Untalented but Successful*

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Abstract

When studying the problem of the emergence of superstars, scholars face 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 a 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. Using semi-parametric estimation techniques, we find that the seminal theories of superstars developed by Rosen (1981) and Adler (1985) are complementary and not, as is often claimed, mutually exclusive. In short this paper shows that fame is not the prerogative of the most talented individuals.

Keywords: Superstars, Semi-parametric Estimation, Hedonic Prices, Quasi-experimental Data

JEL Classification: C4, D4, Z19

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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, 2006).

A recurrent question in the economic literature is which of Rosen's or Adler's theory better predicts the emergence of superstars or, in other words is superstardom related to talent at all? Empirical findings mostly point in Adler's direction but cannot lead to a clear rejection of Rosen's hypothesis since talent itself is generally poorly measured (see Adler, 2006).

Theories of superstardom are inevitably difficulty to test and it is essential to rely on a dataset created in a quasi-experimental setup where talent is explicitly measurable, quantified independently of rarity, cuteness or any other factor that could have an effect on economic success. Also it needs to be able to identify objectively the differences between individuals so that the confounding effects can be identified and measured efficiently.

As far as we know, there is no empirical paper in the existing literature that addresses these issues at the same time (see section 2 for more details on available tests of both theories).

In this paper, we answer this question by using some new data from 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[1].

Collectible card games are well suited to testing for the predictions of the two competing superstar theories since they have the intrinsic characteristics assumed in both models. Indeed, the potential audience is large since the game is played in almost all schoolyards around the world and cards are not substitutable. Note however that, as in the case of sports, the constant marginal cost of duplication will be of secondary importance here. The card supplier has indeed no interest in duplicating top cards extensively. They would rather actually print a limited number of strong cards to maintain some rivalry among consumers. As in the case of congestion in the music industry, the large earnings from top cards will thus come from a more than proportional increase in prices rather than from the actual number of cards sold.

As far as the characteristics of the dataset are concerned, they are particularly useful here 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 economic success; no role whatsoever is played by managers and, most importantly, Pokemons are particularly well suited to analyzing the emergence of idols, given

[1] A TCG is a game played using specially designed sets of playing cards that combine collecting with strategic gameplay purposes. Only a subset of the existing cards is used in the game and each card has a specific effect on the game. Some cards are more powerful than others. These are also generally more difficult to find on the market.

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 experimental design was not specifically engineered to answer the questions we raise, we believe that consumers' behavior is spontaneous and not biased in favor or against a specific hypothesis.

As stated previously, Rosen's (1981) main result is based on the possibility for the best performer of reproducing massively (at almost zero cost) his/her performance. A second non-degenerate equilibrium (with several suppliers) exists when such cloning is not possible. In this case the larger earnings of the best performers will come from the price charged by the best performers rather than by the quantities sold. In our data setup, this is clearly the second scenario since it is impossible to reproduce performance (i.e. cards). We therefore expect, if Rosen's intuitions prove right, that the congestion due to the limited supply of top cards, will induce a convex relation between card strength and their price with the slope of the gradient increasing sharply for the very best ones. On the other hand, if Adler's predictions are right, we expect to observe cards sold at much higher prices than their competitors for all levels of talent.

Our empirical strategy is to estimate a hedonic price equation for this TCG, taking into account the possible existence of superstars. This is done using a semiparametric regression model where only very weak assumptions are made on the function linking earnings and talent. The estimations show that superstars *à la Rosen* may coexist with superstars *à la Adler.* In the long run there is some evidence suggesting that both types of superstars might disappear even if the latter tends to disappear faster.

The paper is organized as follows: section 2 reviews briefly the economics of superstars, section 3 presents the game and section 4 describes the data. Section 5 lays down the empirical strategy, and section 6 presents the results. Finally, section 7 concludes.

2 The Economics of Superstars

2.1 Rosen (1981) and Adler (1985)

A key issue in the economics of superstars literature is to learn which of Rosen (1981) and/or Adler (1985) better predicts their emergence or, stated differently, to what extent fame is related to talent (*à la Rosen*) or not (*à la Adler*). The question is of primary interest in our modern societies as earnings differences tend to grow rapidly and huge bonuses are often the reward for questionable economic performances.

Rosen (1981) and Adler (1985) arrive at these conflicting conclusions as they have widely different visions of the demand side, even though they agree that superstardom hinges upon large economies of scale on the supply side.[2]

More precisely, Rosen (1981) believes that lower talent is an imperfect substitute for higher talent and, assuming that talent is fully observable, concludes that the (slightly) more talented individuals attract the market demand towards them. A central point of the Rosen's

[2] In the music industry, for instance, the economies of scale associated to the reproduction of CD's are enormous.

model is the possibility of reproducing the performance of artists at almost zero cost. In this setup the most talented performer will be able to reproduce his/her performance extensively and make it available to all. This will generate huge earnings. Note however that Rosen (1981) emphasizes that his model is not restrained to only those activities where some form of cloning is possible. Schulze (2003) provides a good illustration of this point using the notion of club goods. More specifically, he considers a public performance (such as a concert) where unit costs decrease with rising audience size. He believes that there will be congestion at some point since “a classical live concert is more enjoyable in a medium-sized concert hall than in a football stadium” (p. 432). These congestion costs will put a limit on the optimal size of audience and lead to non-degenerate market equilibria where more than one supplier will exist. Nevertheless, higher quality artists will charge higher prices (for at least the same audience) and will consequently have larger earnings.

