

# Untalented but Successful\*

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## Abstract

When studying the problem of the emergence of superstars, scholars face great difficulties in measuring talent, obtaining confidential data on earnings, and finding econometric techniques that are robust to the presence of outliers (superstars). In this paper we use an original quasi-experimental dataset from the Pokemon trading card game in which (i) there is no unidentifiable heterogeneity, (ii) rarity can be separated from talent and (iii) objective earnings are observable (through transaction prices). To prevent the results from being distorted by the presence of outliers, we estimate the “fair” price of each individual, using the robust Least Trimmed of Squares regression technique in a hedonic prices framework,

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and check the effective price at which they are sold. This allows to identify superstars, i.e. individuals that are sold at a price which is much higher than their competitors. We find that the two main theories of superstars developed by Rosen (1981), which awards a central importance to talent, and by Adler (1985), which awards more importance to the need of consumers to share a common culture, are complementary and not, as is often claimed, mutually exclusive.

**Keywords:** Superstars, Robust Estimation, Hedonic Prices, Quasi-experimental Data

**JEL Classification:** C4, D4, Z19

## 1 Introduction

Success stories (and superstardom) are commonly believed to be related to talent. Relying on this idea, Rosen (1981) developed an elegant theoretical model showing how “small differences in talent become magnified in large earnings differences, with greater magnification of the earnings-talent gradient increasing sharply near the top of the scale” (p.846). This vision was refuted by Adler (1985) who suggests that superstars may emerge even among equally-talented individuals. He argues that superstars are those artists who happen to be known by the group, not necessarily because of their talent, and benefit from the network effects induced by the need of consumers to share a common culture (Adler, 2005).

Rosen (1981) and Adler (1985) arrive at these conflicting conclusions since, although they

agree on the fact that superstardom rests on large economies of scale on the supply side<sup>1</sup>, they have a very different vision of the demand side. Rosen (1981) believes that lower talent is an imperfect substitute of higher talent and, assuming that talent is fully observable, concludes that the (slightly) more talented individuals attract the market demand towards them. Adler (1985), on the other hand, awards a substantial importance to network effects. Relying on the well-known Stigler and Becker (1977) notion of consumption capital, he states that a consumer's appreciation of an artistic good depends both on his past consumption and the interaction he has with other experienced consumers. Since more popular artists have higher interaction potential (search costs needed to find an interesting interlocutor are lower), he concludes that networks can snowball an individual into becoming a superstar, even if he is not very talented. For Adler, superstardom is driven by the initial advantage of being identified (and "consumed") by some members of the group, and social links do the rest. In a more recent paper, Adler (2005) even states that this is probably why artists use publicity such as appearances on talk shows and coverage in tabloids and magazines to signal their popularity.

A recurrent question is whether Rosen's or Adler's theory better predicts the emergence of superstars or, stated differently, if superstardom is related to talent or not. Empirical findings point mostly in Adler's direction but cannot lead to a clear rejection of Rosen's hypothesis since talent itself is generally poorly measured (see Adler, 2005).

Hamlen (1991, 1994) for instance, studying the music industry, finds that talent, proxied

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<sup>1</sup>In the music industry, for instance, the economies of scale associated to the reproduction of CD's are enormous.

by voice quality, improves record sales with rewards for talent that are far less than proportional to differences in talent. This may be seen as evidence against Rosen's theory but, can voice quality be considered as a good proxy for talent? Studying the same industry, Chung and Cox (1994) find that the superstardom phenomenon is mainly the result of a probability mechanism which predicts that "artistic outputs will be concentrated among a few lucky individuals" (p.771), but do these few lucky individuals have the same objective level of talent as the unsuccessful artists?

Even worse, proxies for talent are often only ex-post measures of career success and are, therefore, endogenous. Lucifora and Simmons (2003) for example, use, among other indicators, the number of goals scored by a soccer player as a proxy for his talent. But, if we accept the fact that a player is more productive if he plays in a good environment, an average player may well end up playing for a top team, for example thanks to his skilled agent, and consequently become a heavy scorer. The endogeneity of the measure is evident. This example also points out that a measure of the talent of an artist should not be influenced by the skills of his manager. Indeed, a well managed mediocre artist could reach fame and success, while an excellent performer could remain unknown if his agent is inefficient. Finally, talent must be quantified independently of rarity, which may complicate the measurement substantially. For instance, are minor paintings from icon painters more valuable because of their quality or because of their limited supply?

Earnings are also imperfectly quantified. As argued by Rosen (1981), privacy and confidentiality make data collecting (especially on earnings) very problematic.

To summarize, theories of superstardom can only be tested with great difficulty and it is essential to rely on a dataset created in a quasi-experimental setup, where talent is explicitly measurable and all differences between individuals can be objectively identified, to be able to treat confounding effects properly.

