards is the sum of the respective and the special card coefficient. The final model has an adjusted R^2 of 8.5% which is better than the previous models. The coefficient for OVR is only 0.059. The key takeaways are that players from the top 5 leagues, France, Belgium, Argentina and Germany are significantly more expensive, attackers are more expensive than defenders, prices increase over time and special cards are a lot more expensive than their OVR, position, league or nation suggests. The model may be more appropriate to use for a more restricted sample.

OVR and Other Confounding Factors (Other Samples)

	Dependent variable:			
	XBOX			
	(A)	(B)	(C)	(D)
OVR	0.059^{***}	0.110^{***}	0.132^{***}	0.131^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Premier League	0.592^{***}	0.929^{***}	0.228^{***}	0.200^{***}
	(0.037)	(0.051)	(0.061)	(0.050)
Bundesliga	0.169^{***}	0.574^{***}	0.026	-0.015
	(0.043)	(0.064)	(0.073)	(0.059)
LaLiga Santander	0.423^{***}	0.737^{***}	0.135^{**}	0.105^{*}
	(0.041)	(0.058)	(0.067)	(0.055)
Ligue 1 Conforama	0.223^{***}	0.596^{***}	0.097	0.033
	(0.046)	(0.064)	(0.072)	(0.059)
Serie A TIM	0.377^{***}	0.667^{***}	0.061	-0.020
	(0.041)	(0.056)	(0.065)	(0.054)
Argentina	0.127^{***}	0.185^{***}	0.079	0.098^{*}
	(0.049)	(0.067)	(0.063)	(0.052)
Belgium	0.377^{***}	0.241^{***}	0.106	0.110^{*}
	(0.071)	(0.076)	(0.069)	(0.057)
Brazil	0.310^{***}	0.252^{***}	0.239^{***}	0.149^{***}
	(0.043)	(0.051)	(0.050)	(0.042)
England	-0.143^{***}	-0.017	-0.020	-0.010
	(0.052)	(0.066)	(0.056)	(0.046)
France	0.204^{***}	0.243^{***}	0.278^{***}	0.259^{***}
	(0.044)	(0.052)	(0.049)	(0.040)
Germany	0.151^{***}	0.164^{**}	0.082	0.087
	(0.053)	(0.067)	(0.065)	(0.053)
Italy	-0.165^{***}	-0.198^{***}	-0.189^{***}	-0.148^{***}
	(0.054)	(0.063)	(0.062)	(0.051)
Holland	0.039	0.147^{**}	0.166^{***}	0.124^{**}
	(0.058)	(0.065)	(0.061)	(0.050)
Portugal	0.109^{*}	0.255^{***}	0.225^{***}	0.095^{*}
	(0.056)	(0.069)	(0.066)	(0.055)
Spain	-0.044	-0.176^{***}	-0.146^{**}	-0.157^{***}
	(0.043)	(0.055)	(0.058)	(0.047)
Icon	3.069^{***}	2.630^{***}	1.372^{***}	1.275^{***}
	(0.056)	(0.057)	(0.062)	(0.051)
TOTS	0.796^{***}	0.405^{***}	0.241^{***}	0.183^{***}
	(0.056)	(0.047)	(0.044)	(0.037)
TOTY	3.306^{***}	2.282^{***}	1.560^{***}	1.274^{***}
	(0.220)	(0.167)	(0.127)	(0.140)
Special Card	2.302^{***}	1.574^{***}	0.590^{***}	0.584^{***}
	(0.025)	(0.041)	(0.063)	(0.052)
Striker	0.264^{***}	0.243^{***}	0.151^{***}	0.114^{***}
	(0.039)	(0.049)	(0.049)	(0.041)
Forward	0.599^{***}	0.473^{***}	0.255^{***}	0.167^{***}
	(0.087)	(0.084)	(0.072)	(0.060)
Winger	0.418^{***}	0.394^{***}	0.213^{***}	0.190^{***}
	(0.052)	(0.060)	(0.057)	(0.047)
Wide Midfielder	0.126^{***}	0.033	-0.183^{***}	-0.160^{***}
	(0.044)	(0.059)	(0.063)	(0.052)
Central Attacking Midfielder	0.211^{***}	0.170^{***}	0.085	0.067
	(0.050)	(0.061)	(0.060)	(0.050)
Central Defending Midfielder	-0.097^{*}	-0.107	-0.162^{**}	-0.118^{*}
	(0.051)	(0.072)	(0.079)	(0.065)
Fullback	-0.034	0.208^{***}	-0.127^{**}	-0.110^{**}
	(0.044)	(0.062)	(0.054)	(0.045)
Centre-back	0.028	0.036	-0.117^{**}	-0.095^{**}
	(0.041)	(0.052)	(0.054)	(0.044)
Time	0.0002^{***}	-0.002^{***}	-0.004^{***}	-0.004^{***}
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Constant	2.520^{***}	-0.395^{**}	0.228	0.377^{**}
	(0.145)	(0.201)	(0.185)	(0.176)
Observations	819,789	383,402	167,224	155,778

R^2	0.085	0.286	0.713	0.756
Adjusted R^2	0.085	0.286	0.713	0.756
F Statistic	76,101***	153,589***	416,015***	481,941***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: The model fits the data for more restricted players a lot better. This is no surprise, high-end META players are used a lot by several gamers and their prices should be based on their several characteristics. The most coefficients for the sample C are quite robust towards outliers, see sample (D).