On the other hand, Adler (1985) places great emphasis on network effects. Drawing on Stigler and Becker’s (1977) well-known notion of consumption capital, he states that a consumer’s appreciation of an artistic good depends both on his/her past consumption and his/her interaction with other experienced consumers. Since more popular artists have higher interaction potentials (search costs needed to find an interesting interlocutor are lower), he concludes that networks can snowball an individual into becoming a superstar, even if s/he is not highly 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 (2006) even states that this is probably why artists use publicity such as appearances on talk shows and coverage in tabloids and magazines to enhance their popularity.

2.2 Available Empirical Evidence

Available empirical evidence we have on the relationship between economic success and talent are sparse and fuzzy essentially because of a lack of appropriate data to test these theories adequately.

Lucifora and Simmons (2003) claim that Rosen's (1981) and Adler's (1985) theories can be used to explain the emergence of superstars in sports. They argue that the necessary (and sufficient) conditions underpinning the original models are met since the potential audiences are large (thanks to the size of stadiums and the media coverage) and performers are perceived by consumers as imperfectly substitutable. They highlight, however, that the constant marginal cost of duplication underlying Rosen's hypothesis is, in the case of sports, of secondary importance. Indeed, each sport event is unique and "live" performances are much more valuable than video replays.

Hamlen (1991, 1994), studying the music industry, find that talent, proxied by voice quality as measured by musicologists, 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 reasonably 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?

Proxies for talent are often only ex-post measures of career success and are therefore endogenous in some emprirical studies. Lucifora and Simmons (2003) for example use, among other indicators, the number of goals scored by a soccer player as a proxy for his/her talent. But, if we accept the fact that a player is more productive if s/he plays in a good environment, an average player may well end up playing for a top team, for example thanks to his/her skilled agent, and consequently become a heavy scorer. The endogeneity of the measure is evident. This example also points out that a measure of an artist's talent should not be influenced by the skills of his/her manager. Indeed, a well managed mediocre artist could reach fame and success, while an excellent performer could remain unknown if his/her 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?

Another difficulty is that earnings are also imperfectly quantified. As Rosen (1981) argues, privacy and confidentiality make data collecting (especially on earnings) very problematic.

3 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. Note, however, that 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 his/her 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, s/he wins the game. Each pokemon card has a "level" of training indicating its strength in the game. The higher the card level, the higher the damages the pokemon can induce and the higher its resistance to the opponents' attacks. It is thus extremely easy for players to identify the most "talented" individuals.

4 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 (the cards supplier).

Cards are commercialized in decks[3] and individually. Note that the strongest cards are rarely if not included in these decks. We collected data (including prices) on objective characteristics of all 442 Pokemon cards available in the market as of January 2003. Our source of information for prices is SCRYE, the guide to collectible games, a monthly magazine reputed to be 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 cover the market evolution of 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.

Pokemons' characteristics can be divided into three groups: creature's specificities, settings and rarity. These are printed directly on cards and thus readily available.

4.1 Creature's Characteristics

Pokemon cards possess 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 equally important characteristic is its resistance to attacks, which 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, unlike a combination of "resistance" and "weakness" in the present case. However, as

[3] Either on the Internet or through specialized games shops.

stated previously, both features are generated by a single factor that is the "level" of training of the card. Indeed, the concept of the pokemon game is that monsters are born weak and their skills (both in attacking and defending) increase jointly thanks to training. Since this level is available, we can consider it as a one-dimensional measure of talent as assumed by Rosen. To corroborate this point it is important to note that the level of pokemon cards turned out to be highly (and positively) correlated[4] with both "resistance" and "weakness" suggesting that it is indeed a good composite index of both features.

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 when opposed to a "psychic" one and a "fire" Pokemon is weak when opposed to a "water" one. This influences the efficiency of attacks and defense. The elements associated with pokemons are converted into zero-one dummies, in order to control for the potential influence of the type in the hedonic price estimation. Let us precise that there is no Condorcet winner in this setup for none of these elements. Accordingly, we do not expect any of these characteristics to be valued more than the others by consumers.

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

[4]This auxiliary regression is available from: authors upon request.

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, reduction in the damages that the "Defendent Pokemon" can cause in the counter-attack). This information is summarized using dummy variables in the regression analysis.

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

First, 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. Similarly, if we look at it from a collector's perspective, the value of cuteness should become negligible once rarity is being taken into account. 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. However, we created seven dummies identifying all the artists who designed the creatures, in order to capture part of the cuteness of the character, but none turned out to be significantly different from zero. Furthermore, looking at the R-squared of the estimated hedonic price equation (see below), our model, based on the objective characteristics, appears to explain almost perfectly the variations in the log of the price level ($R^2 = 99\%$). This means that the role of non-objective variables, such as cuteness, eventually excluded from the specification, is extremely marginal. Yet, cuteness can be considered as the element that generated the Adler phenomenon.