In the existing literature, as far as we know, there are no empirical papers that cope with all of these problems at the same time. In this paper, we address the question by using some new data on the Pokemon Trading Card Game (TCG), in a similar way as Mullin and Dunn (2002) for baseball player cards or Lucking-Reiley (1999) for the Magic Trading Card Game.

We believe that the Pokemon TCG dataset is well-suited since talent is fully observable, totally objective and explicitly provided in the cards; the supply of cards is exogenously controlled by a single firm (Wizard of the Coast) that provides objective rarity indicators; the trading price of cards is available and represents an adequate measure of success; no role whatsoever is played by managers and, most importantly, Pokemons are particularly well adapted to analyze the emergence of idols, given their huge commercial success.

The Pokemon TCG can be considered as a quasi-experimental dataset in the sense that all characteristics of individuals are objectively measured. Furthermore, since the experiment design was not specifically engineered to answer the questions we raise, we believe that the consumers' behavior is spontaneous and not biased in favor or against a specific hypothesis.

As far as our empirical strategy is concerned, we estimate a hedonic price equation for the TCG, taking into account that, as superstars are outliers, they distort OLS estimations. This is done using the Least Trimmed of Squares (LTS) estimator. Fitted residuals are then

used to identify overpriced and underpriced characters. If Rosen's assumption, we should observe large positive residuals for the highest levels of talent while, if Adler is right, we should observe such outliers everywhere.

The estimations show that superstars *à la Rosen* may coexist with superstars *à la Adler*. In the long-run there is some evidence pointing out that both types of superstars might disappear even if the latter tends to disappear faster.

The paper is organized as follows: section 2 presents the game and section 3 describes the data. Section 4 lays down the empirical strategy, while section 5 presents the results. Finally, section 6 concludes.

## 2 The Game

In this section, we very briefly present the fundamentals of the extremely sophisticated rules of the Pokemon Trading Card Game. More complete explanations are provided in Appendix 1 and, for further details, we refer to the complete rules available in reference sites dedicated to pocket monsters such as [pojo.com](http://pojo.com). Note however that a full knowledge of the rules is not indispensable for the understanding the paper.

Basically, the game is played as follows: two players take turns playing cards from their hands. At each turn, the player chooses one Active Pokemon to attack with it. This will either cause some damage to the opponent's Active "Defending Pokemon" or has some other effect (such as making it fall asleep, confused, paralyzed, or poisoned) that will affect its ability for the following counter-attack. If the attack does enough damage to knock out the

defending pokemon, the winning player gets 1 Point. When a player has knocked out 6 of the opponent's active Pokemons, he wins the game. Each pokemon card has a specific strength (measured in damage points) and resistance (measured in health or hit points). These two features are strongly correlated and are summarized in a single "level" indicator printed on the card. It is thus extremely easy for players to identify the most "talented" individuals.

### **3 The Data**

In 2003, there were more than 400 pokemon cards (and around 200 in 2000) for 152 documented Pokemon species . Each creature has its own special fighting abilities or characteristics. Creatures come in different shapes (mouse, rat, virtual, magnet, pig monkey, etc.) and sizes. Some Pokemon characters, such as Pikachu, are cute, while others, like Alakazam, are terrifying. In addition, each card has a specific rarity level which is exogenously determined by "Wizard of the Coast".

Cards are commercialized in decks but, since these are not complete and some specific cards are very rarely included, they are also available on the single card market either on the Internet or through specialized games shops. We collected data (including prices) on objective characteristics of all 442 Pokemon cards which existed in in January 2003. Our source of information for prices is SCRYE the guide to collectible games, a monthly magazine recognized as the most accurate source of game card prices among gamers. SCRYE provides the median price charged by a large sample of retail outlets (around 40) across the United States (and Canada). These prices reflect actual market transactions. SCRYE does not

sell cards. In order to follow-up the most overpriced characters, we collected price data for March 2000 (the booming period of Pokemons), July 2000, September 2000, November 2000, January 2001, April 2002, October 2002 and January 2003. As far as the characteristics of Pokemons are concerned, they are printed directly on cards and thus readily available.

Pokemons' characteristics can be divided into three groups: creature's specificities, settings and rarity.

### **3.1 Creature's Characteristics**

Pokemon cards have very different characteristics. The first and most important one is its strength: each Pokemon is associated with a given number of damage points that it can cause to the opponent (ranging from 0 to 120). The second and as important characteristic is its resistance to attacks, that is calculated in terms of hit points (ranging from 30 to 120). It is important to highlight that the superstar theory is based on a one-dimensional measure of talent, while in the Pokemons' case we have a combination of "resistance" and "weakness". Fortunately, such a one-dimensional measure is readily available through the level of the card, which is an explicit indicator of absolute talent (linear index ranging from 5 to 76) printed on the cards. This explicit indicator is highly (positively) correlated with both "resistance" and "weakness".