Position Based Model for Strikers

	Dependent variable:			
	Log-Price (Xbox One)			
	(I)	(II)	(III)	(IV)
OVR	0.150***			0.141***
	(0.005)			(0.011)
PAC		0.048***	0.039***	
		(0.004)	(0.004)	
SHO		0.053***	0.056***	
		(0.005)	(0.005)	
Correct PAC				0.025***
				(0.003)
Correct SHO				−0.020**
				(0.008)
Artificial PAC				0.051
				(0.031)
Artificial SHO				0.075**
				(0.035)
Heading Accuracy		0.016***	0.018***	0.007***
		(0.003)	(0.003)	(0.002)
Skill Moves			0.216***	0.161***
			(0.050)	(0.042)
Weak Foot			0.229***	0.174***
			(0.042)	(0.035)
High Attacking Workrate			0.004	−0.052
			(0.061)	(0.051)
Premier League	0.587***	0.459***	0.401***	0.207*
	(0.129)	(0.144)	(0.141)	(0.121)
Bundesliga	0.143	0.121	0.057	−0.182
	(0.142)	(0.153)	(0.151)	(0.129)
LaLiga Santander	0.296**	0.411***	0.406***	0.060
	(0.137)	(0.148)	(0.146)	(0.128)
Ligue 1 Conforama	0.332**	0.308*	0.240	−0.067
	(0.150)	(0.167)	(0.163)	(0.139)
Serie A TIM	−0.089	−0.055	−0.048	−0.353***
	(0.144)	(0.155)	(0.148)	(0.129)
Argentina	−0.110	0.143	0.088	−0.039
	(0.096)	(0.102)	(0.097)	(0.081)
Belgium	−0.331**	−0.251	−0.168	−0.288**
	(0.161)	(0.170)	(0.163)	(0.138)
Brazil	0.441***	0.445***	0.371***	0.199*
	(0.133)	(0.144)	(0.138)	(0.115)
England	−0.255***	−0.203**	−0.069	−0.095
	(0.093)	(0.099)	(0.096)	(0.080)
France	0.142	0.030	−0.050	0.017
	(0.087)	(0.093)	(0.089)	(0.075)
Germany	0.038	−0.213*	−0.056	0.056
	(0.121)	(0.128)	(0.128)	(0.109)
Italy	−0.222**	−0.210*	−0.165	−0.148
	(0.110)	(0.116)	(0.110)	(0.092)
Holland	−0.307***	−0.182*	−0.116	−0.280***
	(0.098)	(0.104)	(0.099)	(0.083)
Portugal	2.018***	2.179***	1.802***	1.748***
	(0.176)	(0.185)	(0.193)	(0.165)
Spain	−0.284**	−0.737***	−0.598***	−0.356***
	(0.114)	(0.121)	(0.116)	(0.099)
Icon	1.403***	1.360***	1.326***	1.066***
	(0.128)	(0.139)	(0.134)	(0.118)
Icon Moment				0.527***
				(0.110)
TOTS	0.250***	0.280***	0.281***	0.132*
	(0.087)	(0.092)	(0.087)	(0.078)
TOTY	0.514	0.525	0.538	0.388
	(0.381)	(0.403)	(0.379)	(0.314)
Special Card	0.820***	0.610***	0.626***	0.722***
	(0.116)	(0.123)	(0.116)	(0.099)

Time	-0.004^{***}	-0.004^{***}	-0.004^{***}	-0.004^{***}
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Constant	-1.443^{***}	1.943^{***}	0.607	-2.466^{***}
	(0.422)	(0.366)	(0.394)	(0.434)
Observations	38,859	38,859	38,859	38,859
R^2	0.742	0.735	0.742	0.768
Adjusted R^2	0.742	0.734	0.742	0.768
F Statistic	$111,488^{***}$	$107,456^{***}$	$111,835^{***}$	$128,549^{***}$

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 13: META strikers tend to be more expensive per PAC and SHO unit. The OVR model fits the data as well as the CS/IGS models. Gamers may pay more for strikers with an artificially higher SHO stat. Certain coefficients and significance tests should be taken with caution. E.g. there is only one unique TOTY striker in the game.

Position Based Model for Forwards

	Dependent variable:			
	Log-Price (Xbox One)			
	(I)	(II)	(III)	(IV)
OVR	0.242^{***}			0.002
	(0.033)			(0.056)
PAC		0.109^{***}	0.081^{***}	
		(0.019)	(0.023)	
SHO		0.081^{***}	0.027	
		(0.020)	(0.024)	
PAS		0.139^{***}	0.164^{***}	
		(0.028)	(0.027)	
DRI		-0.080^{**}	-0.017	
		(0.032)	(0.033)	
Correct PAC				0.102^{***}
				(0.024)
Correct SHO				-0.003
				(0.027)
Correct PAS				0.172^{***}
				(0.035)
Correct DRI				-0.065^{**}
				(0.032)
Artificial PAC				0.302
				(0.187)
Artificial SHO				0.078
				(0.159)
Artificial PAS				-0.166
				(0.235)
Artificial DRI				0.033
				(0.301)
Skill Moves			-0.656^{***}	-0.538^{***}
			(0.205)	(0.200)
Weak Foot			0.371^{***}	0.433^{***}
			(0.115)	(0.121)
High Attacking Workrate			0.048	-0.164
			(0.186)	(0.214)
Premier League	1.100^{**}	2.238^{***}	1.083^{*}	1.127^{**}
	(0.471)	(0.445)	(0.565)	(0.511)
Bundesliga	-0.171	0.404	0.435	1.217^{**}
	(0.558)	(0.506)	(0.518)	(0.571)
LaLiga Santander	1.617^{**}	4.045^{***}	2.064^{**}	2.328^{***}
	(0.803)	(0.791)	(0.866)	(0.812)
Ligue 1 Conforama	0.935	2.127^{***}	1.516^{***}	1.346^{**}
	(0.578)	(0.529)	(0.557)	(0.535)
Serie A TIM	0.942^{*}	2.044^{***}	0.904	0.708
	(0.566)	(0.567)	(0.706)	(0.612)
Argentina	-0.867	-2.502^{***}	-0.456	0.068
	(0.622)	(0.551)	(0.682)	(0.618)
Belgium	-0.530	-1.421^{***}	-0.180	0.633
	(0.626)	(0.545)	(0.589)	(0.561)
Brazil	-0.453	-0.718^{*}	0.516	1.029^{***}
	(0.444)	(0.381)	(0.421)	(0.398)
France	-0.618	-3.036^{***}	-0.182	-0.083
	(0.937)	(0.861)	(0.980)	(0.844)
Italy	-0.549	-0.663^{**}	-0.294	0.150
	(0.354)	(0.323)	(0.296)	(0.266)
Holland	-0.083	0.007	0.527	0.835^{***}
	(0.399)	(0.342)	(0.335)	(0.315)
Portugal	0.384	-0.269	0.267	0.592^{*}
	(0.423)	(0.430)	(0.385)	(0.330)
Spain	-0.462	0.364	1.021^{**}	1.569^{***}
	(0.399)	(0.399)	(0.415)	(0.481)
Icon	2.135^{***}	2.099^{***}	1.922^{***}	1.994^{***}
	(0.379)	(0.358)	(0.369)	(0.393)
Icon Moment				0.798^{***}
				(0.203)