Pokemons have other characteristics that are not related to absolute talent. For example, each monster is characterized by a particular element (lightning, fighting, fire, grass, psychic, water or colorless). There is no best element but creatures are sensitive to the element

associated with the opponent. For example, a “fighting” Pokemon is weak with respect to a “psychic” one and a “fire” Pokemon is weak with respect to a “water” one. This influences the efficiency of attacks and defense. The elements associated to pokemons are converted into zero-one dummies, to control for the type in the hedonic price estimation.

Similarly, the attacks of Pokemons can be strengthened (in the short-run) by playing trainer cards. Each Pokemon is associated with a trainer. This information is converted into dummies, identifying all trainers. Finally, additional dummies are created to discriminate between basic, evolution-one and evolution-two cards. Additionally, some cards can launch sophisticated attacks i.e. attacks producing specific damage which are expressed in terms of other characteristics than hit points (such as, for example, a reduction in the damages that the “Defendent Pokemon” can cause in the counter-attack)

It might be argued that cuteness could also explain prices and not considering it in the hedonic equation could bias the results. We do not agree with this for several reasons.

If we look at the problem from a player’s perspective, we conclude that the influence of cuteness is negligible since being good-looking does not affect the odds of winning the game. On the other hand, if we look at it from a collector’s perspective, we expect cuteness to be valuable. Nevertheless, this value should become negligible once rarity is being taken into account as the latter is what really interests collectors. It is important to emphasize that even if cuteness was significantly prized, its introduction in the estimated model should not affect the generality of our results as the variables identifying the strength of cards and the cuteness of monsters are orthogonal. Furthermore, looking at the estimated  $R^2$  of the

estimated hedonic price equation in the empirical implementation, we see that our model, based on the objective characteristics, explains almost perfectly the variations in the log of prices ( $R^2 = 99.9\%$ ). This means that the role of non-objective variable, such as cuteness, eventually excluded from the specification, is extremely marginal. Yet, cuteness can be considered as the element that generated the Adler phenomenon.

### **3.2 The Setting**

Each Pokemon card is a member of a set (also called expansion). Six expansions were registered in March 2000. They were published in the following order over time: 1. Basic (January 1999), 2. Jungle (June 1999), 3. Fossil (October 1999), 4. Team Rocket (April 2000), 5. Gym Heroes (August 2000) and 6. Gym Challenge (October 2000). Each expansion is characterized by a simple dummy variable which takes the value 1 if the Pokemon is a member of the expansion, and 0 otherwise. The latter provides an indication on the age of the character.

### **3.3 Rarity**

Cards are sold in sets. Nevertheless, not all of the cards are commercialized with the same frequency. For this reason, the supplier provides a rarity index indicating the frequency of commercialization of all cards. This index is a categorical variable having four homogeneous levels of rarity, with level one corresponding to the rarest.

This rarity indicator obviously allows us to quantify the effect of limited supply on prices.

Interestingly, it also permits to separate collecting and playing purposes. Indeed, after controlling for rarity, the only message conveyed by the level of a card is its strength in the game. Collectors are ready to pay high prices for rare cards but do not award any importance to the level of the card itself. Their objective is not to play the game but rather to possess all of the cards. Thus, once controlling rarity, we can read the coefficient associated to the level of the card as the influence that the talent of a pokemon card has (in the game) on its price.

Finally, we control for the number of variants a card possesses. For example, there are 4 different Pikachu cards (Basic, Jungle, Gym Heroes and Gym Challenge), 2 Squirtle cards and only one Chansey card. These variants explain why there are more cards (442) than Pokemons (152). This variable ranges from 1 to 6 and allows us to control for the fact that for the purpose of the game, it might not necessarily be useful to buy 4 versions of the same character that are almost perfect substitutes.

## 4 The Estimations

Several very informative features emerge from a descriptive analysis of the data. In Table 1, we summarize the most interesting statistics.

We observe first that both talent and price are highly related to rarity. This means that not controlling for scarcity in a hedonic price setup, would lead to large biases rendering an accurate analysis of the superstar phenomenon impossible. As will be checked later on, rarity captures around one-third of the overall variance of prices. In our case, controlling for it is easy since objective rarity measurements are available. This is a major advantage since

accurate indicators for rarity are generally not available in arts and sports.

As far as the distribution of talent is concerned, it may be argued that a concentration of highly talented individuals among the rarest ones is not consistent with true life situations, since it is as exceptional to find extremely talented individuals as to find extremely untalented ones. Although we agree with this, we do not think it is pertinent in artistic fields (or sports) since very untalented individuals generally remain out of the market. We thus believe that this distribution is perfectly in line with what should be intuitively expected.

**[INSERT TABLE 1 HERE]**

Considering the relation between rarity, talent and prices, it seems that Rosen's hypothesis is confirmed by the data. Indeed, the average price charged for one of the most common cards is \$0.26 and the average level (or talent) in that class is 14.11. In the rarity class immediately above (Uncommon), the average price charged is \$1 and the average level is 25.45. Finally, in the two rarest groups (Rare and Holofoil Rare), the average levels are respectively 31 and 35 and the corresponding prices are \$6.10 and \$14.63. For the two last classes, the improvement in the average level is rather small while the increase in prices is huge. Moreover, the Inter-quartile range of price increases with the degree of rarity and talent. This may be evidence in favor of Rosen's hypothesis suggesting that the relation between earnings and talent is convex and "with greater magnification of the earnings-talent gradient increasing sharply near the top of the scale". Although these preliminary findings are interesting, we need a more precise analysis before being able to conclude anything on the superstardom phenomenon.

This is done by estimating a hedonic price function. As indicated by Rosen (1974) and reasserted later by Nerlove (1995), hedonic prices are determined by both the distribution of consumer tastes and of producer costs. Therefore, with the exception of a few specific cases like this one, where supply is exogenously determined, implicit prices are difficult to interpret and do not exclusively reflect consumer preferences. Given the specificities of our data described above, we believe that this method is particularly well suited here.

Econometrically, we estimate a linear multiple regression where the dependent variable is the log of the price and the explanatory variables are, on the one hand, the vectors of characteristics (i.e. creatures' characteristics  $Z_i$ , cards' settings  $SET_i$ , supply conditions  $SUP_i$  and rarity  $RAR_i$ ) and on the other hand the level (or talent) of the card  $LEVEL_i$ . The relation is of the type:

$$\text{Log}(p_i) = \theta_0 + \theta_1 Z_i + \theta_2 SET_i + \theta_3 SUP_i + \theta_4 RAR_i + \theta_5 LEVEL_i + \theta_6 LEVEL_i^2 + \varepsilon_i \quad (1)$$

where  $\theta_1$ ,  $\theta_2$ ,  $\theta_3$  and  $\theta_4$ , are (vectors of) coefficients to be estimated,  $\theta_5$  and  $\theta_6$  are parameters to be estimated and  $\varepsilon_i$ , is the error term.  $LEVEL_i^2$  is introduced in the regression to test for the convexity of the function that translates quality into income. To test Rosen's theory, we furthermore need a strongly increasing slope of the curve when reaching very high levels of talent. This is done by analyzing the residuals. In our framework we expect  $R^2$  to be extremely high (very close to one) since we control for all objective characteristics including rarity, which is not common in the Hedonic Prices literature. This guarantees that residuals

can be used as a diagnostic tool. The fact that an individual has a positive residual, means that his price is higher than it should, given his objective characteristics. The major drawback is that if outliers (superstars) exist, *OLS* will not yield representative results. Indeed, the *OLS* regression line (or hyperplane) will be attracted by extreme points and the residuals will lose any informative power. To solve the problem, the residuals should be estimated with respect to a robust regression line, i.e. a line that is not attracted by extreme points. In this paper, we chose to use the Least Trimmed Squares<sup>2</sup> (*LTS*) method both for its simple interpretation and its excellent robustness to outliers. The method is described in Appendix 2. It could be argued that a much simpler method such as the quantile (median) regression could be used. Unfortunately, if the effect predicted by Rosen exists, some individuals will be outlying in the design space (in other words, in the  $x$ -dimension and in particular in talent) as well as in the earnings variable (i.e. the  $y$ -dimension). In statistical terms, these points are defined as bad leverage points and their existence influences the quantile (median) regression that turns out to be inappropriate (see Rousseeuw and van Zomeren, 1991). Note that we compared our results with those obtained using alternative robust estimation methods (such as MM-estimates, S-estimates and Least Median of Squares-estimates) and find, as expected, that they are not sensitive to the type of robust estimation method used. Once the outliers are identified, an efficient estimation can be achieved by estimating the hedonic equation using weighted least-squares where weights are attributed inversely to the degree of outlyingness of observations. Two criteria will be used here: a hard criteria (where a weight equal to one is

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<sup>2</sup>The authors have written a Stata code for the *LTS* estimation that is available upon request.

awarded to observations associated to robust standardized residuals smaller than three and zero to the others) and a soft criteria (where a weight equal to one is awarded to observations with a standardized residual smaller than 2.5, a weight zero is attributed to observations associated to a standardized residual larger than 3.5 and a linearly decaying weight is given between the two bounds). These estimations are presented in Table 1.