TOTS	-0.152	-0.628^{**}	-0.837^{***}	-0.372
	(0.344)	(0.316)	(0.297)	(0.332)
TOTY	0.466	-1.027^{**}	-0.736^{*}	-0.556
	(0.542)	(0.487)	(0.434)	(0.853)
Special Card	0.740^{**}	0.596^{**}	0.500^{**}	0.574^{***}
	(0.306)	(0.242)	(0.200)	(0.222)
Time	-0.004^{***}	-0.004^{***}	-0.004^{***}	-0.004^{***}
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Constant	-9.855^{***}	-9.331^{***}	-9.191^{***}	-6.108^{***}
	(2.633)	(1.987)	(1.930)	(1.983)
Observations	12,428	12,428	12,428	12,428
R^2	0.724	0.741	0.760	0.779
Adjusted R^2	0.724	0.740	0.759	0.778
F Statistic	$32{,}569^{***}$	$35{,}438^{***}$	$39{,}239^{***}$	$43{,}599^{***}$

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 14: The estimates suggest gamers spend more for fast forwards with good passing abilities. Note that the number of unique forwards in the sample is quite low.

Position Based Model for Wingers

	Dependent variable:			
	Log-Price (Xbox One)			
	(I)	(II)	(III)	(IV)
OVR	0.239^{***}			0.204^{***}
	(0.006)			(0.023)
PAC		0.025^{***}	0.021^{**}	
		(0.008)	(0.008)	
SHO		0.128^{***}	0.131^{***}	
		(0.006)	(0.006)	
DRI		-0.015	-0.020^{*}	
		(0.010)	(0.011)	
Correct PAC				-0.007
				(0.008)
Correct SHO				0.042^{***}
				(0.010)
Correct DRI				-0.069^{***}
				(0.012)
Artificial PAC				0.098
				(0.064)
Artificial SHO				0.135^{**}
				(0.055)
Artificial DRI				0.448^{***}
				(0.047)
Skill Moves			0.058	0.082
			(0.114)	(0.104)
Weak Foot			0.271^{***}	0.185^{***}
			(0.061)	(0.054)
High Attacking Workrate			0.151	0.146
			(0.105)	(0.096)
Premier League	0.537^{**}	0.896^{***}	0.847^{***}	0.296
	(0.224)	(0.227)	(0.224)	(0.206)
Bundesliga	0.576^{**}	0.477^{*}	0.626^{**}	0.362
	(0.281)	(0.283)	(0.295)	(0.266)
LaLiga Santander	0.787^{***}	1.147^{***}	0.993^{***}	0.589^{***}
	(0.249)	(0.251)	(0.249)	(0.225)
Ligue 1 Conforama	0.830^{***}	1.266^{***}	1.149^{***}	0.824^{***}
	(0.279)	(0.280)	(0.293)	(0.274)
Serie A TIM	1.056^{***}	1.345^{***}	1.355^{***}	0.981^{***}
	(0.278)	(0.281)	(0.276)	(0.259)
Argentina	-0.408^{**}	0.266	0.480^{***}	-0.124
	(0.174)	(0.176)	(0.182)	(0.169)
Belgium	0.028	0.977^{***}	0.894^{***}	0.684^{***}
	(0.169)	(0.172)	(0.175)	(0.165)
Brazil	-0.223	0.326^{**}	0.196	-0.190
	(0.137)	(0.141)	(0.150)	(0.136)
England	-0.123	0.309^{**}	0.430^{***}	0.355^{***}
	(0.135)	(0.140)	(0.144)	(0.129)
France	0.066	0.079	0.013	0.201^{*}
	(0.138)	(0.141)	(0.139)	(0.122)
Germany	0.007	-0.107	0.004	-0.098
	(0.151)	(0.160)	(0.164)	(0.147)
Italy	-0.849^{***}	-0.551^{**}	-0.799^{***}	-1.138^{***}
	(0.248)	(0.250)	(0.251)	(0.227)
Holland	-0.359	-0.286	-0.561^{**}	-0.383^{*}
	(0.232)	(0.236)	(0.253)	(0.227)
Portugal	-0.277	0.265	0.175	-0.182
	(0.174)	(0.175)	(0.179)	(0.163)
Spain	-0.931^{***}	-0.957^{***}	-0.781^{***}	-1.137^{***}
	(0.250)	(0.251)	(0.257)	(0.228)
Icon	1.670^{***}	2.170^{***}	2.181^{***}	1.690^{***}
	(0.242)	(0.245)	(0.252)	(0.238)
Icon Moment				0.607^{***}
				(0.197)
TOTS	0.048	0.237	0.293^{**}	0.116
	(0.144)	(0.144)	(0.142)	(0.129)

TOTY	0.908***	1.327***	1.204***	0.798***
	(0.290)	(0.289)	(0.286)	(0.250)
Special Card	0.609***	0.507***	0.501***	0.429***
	(0.129)	(0.130)	(0.127)	(0.113)
Time	−0.004***	−0.004***	−0.004***	−0.004***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Constant	−9.183***	−0.192	−0.932	−4.022***
	(0.582)	(0.724)	(0.841)	(1.013)
Observations	17,845	17,845	17,845	17,845
R^2	0.758	0.758	0.762	0.781
Adjusted R^2	0.758	0.758	0.761	0.781
F Statistic	55,798***	55,926***	56,892***	63,590***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 15: Gamers tend to pay more for fast wingers with good shooting abilities. Surprisingly, there are no significant price effects for dribbling. Note that gamers pay large premiums for players with artificially increased CS.