#### 4.1 Superstardom vs. “fair” success

The "fair price" of a card can be defined as the price at which it should be sold given its objective characteristics. In this context, it can be computed as the linear prediction of the hedonic price  $\hat{p}$  estimated with a robust regression. It is then possible to calculate the overpricing  $\frac{p_i}{\hat{p}_i} - 1$ , (i.e. the ratio of observed prices over fair prices minus one). Note that since the estimated regression is log-linear, the overprice should be calculated following  $\frac{p_i}{\hat{p}_i} - 1 = \exp(r + \frac{\hat{\sigma}^2}{2}) - 1$  where  $\hat{\sigma}^2$  is the estimated *LTS* scale parameter (see Appendix 3 for details). Since a superstar is defined as an individual that earns much more than its competitors, it is also an individual which is highly overpriced. Rosen predicts that this will occur only for extremely talented individuals, while Adler believes that this could occur at any level of talent.

## 5 The Results

Table 1 summarizes the results of the hedonic pricing estimation. In the first column we present the results associated with the hard weighting criteria of outliers, while in the second

we present those associated with the soft criteria. As expected, results are very similar.

**[INSERT TABLE 2 HERE]**

The quality of the fit is extremely good as expected, since we control for all objective characteristics. The most important variables in explaining the price are rarity, the number of variants a card possesses and talent. Rarity plays a particularly important role: being among the most common individuals, decreases the price of a card by 98% ( $\exp^{-3.947} - 1$ ) with respect to being among the rarest ones, all other things being equal. Belonging to the second and third most common groups of individuals reduces the price of respectively by 92% and 54% (again with respect to being among the rarest individuals). This result clearly shows that rarity must be taken into account when studying the emergence of superstars.

The negative coefficient associated with the number of variants indicates that if direct substitutes exist for a given individual, his earnings will decrease. This is in line with Rosen's assumption that higher earnings are related to the impossibility of finding alternative performers of equivalent quality. Inferior talent is not a substitute for superior talent.

Finally, looking at the coefficients of Talent and Talent squared, it appears that the relation between prices and talent is convex. This suggests that, as predicted by Rosen, the reward for talent is more than proportional. His main prediction is nevertheless that the slope should increase sharply for very talented individuals (there may even be a discontinuity). This can be tested by looking at estimated overprices. The result is striking: the most talented individual (Charizard), is sold at more than twice its fair price, while its closest competitors are sold at a price that can be explained by the estimated convex function. The sharp increase

of the slope at the highest levels of talent seems to exist. But this is only part of the story. Superstars can also be found at other levels of talent. This can be easily shown with a graphical tool (see Figure 1). Considering a chart in which the horizontal axis represents “talent” (monster level) and the two vertical axes represent respectively the density of talent (left hand side) and the relative over-pricing ( $\frac{p_i}{\hat{p}_i} - 1$ ) of individuals (right-hand side) it is possible to identify outliers and check at what level of talent they emerge. To simplify the reading, a line is drawn at the fair-price level (overpricing of 0) and only the individuals corresponding to an overpricing larger than 25% are shown.

Looking at the distribution of talent, as expected, there are many average talented individuals while only a very limited number of characters have superior talent.

**[INSERT FIGURE 1 HERE]**

Interestingly, Superstars appear at all levels of talent. Unsurprisingly, Pikachu turns out to be highly overpriced though it is a mediocre element. This could be explained by Adler’s theory: Pikachu, initially selected among equally talented individuals (probably for its cuteness), benefitted from some specific and efficient merchandising and snowballed into a star due to the network communication effect.

Adler (2005) states that “artists use publicity such as appearances on talk shows and coverage in tabloids and magazines to signal their popularity”. In such a way, they hope to increase their fame and, since consumers prefer popular artists, hope that other consumers will switch to them as well. In the case of Pikachu this advertising was done through its predominant role in the movie “Pokemon: The First Movie”. Giving it this leading position,

signaled its popularity and guaranteed a high demand from consumers for this character (inducing a large overpricing). The same mechanism prevails with Squirtle. This is again evidence in favor of Adler’s assumption since both characters benefited from a similar primary role in the movie. An interesting feature to analyze is how these “superstars” have evolved over time. To do so, we run the same regression in different periods. Figure 2 shows the evolution of relative pricing from March 2000 up to January 2003 for the five superstars detected during the booming period. The convex relation holds for most periods and only disappears during the last one (these results are available from the authors upon request.). On the other hand, the degree of “network-generated” overpricing decreases quickly and vanishes for all the “non-Rosen” superstars (it even becomes slightly negative for Squirtle). Except for Pikachu, for whom the effect is slightly larger, the overpricing drops to less than 25% in about 10 months (from March 2000 to January 2001). At the end of this same period, the overpricing of Charizard was still 150%. This may mean that while high earnings related to talent last longer, high earnings related to “the need of consumers to share a common culture” disappear quickly. Even if we are aware of the fact that the market for collectible cards might be different from that of art, this could be seen as evidence that superstars *à la Adler* might vanish rapidly if they do not manage to renew their popularity through some very original merchandizing, while superstars *à la Rosen* could last longer.