Position Based Model for Wide Midfielders

	Dependent variable:			
	Log-Price (Xbox One)			
	(I)	(II)	(III)	(IV)
OVR	0.121***			0.083***
	(0.004)			(0.010)
PAC		0.058***	0.053***	
		(0.008)	(0.008)	
SHO		0.031***	0.029***	
		(0.005)	(0.006)	
DRI		0.076***	0.082***	
		(0.013)	(0.015)	
Correct PAC				0.048***
				(0.007)
Correct SHO				0.006
				(0.006)
Correct DRI				0.019
				(0.020)
Artificial PAC				0.098**
				(0.043)
Artificial SHO				0.063***
				(0.024)
Artificial DRI				−0.084**
				(0.038)
Skill Moves			−0.058	0.084
			(0.077)	(0.076)
Weak Foot			0.017	0.035
			(0.046)	(0.042)
High Attacking Workrate			0.084	0.089
			(0.101)	(0.093)
Premier League	0.379***	−0.080	−0.044	0.019
	(0.146)	(0.162)	(0.165)	(0.148)
Bundesliga	0.199	−0.008	0.032	0.027
	(0.160)	(0.172)	(0.177)	(0.161)
LaLiga Santander	0.546***	0.268	0.314	0.138
	(0.187)	(0.204)	(0.214)	(0.195)
Ligue 1 Conforama	0.661***	0.060	0.067	0.211
	(0.149)	(0.168)	(0.169)	(0.153)
Serie A TIM	0.085	−0.414**	−0.331*	−0.493***
	(0.163)	(0.190)	(0.198)	(0.179)
Argentina	−0.708**	−0.247	−0.176	−0.536*
	(0.311)	(0.335)	(0.339)	(0.303)
Belgium	0.002	−0.493	−0.505	−0.542
	(0.369)	(0.389)	(0.389)	(0.359)
Brazil	0.137	−0.245*	−0.261*	−0.154
	(0.126)	(0.139)	(0.138)	(0.132)
England	1.409***	1.092***	1.193***	1.259***
	(0.331)	(0.357)	(0.358)	(0.325)
France	−0.155	−0.050	0.003	−0.125
	(0.105)	(0.113)	(0.120)	(0.109)
Germany	0.263	0.129	0.094	0.128
	(0.180)	(0.199)	(0.198)	(0.178)
Italy	0.416*	0.432	0.372	0.463**
	(0.249)	(0.268)	(0.266)	(0.236)
Holland	−0.166	−0.390**	−0.401**	−0.334**
	(0.170)	(0.185)	(0.181)	(0.161)
Portugal	0.146	0.507**	0.420**	0.336*
	(0.185)	(0.199)	(0.213)	(0.190)
Spain	−0.144	0.780***	0.690***	0.736***
	(0.171)	(0.219)	(0.221)	(0.200)
Icon	1.520***	1.420***	1.421***	1.336***
	(0.133)	(0.148)	(0.160)	(0.152)
Icon Moment				−0.060
				(0.212)
TOTS	−0.038	−0.414***	−0.398***	−0.245*
	(0.124)	(0.138)	(0.139)	(0.131)

Special Card	0.658*	0.556	0.550	0.536
	(0.375)	(0.394)	(0.387)	(0.356)
Time	−0.003***	−0.003***	−0.003***	−0.003***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Constant	0.854	−2.586***	−2.450***	−2.415***
	(0.537)	(0.860)	(0.872)	(0.890)
Observations	9,812	9,812	9,812	9,812
R^2	0.832	0.820	0.826	0.848
Adjusted R^2	0.832	0.820	0.825	0.847
F Statistic	48,624***	44,714***	46,308***	54,402***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 16: For wide midfielders I find that the coefficients are quite different compared to wingers, especially the significant effect for dribbling. Note that gamers tend to pay more for artificially increased PAC and SHO, but the coefficient for artificial DRI is negative.

Position Based Model for Central Attacking Midfielders

	Dependent variable:			
	Log-Price (Xbox One)			
	(I)	(II)	(III)	(IV)
OVR	0.017***			−0.054***
	(0.005)			(0.009)
PAC		0.037***	0.040***	
		(0.013)	(0.013)	
SHO		0.083***	0.096***	
		(0.010)	(0.011)	
DRI		−0.046***	−0.071***	
		(0.014)	(0.015)	
Correct PAC				0.053***
				(0.011)
Correct SHO				0.079***
				(0.010)
Correct DRI				−0.030*
				(0.016)
Artificial PAC				0.014
				(0.081)
Artificial SHO				0.192***
				(0.064)
Artificial DRI				0.142**
				(0.068)
Skill Moves			0.424***	0.416***
			(0.107)	(0.095)
Weak Foot			0.053	0.119**
			(0.059)	(0.051)
High Attacking Workrate			−0.300**	−0.259**
			(0.128)	(0.108)
Premier League	1.378***	1.982***	1.895***	1.846***
	(0.261)	(0.311)	(0.323)	(0.291)
Bundesliga	1.144***	1.785***	1.481***	1.666***
	(0.298)	(0.370)	(0.373)	(0.323)
LaLiga Santander	0.973***	1.572***	1.355***	1.461***
	(0.334)	(0.394)	(0.400)	(0.348)
Ligue 1 Conforama	2.102***	2.521***	2.261***	2.210***
	(0.264)	(0.324)	(0.337)	(0.306)
Serie A TIM	0.376	1.134***	1.293***	1.117***
	(0.264)	(0.324)	(0.332)	(0.281)
Argentina	1.009***	0.791***	0.721***	0.742***
	(0.149)	(0.177)	(0.218)	(0.190)
Belgium	0.973***	0.898***	1.059***	1.272***
	(0.177)	(0.214)	(0.218)	(0.196)
Brazil	1.241***	1.001***	0.898***	0.870***
	(0.116)	(0.134)	(0.161)	(0.138)
England	−0.741***	−0.728***	−0.793***	−0.602***
	(0.212)	(0.243)	(0.257)	(0.227)
France	−0.847***	−0.544**	−0.219	−0.104
	(0.180)	(0.217)	(0.229)	(0.192)
Germany	0.642***	0.219	0.294	0.141
	(0.186)	(0.273)	(0.269)	(0.247)
Italy	0.351*	0.569**	0.129	0.065
	(0.191)	(0.223)	(0.241)	(0.206)
Holland	0.174	0.171	0.173	0.196
	(0.172)	(0.196)	(0.196)	(0.169)
Portugal	−0.157	0.272	0.221	0.247*
	(0.142)	(0.169)	(0.168)	(0.145)
Spain	−0.380	0.716**	1.150***	1.188***
	(0.260)	(0.350)	(0.370)	(0.313)
Icon	2.583***	2.940***	2.709***	2.794***
	(0.231)	(0.270)	(0.281)	(0.253)
Icon Moment				0.438***
				(0.125)
TOTS	1.566***	1.042***	1.042***	1.054***
	(0.122)	(0.146)	(0.146)	(0.132)