**[INSERT FIGURE 2 HERE]**

## 6 Conclusion

Adler (2005) raised the following question: “Is stardom the reward for superior talent or does stardom arise because consumers need to share a common culture?”. Empirical findings point in several directions and, as stated by Adler (2005) the study of the Economics of Superstars is still rife with open questions. The major problem in testing the theories of the emergence of superstars resides in defining talent objectively. Very often, proxies are used to tackle this issue, but they are generally imperfect (or even endogenous) measures. Furthermore, the success of a performer relies strongly on the talent of his manager and this aspect is often neglected. Finally, problems of confidentiality also emerge when measuring incomes.

We address the problem by using some new quasi-experimental data on the Pokemon Trading Card Game (TCG). The dataset presents several advantages: first, talent is fully observable, totally objective and explicitly provided in the cards. Second, the supply of cards is exogenously controlled by a single firm that provides objective rarity indicators. Third, the market transaction price of cards is available in reference magazines over a long period of time and represents an adequate measure of success. Finally, the talent of the cards does not depend on that of a manager. As far as we know, this is the first paper that deals with all of these problems at the same time. Even when data are available, an extra problem appears: if superstars exist, by nature they will be outliers and their presence will not be properly detected by classical OLS estimations. We deal with this problem by using the Least Trimmed of Squares estimator. This method has the advantage of fitting the bulk of data well and not being distorted by extreme values. The results of the estimations are unambiguous:

the two main theories of superstars (that of Rosen (1981) which emphasizes the role of talent, and that of Adler (1985), which puts more emphasis on the need of consumers to share a common culture), are complementary and not substitutes as is often claimed. Nevertheless, it seems that Adler's superstars disappear more rapidly than Rosen's.

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## 7 Appendix

### 7.1 Appendix 1: The object of the game

The Pokemon TCG is played as follows: two opponents (defined as Pokemon trainers) start with a deck of 60 cards each and fight to determine who is the best “monster” trainer. These 60 cards are chosen among the cards a player has in his possession, with the restriction that all characters should be different. Each player draws randomly a start-off hand of 7 cards from his deck (we call this the active hand). Among these he chooses a so-called “Active Pokemon”. The objective of both players is to knock out the opponent’s active monster while keeping his in play. A Pokemon is declared to have been knocked out as soon as the total damage it has received from the opponent is equal to its number of hit points (or health points), which is printed on the card. Once the active Pokemon has been knocked out, it must be replaced by another one available in the active hand. If no Pokemon is available in the active hand, at each turn the player must pick a card from the deck until he gets one. Players take turn to pick a card from the deck, putting it in their active hand and launching an attack if possible. In the game, there are three types of cards: Pokemon cards, energy cards and trainer cards.

To attack, a player has to take from his active hand the energy cards needed to launch the specific assault and discard them at the end of his turn. Different attacks are associated with different energy cards (Grass, Lightning, Colorless, Fire, Psychic, Darkness, Water, Fighting and Metal). The type and the number of energy cards needed for an attack are defined on

the active Pokemon card.

At each turn a player can increase the power of the assault by using a trainer card he has in his active hand. This has a single period effect: it implies that the card must be sent to the discard pile once played. There are 9 trainers (Erika, Rocketr, Blaine, Koga, Lt Surge, Brock, Giovanni, Sabrina and Misty) that have different empowering effects. A player can also strengthen his active Pokemon permanently by making it change using evolution cards. For each Pokemon card, say  $x$ , there is a Pokemon card called " $x - evolution - one$ " and another called " $x - evolution - two$ ". Evolution cards can only be played together with the basic card, not alone.

Before the game starts, each player randomly draws six prize cards from his deck and sets them aside without unmasking them. Each time a player knocks out one of the opponent's Pokemons, he randomly selects one of his own prizes (not the opponent's) and put it into his hand. The first player who manages first to take his 6 prizes wins the game.

## 7.2 Appendix 2: The LTS Regression

In the classical regression framework, various techniques have been proposed to identify outliers. Among these, the most commonly used are standardized residuals, studentized residuals and Cook distances. Even if these are theoretically appealing, they suffer from being based on residuals estimated with respect to a non-robust regression line (or hyperplane), i.e. a line that has been attracted by outlying observations. All distances with respect to this line will then be inappropriate measures of outlyingness. To avoid this, the only solution is

to rely on a line that resists the attraction, and fits the bulk of data well. In this paper we use the Least Trimmed of Squares (*LTS*) estimator that we briefly explain here below:

Assume we want to estimate a regression model of the type

$$y_i = \theta_0 + x_{i1}\theta_1 + \dots + x_{ip-1}\theta_{p-1} + \varepsilon_i \quad \text{for } i = 1, \dots, n \quad (2)$$

where  $n$  is the sample size,  $x_{i1}, \dots, x_{ip-1}$  are the explanatory variables,  $y_i$  the dependent variable,  $\varepsilon_i$  the error term ( $\varepsilon_i$  are assumed to be independent of the explanatory variables and *i.i.d.*  $N(0, \sigma)$ ,  $\sigma$  being the residual scale parameter) and where  $\theta = [\theta_0, \dots, \theta_{p-1}]'$  is the vector of regression parameters. To estimate the parameters, the classical ordinary least squares minimizes the sum of squared residuals. More precisely:

$$\hat{\theta}_{LS} = \arg \min_{\hat{\theta}} \sum_{i=1}^n r_i^2 \quad \text{where } r_i = y_i - \hat{\theta}_0 - x_{i1}\hat{\theta}_1 - \dots - x_{ip-1}\hat{\theta}_{p-1} \quad (3)$$

*OLS* estimators are known for their sensitivity to outliers. Results can be strongly influenced by the presence of just one “bad” outlier. Several “robust to outliers” regression techniques have been proposed in the literature. A powerful one is the Least Trimmed Squares (*LTS*) proposed by Rousseeuw (1984). This method is equivalent to running an *OLS* regression in all the possible sub-samples composed of  $h\%$  of the available observations. More precisely:

$$\hat{\theta}_{LTS} = \arg \min_{\hat{\theta}} \sum_{i=1}^h r_i^2 \quad \text{where } r_i = y_i - \hat{\theta}_0 - x_{i1}\hat{\theta}_1 - \dots - x_{ip-1}\hat{\theta}_{p-1} \quad (4)$$

$r_{(1)}^2 \leq r_{(2)}^2 \leq \dots \leq r_{(n)}^2$  are the ordered squared residuals and  $h$  is defined in the range  $\frac{n}{2} + 1 \leq h \leq \frac{3n+p+1}{4}$  (in this paper we use  $h = \frac{n+p+1}{2}$  ( $\approx 50\%$  of trimming) to guarantee

extreme robustness to outliers). Since we do not expect such a large number of superstars, we could have used a much less demanding trimming. Nevertheless, when we reduce the trimming to 10% (i.e. allowing up to 10% of outliers) the generality of the results remains unchanged. The minimizing problem related to *LTS* is very similar to the one of *OLS*, the only difference being that the largest squared residuals are not used in the summation, thereby allowing the fit to be independent of the outliers. It should be noted that the *LTS* method does not “discard” 50 percent of the data. Instead, it finds a regression hyperplane that fits the majority of data well and, on the basis of this hyperplane, allows to estimate residuals and standardized residuals (measured as the residual divided by the *LTS* scale parameter estimate i.e.  $\frac{r_i}{\hat{\sigma}}$ ) for all observations. They can then be used to detect the outliers. The scale parameter  $\sigma$  needed for the standardization has to be estimated on the basis of the trimmed residuals using the following formula:  $\hat{\sigma} = C \sqrt{\frac{1}{n} \sum_{i=1}^h r_i^2}$  where  $C$  is a factor used to achieve consistency of Gaussian error distributions.

### 7.3 Appendix 3: Estimation of Fair Prices in a Semi-Log Model

A non-negative continuous random variable  $p$  is said to have a lognormal distribution with mean  $E(p)$  and variance  $Var(p)$  if the random variable  $\log(p)$  has a normal distribution with mean  $E(\log(p))$  and variance  $Var(\log(p))$ .

The mean of the random variable  $p$  is then  $E(p) = \exp(E(\log(p)) + \frac{Var(\log(p))}{2})$ .

$E(p)$ ,  $E(\log(p))$  and  $Var(\log(p))$  are not known but can be estimated (in the sample) by:  $\hat{p}$ ,  $\widehat{\log(p)}$  and  $Var(\widehat{\log(p)})$  respectively. Of course, the latter is nothing else than the squared

scale parameter. We then have that

$$\hat{p} = \exp(\widehat{\log(p)} + \frac{\hat{\sigma}^2}{2})$$

$$\frac{p}{\hat{p}} = \frac{p}{\exp(\log(p) + \frac{\hat{\sigma}^2}{2})}$$

Obviously, residuals and the scale parameter are robustly estimated by *LTS*. In practice, to identify superstars, we will look for individuals who are sold at at least twice their fair price (or the price of competitors with equal talent), i.e. individuals that are such that  $\frac{p}{\hat{p}} \geq 2$ . Similarly, individuals who are sold at less than half their fair price, i.e.  $\frac{p}{\hat{p}} \leq \frac{1}{2}$  are considered as superlosers.