TOTY	1.635^{***}	1.009^{**}	0.886^{**}	0.827^{**}
	(0.346)	(0.401)	(0.398)	(0.345)
Special Card	0.617^{***}	0.553^{***}	0.638^{***}	0.429^{***}
	(0.166)	(0.193)	(0.190)	(0.165)
Time	-0.004^{***}	-0.004^{***}	-0.004^{***}	-0.004^{***}
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Constant	9.071^{***}	4.160^{***}	3.315^{***}	4.737^{***}
	(0.533)	(0.750)	(0.830)	(0.846)
Observations	19,760	19,760	19,760	19,760
R^2	0.738	0.728	0.730	0.749
Adjusted R^2	0.738	0.727	0.730	0.749
F Statistic	$55{,}639^{***}$	$52{,}764^{***}$	$53{,}337^{***}$	$58{,}971^{***}$

Note: *p<0.1; **p<0.05; ***p<0.01

Table 17: For CAMs I find a positive significant effect for PAC and SHO, but a negative coefficient for DRI. Note that players shouldn't decrease in price with better relevant stats and that the relationship is spurious. The multicollinearity issue couldn't be solved with the model specification procedure. Gamers pay premiums for players with artificially increased SHO and DRI stats.

Position Based Model for Central Midfielders

	Dependent variable:			
	Log-Price (Xbox One)			
	(I)	(II)	(III)	(IV)
OVR	0.139***			0.020
	(0.009)			(0.023)
PAC		0.017***	0.013**	
		(0.005)	(0.005)	
SHO		0.006	0.008	
		(0.007)	(0.007)	
PAS		0.067***	0.069***	
		(0.008)	(0.009)	
DEF		−0.001	−0.007	
		(0.005)	(0.005)	
PHY		0.007	0.011	
		(0.008)	(0.008)	
Correct PAC				0.013**
				(0.006)
Correct SHO				0.016**
				(0.007)
Correct PAS				0.025*
				(0.015)
Correct DEF				−0.010**
				(0.005)
Correct PHY				0.005
				(0.008)
Artificial PAC				0.193**
				(0.088)
Artificial SHO				0.174***
				(0.034)
Artificial PAS				0.294***
				(0.093)
Artificial DEF				−0.129*
				(0.072)
Artificial PHY				0.063
				(0.050)
Weak Foot			0.004	0.030
			(0.054)	(0.049)
High Attacking Workrate			−0.071	−0.153*
			(0.089)	(0.079)
High Defensive Workrate			0.268***	0.168*
			(0.099)	(0.092)
Premier League	−0.219	−0.036	0.016	−0.079
	(0.286)	(0.293)	(0.302)	(0.287)
Bundesliga	−0.562*	−0.549*	−0.452	−0.570*
	(0.325)	(0.330)	(0.343)	(0.335)
LaLiga Santander	−0.458	−0.276	−0.266	−0.469
	(0.303)	(0.308)	(0.316)	(0.311)
Ligue 1 Conforama	−0.653**	−0.562*	−0.522	−0.642*
	(0.316)	(0.341)	(0.352)	(0.329)
Serie A TIM	−0.199	0.027	0.160	0.070
	(0.311)	(0.309)	(0.321)	(0.311)
Argentina	0.038	−0.330*	−0.176	−0.362*
	(0.190)	(0.192)	(0.210)	(0.206)
Belgium	0.493***	0.462***	0.347**	0.285*
	(0.140)	(0.153)	(0.165)	(0.147)
Brazil	0.520***	0.365**	0.324*	0.277*
	(0.167)	(0.172)	(0.179)	(0.164)
England	−0.011	−0.274	−0.093	−0.248
	(0.153)	(0.170)	(0.194)	(0.179)
France	1.167***	1.147***	1.230***	1.081***
	(0.124)	(0.154)	(0.163)	(0.155)
Germany	0.303**	0.154	0.173	0.070
	(0.131)	(0.135)	(0.142)	(0.128)
Italy	0.070	0.267	0.231	0.199
	(0.213)	(0.220)	(0.229)	(0.238)

Holland	0.711***	0.247	0.407**	0.378*
	(0.183)	(0.185)	(0.200)	(0.194)
Portugal	−0.061	−0.389**	−0.198	−0.482**
	(0.180)	(0.190)	(0.216)	(0.208)
Spain	0.232*	0.165	0.257*	0.152
	(0.121)	(0.129)	(0.144)	(0.127)
Icon	1.290***	1.623***	1.550***	1.617***
	(0.286)	(0.282)	(0.291)	(0.299)
Icon Moment				0.723***
				(0.167)
TOTS	0.173	0.280**	0.206	0.321**
	(0.118)	(0.134)	(0.143)	(0.139)
TOTY	2.126***	2.342***	2.326***	2.350***
	(0.345)	(0.351)	(0.362)	(0.477)
Special Card	0.691***	0.644***	0.673***	0.397**
	(0.194)	(0.191)	(0.198)	(0.193)
Time	−0.004***	−0.004***	−0.004***	−0.004***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Constant	−0.356	3.829***	3.679***	6.088***
	(0.867)	(0.713)	(0.773)	(1.241)
Observations	17,740	17,740	17,740	17,740
R^2	0.802	0.805	0.802	0.820
Adjusted R^2	0.802	0.804	0.801	0.819
F Statistic	71,690***	72,981***	71,513***	80,502***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 18: For CMs I find that gamers pay large premiums for artificial stats.

Position Based Model for Central Defensive Midfielders

	Dependent variable:			
	Log-Price (Xbox One)			
	(I)	(II)	(III)	(IV)
OVR	0.402^{***}			0.063^{**}
	(0.015)			(0.026)
PAC		0.050^{***}	0.050^{***}	
		(0.002)	(0.002)	
PAS		0.067^{***}	0.054^{***}	
		(0.010)	(0.011)	
DEF		0.075^{***}	0.083^{***}	
		(0.013)	(0.014)	
PHY		-0.032	-0.037	
		(0.020)	(0.023)	
Correct PAC				0.043^{***}
				(0.004)
Correct PAS				0.035^{***}
				(0.011)
Correct DEF				0.033^{*}
				(0.018)
Correct PHY				0.014
				(0.020)
Artificial PAC				-0.086
				(0.174)
Artificial PAS				-0.134^{*}
				(0.075)
Artificial DEF				0.469^{**}
				(0.238)
Artificial PHY				0.180^{**}
				(0.081)
High Attacking Workrate			0.355^{**}	0.211^{*}
			(0.156)	(0.111)
High Defensive Workrate			0.083	0.145
			(0.114)	(0.128)
Premier League	1.404^{***}	-0.440	-0.251	0.628
	(0.457)	(0.284)	(0.279)	(0.420)
Bundesliga	0.458	0.305	0.454	0.582^{***}
	(0.437)	(0.284)	(0.291)	(0.199)
LaLiga Santander	0.273	0.207	0.326	0.909^{**}
	(0.487)	(0.345)	(0.329)	(0.385)
Ligue 1 Conforama	0.937^{**}	-0.476^{*}	-0.585^{**}	-0.130
	(0.422)	(0.265)	(0.279)	(0.324)
Serie A TIM	1.016^{**}	-0.495	-0.745^{**}	0.343
	(0.472)	(0.320)	(0.316)	(0.438)
Argentina	0.405	-1.539^{***}	-1.225^{***}	-0.377
	(0.403)	(0.337)	(0.355)	(0.328)
Belgium	2.419^{***}	-0.453^{**}	-0.398^{*}	-0.182
	(0.312)	(0.217)	(0.205)	(0.234)
Brazil	1.123^{***}	-0.287^{*}	-0.264	-0.312
	(0.263)	(0.173)	(0.172)	(0.196)
England	2.046^{***}	-0.767^{**}	-0.306	0.0001
	(0.413)	(0.355)	(0.416)	(0.363)
France	1.257^{***}	-0.451^{**}	-0.389^{**}	-0.442^{**}
	(0.276)	(0.195)	(0.187)	(0.218)
Germany	1.019^{***}	-1.427^{***}	-1.509^{***}	-0.824^{***}
	(0.350)	(0.281)	(0.307)	(0.257)
Italy	1.185^{***}	-0.209	-0.088	-0.258
	(0.356)	(0.226)	(0.215)	(0.227)
Holland	1.463^{***}	-0.695^{***}	-0.384	-0.079
	(0.356)	(0.260)	(0.325)	(0.254)
Spain	1.350^{***}	-0.603^{*}	-0.477	-0.149
	(0.335)	(0.324)	(0.386)	(0.249)
Icon	1.983^{***}	1.328^{***}	1.262^{***}	1.818^{***}
	(0.389)	(0.286)	(0.266)	(0.309)
Icon Moment				-0.001
				(0.184)

TOTS	-1.207^{***}	-0.394^{**}	-0.253	-0.254
	(0.200)	(0.155)	(0.161)	(0.191)
TOTY	-1.051^{***}	0.864^{***}	0.950^{***}	-0.053
	(0.390)	(0.282)	(0.283)	(0.622)
Special Card	0.515^{**}	-0.231	-0.188	-0.077
	(0.215)	(0.159)	(0.152)	(0.133)
Time	-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Constant	-25.509^{***}	0.503	1.007	-3.385^{*}
	(1.557)	(1.264)	(1.401)	(1.837)
Observations	7,268	7,268	7,268	7,268
R^2	0.759	0.826	0.837	0.910
Adjusted R^2	0.758	0.825	0.836	0.909
F Statistic	$22{,}767^{***}$	$34{,}361^{***}$	$37{,}082^{***}$	$72{,}993^{***}$

Note: *p<0.1; **p<0.05; ***p<0.01

Table 19: I find that gamers pay large premiums for CDMs with artificial DEF and PHY stats. This has an effect on the usually high TOTY coefficient, but barely changes the Icon price effect.