# TABLES

**Table 1 : Descriptive Statistics**

Rarity	Level	Hit Points	Damage	Prices in \$US (March-00)	
				Actual	IQR (Q9 - Q1)
Rare - Holofoil	35.54	75.54	47.28	14.63	6
Rare	31.36	70	41.05	6.1	1.5
Uncommon	25.46	61.71	37.64	1	0
Common	14.11	45.79	21.32	0.26	0

**Table 2: Robust Hedonic Price Estimation**

	Hard	Soft
Level	-0.008*** (3.61)	-0.007*** (3.56)
Level <sup>2</sup>	1.67E-04*** (4.98)	1.56E-04*** (4.80)
Rarity 2	-0.776*** (41.22)	-0.779*** (42.04)
Rarity 3	-2.558*** (160.66)	-2.561*** (164.33)
Rarity 4	-3.947*** (181.65)	-3.950*** (190.66)
Number of variants	-0.010** (2.18)	-0.010** (2.30)
Pokemon type = Elec	0.018 (0.61)	0.024 (0.88)
Pokemon type = Fight	-0.016 (0.84)	-0.013 (0.70)
Pokemon type = Fire	-0.008 (0.31)	-0.004 (0.16)
Pokemon type = Grass	-0.005 (0.21)	-0.002 (0.09)
Pokemon type = Psi	-0.026 (0.87)	-0.019 (0.70)
Pokemon type = Water	-0.019 (0.84)	-0.014 (0.69)
No weakness	0.029 (1.14)	0.024 (1.04)
No resistance	-0.011 (0.63)	-0.014 (0.83)
Special power	0.034* (1.78)	0.030 (1.60)
Deck = Jungle	-0.025** (1.96)	-0.025* (1.94)
Deck = Fossil	0.005 (0.40)	0.004 (0.34)
Constant	2.686*** (60.26)	2.685*** (63.15)
Observations	184	184
R-squared	99.86%	99.86%

Robust t statistics in parentheses

\* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

# FIGURES

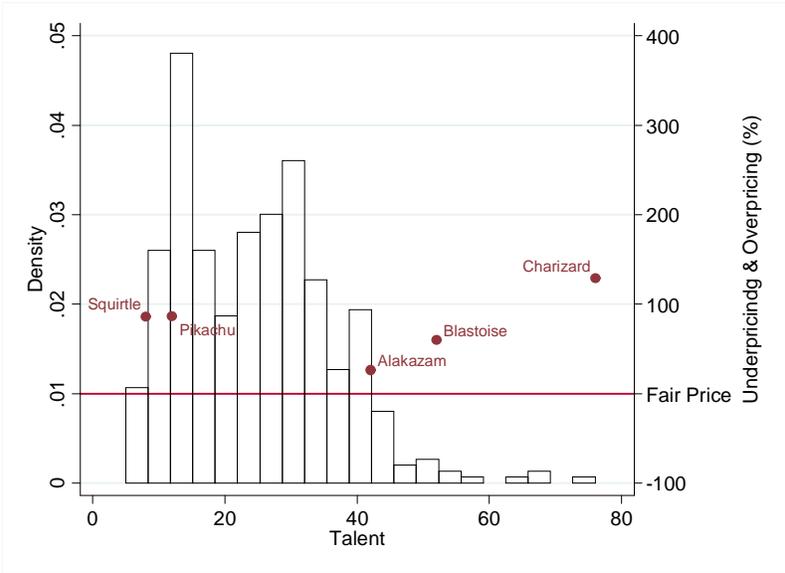


Figure 1: Superstars detection

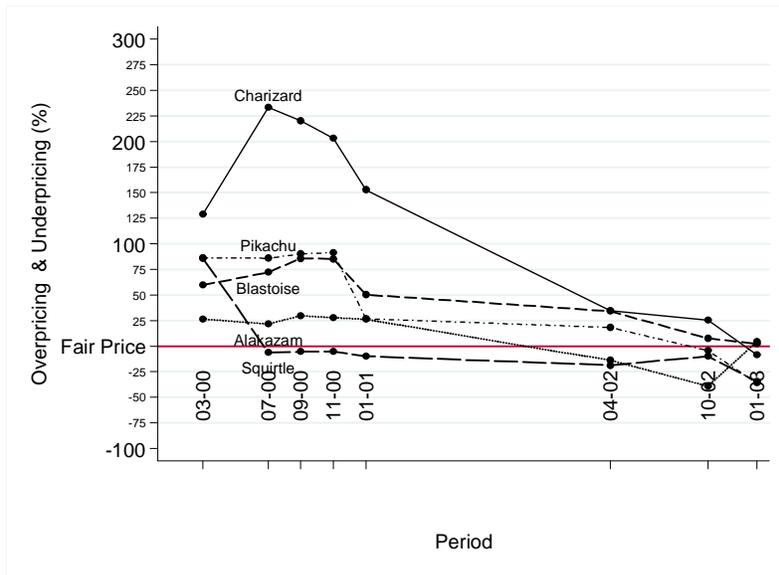


Figure 2 : Superstars in the long run