Position Based Model for Fullbacks

	Dependent variable:			
	Log-Price (Xbox One)			
	(I)	(II)	(III)	(IV)
OVR	0.097***			−0.012
	(0.005)			(0.014)
PAC		0.010**	0.010**	
		(0.005)	(0.005)	
PAS		0.033***	0.033***	
		(0.005)	(0.005)	
DEF		0.028***	0.028***	
		(0.006)	(0.006)	
PHY		0.027***	0.028***	
		(0.006)	(0.007)	
Correct PAC				0.016***
				(0.004)
Correct PAS				0.020***
				(0.006)
Correct DEF				0.044***
				(0.008)
Correct PHY				−0.002
				(0.007)
Artificial PAC				0.060***
				(0.022)
Artificial PAS				0.119***
				(0.019)
Artificial DEF				0.362***
				(0.027)
Artificial PHY				0.083***
				(0.021)
High Attacking Workrate			−0.025	−0.011
			(0.086)	(0.077)
High Defensive Workrate			−0.107	−0.022
			(0.081)	(0.071)
Premier League	0.108	0.182	0.228*	0.220**
	(0.095)	(0.116)	(0.122)	(0.108)
Bundesliga	−0.086	−0.042	−0.062	−0.175
	(0.111)	(0.133)	(0.134)	(0.118)
LaLiga Santander	0.051	0.233**	0.239**	0.357***
	(0.102)	(0.118)	(0.119)	(0.107)
Ligue 1 Conforama	0.150	0.143	0.137	0.168
	(0.127)	(0.150)	(0.151)	(0.132)
Serie A TIM	0.042	0.014	0.040	0.100
	(0.104)	(0.121)	(0.128)	(0.112)
Argentina	−0.269	−0.275	−0.282	−0.091
	(0.167)	(0.196)	(0.197)	(0.173)
Belgium	−0.528***	−0.456*	−0.384	−0.239
	(0.201)	(0.237)	(0.244)	(0.212)
Brazil	−0.106	−0.080	−0.082	−0.068
	(0.101)	(0.117)	(0.117)	(0.104)
England	−0.092	−0.195	−0.217*	−0.238**
	(0.105)	(0.123)	(0.124)	(0.109)
France	−0.062	−0.126	−0.135	0.136
	(0.116)	(0.133)	(0.134)	(0.118)
Germany	−0.200	−0.026	−0.030	0.202
	(0.136)	(0.159)	(0.160)	(0.141)
Italy	−0.406***	−0.282	−0.321*	−0.156
	(0.150)	(0.173)	(0.180)	(0.160)
Holland	0.459	0.137	0.115	0.196
	(0.323)	(0.372)	(0.375)	(0.330)
Portugal	−0.318***	−0.250*	−0.248*	−0.323***
	(0.105)	(0.129)	(0.132)	(0.116)
Spain	−0.101	−0.057	−0.077	−0.144
	(0.107)	(0.133)	(0.135)	(0.118)
Icon	1.578***	1.675***	1.758***	1.899***
	(0.134)	(0.156)	(0.168)	(0.152)

Icon Moment				0.812**
				(0.337)
TOTS	0.164**	−0.092	−0.095	−0.013
	(0.081)	(0.099)	(0.099)	(0.095)
TOTY	1.574***	1.165***	1.143***	1.651***
	(0.331)	(0.383)	(0.386)	(0.341)
Special Card	0.768***	0.617***	0.594***	0.356**
	(0.147)	(0.169)	(0.171)	(0.150)
Time	−0.003***	−0.003***	−0.003***	−0.003***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Constant	3.015***	3.405***	3.473***	5.892***
	(0.400)	(0.430)	(0.434)	(0.543)
Observations	19,421	19,421	19,421	19,421
R^2	0.697	0.664	0.663	0.702
Adjusted R^2	0.697	0.664	0.663	0.701
F Statistic	44,623***	38,292***	38,103***	45,506***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 20: Fullbacks are more expensive per PAC, PAS, DEF and PHY unit and gamers pay large premiums for artificially increased stats. Note that once again TOTY, Icon and special card price effects in general are very high.

Position Based Model for Centre-backs

	Dependent variable:			
	Log-Price (Xbox One)			
	(I)	(II)	(III)	(IV)
OVR	0.120***			0.098***
	(0.004)			(0.013)
PAC		0.029***	0.027***	
		(0.003)	(0.002)	
DEF		0.074***	0.076***	
		(0.006)	(0.006)	
Correct PAC				0.018***
				(0.003)
Correct DEF				−0.017
				(0.014)
Artificial PAC				−0.089***
				(0.017)
Artificial DEF				−0.011
				(0.023)
Jumping		0.001	0.005*	0.003
		(0.003)	(0.003)	(0.003)
Stamina		0.014***	0.024***	0.024***
		(0.004)	(0.004)	(0.004)
Strength		0.032***	0.017***	0.013**
		(0.005)	(0.005)	(0.005)
Aggression		−0.009*	−0.003	0.005
		(0.005)	(0.004)	(0.004)
High Attacking Workrate			0.001	−0.022
			(0.055)	(0.052)
High Defensive Workrate			0.104*	0.072
			(0.054)	(0.051)
Height			0.016***	0.012**
			(0.006)	(0.006)
Weight			0.023***	0.023***
			(0.007)	(0.006)
Premier League	0.048	0.329***	0.341***	0.306***
	(0.140)	(0.113)	(0.102)	(0.096)
Bundesliga	−0.103	0.044	0.138	0.016
	(0.201)	(0.166)	(0.153)	(0.146)
LaLiga Santander	−0.164	0.131	0.275**	0.209*
	(0.166)	(0.136)	(0.124)	(0.118)
Ligue 1 Conforama	−0.376**	−0.012	0.103	0.037
	(0.166)	(0.136)	(0.126)	(0.118)
Serie A TIM	−0.174	−0.055	−0.095	−0.062
	(0.161)	(0.130)	(0.118)	(0.112)
Argentina	−0.457	0.264	0.243	−0.016
	(0.297)	(0.237)	(0.219)	(0.208)
Belgium	0.070	0.231**	0.200**	0.188*
	(0.128)	(0.103)	(0.099)	(0.096)
Brazil	0.436***	0.520***	0.485***	0.503***
	(0.129)	(0.104)	(0.096)	(0.092)
England	0.324***	0.341***	0.403***	0.404***
	(0.120)	(0.096)	(0.102)	(0.096)
France	0.529***	0.367***	0.321***	0.348***
	(0.104)	(0.083)	(0.076)	(0.072)
Germany	0.125	0.396***	0.379***	0.441***
	(0.188)	(0.154)	(0.145)	(0.137)
Italy	0.190*	0.441***	0.543***	0.589***
	(0.099)	(0.088)	(0.081)	(0.076)
Holland	0.638***	0.521***	0.436***	0.422***
	(0.120)	(0.100)	(0.110)	(0.103)
Portugal	0.179	0.747**	0.888***	0.848***
	(0.341)	(0.291)	(0.265)	(0.252)
Spain	0.171	0.343***	0.259***	0.269***
	(0.112)	(0.090)	(0.091)	(0.085)
Icon	1.094***	1.080***	1.136***	1.080***
	(0.162)	(0.126)	(0.115)	(0.110)

Icon Moment				0.431***
				(0.088)
TOTS	0.253***	0.016	0.023	0.055
	(0.085)	(0.071)	(0.064)	(0.065)
TOTY	1.310***	0.927***	0.803***	0.865***
	(0.174)	(0.139)	(0.124)	(0.122)
Special Card	0.397***	0.378***	0.391***	0.435***
	(0.109)	(0.086)	(0.077)	(0.072)
Time	−0.003***	−0.003***	−0.003***	−0.003***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Constant	1.303***	−0.233	−5.706***	−4.653***
	(0.386)	(0.465)	(1.105)	(1.123)
Observations	24,091	24,091	24,091	24,091
R^2	0.756	0.805	0.827	0.839
Adjusted R^2	0.756	0.804	0.826	0.839
F Statistic	74,555***	99,097***	114,692***	125,385***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 21: Gamers tend to pay more for fast defenders with good defending abilities which are strong and have high stamina. The CS/IGS models fit the data better than the OVR model which could be an indicator that defenders should be rated differently. For the artificial PAC stats I find a negative coefficient.

The Final Models Under RE and OLS

	Dependent variable:			
	Log-Price (Xbox One)			
	RE	RE	POLS	POLS
	(1)	(2)	(3)	(4)
OVR	0.132***	0.135***	0.184***	0.175***
	(0.002)	(0.002)	(0.0005)	(0.001)
Top 2.5% Player		−0.109***		0.392***
		(0.006)		(0.007)
Premier League	0.228***	0.229***	0.187***	0.174***
	(0.061)	(0.059)	(0.009)	(0.009)
Bundesliga	0.026	0.025	−0.013	−0.017*
	(0.073)	(0.071)	(0.010)	(0.010)
LaLiga Santander	0.135**	0.139**	−0.021**	−0.048***
	(0.067)	(0.065)	(0.009)	(0.009)
Ligue 1	0.097	0.099	0.138***	0.137***
	(0.072)	(0.070)	(0.010)	(0.010)
Serie A TIM	0.061	0.061	0.045***	0.030***
	(0.065)	(0.064)	(0.009)	(0.009)
Argentina	0.079	0.081	0.083***	0.065***
	(0.063)	(0.061)	(0.006)	(0.006)
Belgium	0.106	0.103	−0.054***	−0.035***
	(0.069)	(0.068)	(0.007)	(0.007)
Brazil	0.239***	0.238***	0.277***	0.272***
	(0.050)	(0.049)	(0.005)	(0.005)
England	−0.020	−0.019	−0.013**	−0.011**
	(0.056)	(0.055)	(0.005)	(0.005)
France	0.278***	0.275***	0.357***	0.364***
	(0.049)	(0.048)	(0.005)	(0.005)
Germany	0.082	0.085	0.090***	0.074***
	(0.065)	(0.063)	(0.006)	(0.006)
Italy	−0.189***	−0.191***	−0.174***	−0.168***
	(0.062)	(0.061)	(0.005)	(0.005)
Holland	0.166***	0.162***	0.144***	0.157***
	(0.061)	(0.060)	(0.005)	(0.005)
Portugal	0.225***	0.229***	0.328***	0.310***
	(0.066)	(0.064)	(0.006)	(0.006)
Spain	−0.146**	−0.149***	−0.080***	−0.071***
	(0.058)	(0.056)	(0.006)	(0.006)
Icon	1.372***	1.371***	1.097***	1.079***
	(0.062)	(0.061)	(0.009)	(0.009)
TOTS	0.241***	0.243***	−0.065***	−0.111***
	(0.044)	(0.043)	(0.006)	(0.006)
TOTY	1.560***	1.611***	0.967***	0.757***
	(0.127)	(0.124)	(0.010)	(0.011)
Special Card	0.590***	0.594***	0.398***	0.388***

	(0.063)	(0.061)	(0.007)	(0.007)
Striker	0.151***	0.147***	−0.056***	−0.050***
	(0.049)	(0.048)	(0.005)	(0.005)
Forward	0.255***	0.247***	0.186***	0.202***
	(0.072)	(0.071)	(0.006)	(0.006)
Winger	0.213***	0.207***	0.003	0.019***
	(0.057)	(0.056)	(0.005)	(0.005)
Wide Midfielder	−0.183***	−0.181***	−0.288***	−0.301***
	(0.063)	(0.062)	(0.007)	(0.006)
Central Attacking Midfielder	0.085	0.082	−0.124***	−0.119***
	(0.060)	(0.059)	(0.005)	(0.005)
Central Defensive Midfielder	−0.162**	−0.166**	−0.240***	−0.239***
	(0.079)	(0.077)	(0.007)	(0.007)
Fullback	−0.127**	−0.116**	−0.282***	−0.311***
	(0.054)	(0.053)	(0.006)	(0.006)
Centre-back	−0.117**	−0.121**	−0.259***	−0.253***
	(0.054)	(0.053)	(0.005)	(0.005)
Time	−0.004***	−0.004***	−0.003***	−0.003***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Constant	0.228	−0.046	−3.996***	−3.182***
	(0.185)	(0.184)	(0.042)	(0.044)
Observations	167,224	167,224	167,224	167,224
R^2	0.713	0.717	0.767	0.771
Adjusted R^2	0.713	0.717	0.767	0.771
F Statistic	416,015***	423,479***	18,935*** (df = 29; 167194)	18,751*** (df = 30; 167193)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 22: Under different model assumptions I find different coefficients for most regressors. Notable similar coefficients are found for OVR, the Premier League, most nations, special cards, incl. Icons and TOTY cards and for more defensive positions. Over time META players seem to decrease in price. These results is quite strong evidence for fixed and not random price effects for individual players cards. But due to the lack of an appropriate estimator, I estimated the coefficients under RE model assumptions or without controlling for individual effects.