4.2 The Setting

Each Pokemon card is member of a set (also called expansion)[5]. 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 dummy variable which takes the value 1 if the Pokemon is a member of the expansion, and 0 otherwise. The latter indicates the age of the character.

4.3 Rarity

Cards are released set by set but the intensity with which each of them is supplied varies from one card to another. For this reason, the supplier provides a rarity index indicating the frequency with which each card is commercialized. This index is a categorical variable having four homogeneous levels of rarity, with level one corresponding to the rarest.

Accordingly, this rarity indicator allows us to quantify the effect of limited supply on prices and makes it easier to separate collecting from playing purposes. Indeed, after controlling for rarity, the only message conveyed by the card level is its strength in the game. Collectors are ready to pay high prices for rare cards but do not put any premium on the card level itself. Their objective is not so much to play the game as to possess all the cards. As a result, the coefficient associated to the card level can be viewed as the influence that the talent of a pokemon card has (in the game) on its price.

[5] Two decks are released per expansion.

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 to control for the fact that for the purposes of the game, it may not be necessary to buy 4 versions of the same character that are almost perfect substitutes.

5 The Estimations

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

As a first observation, both talent and price are highly related to rarity. This means that not controlling for scarcity in the 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 a third of the overall price variance. In this case, it is easy to control for it 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 relevant to artistic fields (or sports) since very untalented individuals generally remain out of the market. We thus believe that this distribution is 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 among 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 substantial. 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 "with greater magnification of the earnings-talent gradient increasing sharply near the top of the scale". However interesting these preliminary findings, we need a more precise analysis before any conclusion can be made 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 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 distinctive features of our data described above, we believe that this method is particularly well suited here.

Econometrically, we estimate a partially linear multiple regression where the dependent variable is the log of the price and the explanatory variables are, on the one hand, the four vectors of characteristics (i.e. creatures' characteristics Z_i, card settings SET_i, supply conditions SUP_i and rarity RAR_i) that enter the equation linearly and on the other hand the level (or talent) of the card for which no assumption is made on the functional form (except that the first derivative of f is bounded). In other words, $LEVEL_i$ enters the equation non-parametrically (see Appendix 2 for further details on the estimation method used).

The estimated relation is of the following type:

$$Log\,(p_i) = \theta_0 + \theta_1 Z_i + \theta_2 SET_i + \theta_3 SUP_i + \theta_4 RAR_i + f(LEVEL_i) + \varepsilon_i \qquad (1)$$

where θ_1, θ_2, θ_3 and θ_4, are (vectors of) coefficients to be estimated and ε_i, is the error term.

If Rosen's predictions are correct, we expect the relation between the price of cards and their level to be convex, with the gradient of the slope increasing sharply for the highest levels of talent. Conversely, if Adler's predictions are correct, we expect to observe highly rewarded individuals at all levels of talent. Furthermore we expect these individuals to coincide with the characters who have been 'arbitrarily' chosen by the supplier and intensively promoted. This is particularly true for Pikachu and Squirtle, two poor and affordable elements in the TCG but heroes (as well as Charizard) in the successive Pokemon movies (1999 and 2000). We expect these cards to be sold, all other things being equal, and in particular after controlling for differences in talent, at higher prices than their closest competitors or substitute cards. A high positive residual value for these cards should be seen as evidence of the existence of positive network effects *à la Adler* (1985).

6 The Results

Table 2 summarizes the results of the hedonic pricing estimation. In the first column we present the results associated with a parametric model considering a quadratic relation bewteen the log of the price and the card level, while in the second column we present those associated with a partial linear regression model. As expected, results are similar.

[INSERT TABLE 2 HERE]

For both models, 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 and talent. Rarity plays a particularly important role: being among the most common individuals, drives down the price of a card by 98% ($exp^{-4} - 1$) compared to being among the rarest ones (Rare Holofoil), all other things being equal. Belonging to the second (Uncommon) and third (Rare) most common groups of individuals reduces the price by 92% and 54% respectively (again compared to being among the rarest individuals). This result clearly shows that rarity must be taken into account when studying the emergence of superstars.

When looking at the coefficients of *Talent* and *Talent squared* in the parametric model, it appears that the relation between prices and talent is convex. If we analyze the residuals, we find that the most talented individual is associated with a large residual value suggesting that Rosen's hypothesis (of a sharp increase in the slope of the function for large levels of talent) seems to be confirmed. However other large residual values came out for inferior levels of talent. This analysis of residuals is more interesting when considering a semiparametric model, where the relation between the log of the price level and the level can take any form. We present this estimation in Figure 1. For clarity purposes we present a shaded area illustrating the confidence interval (CI). The upper bound of the interval is the estimated (nonparametric) fitted value of the dependent variable plus twice the median absolute deviation (MAD) of the estimated (nonparametric) residuals (multiplied by the correction factor of 1.4826 to ensure Gaussian consistency), while the lower bound is the fitted value minus twice the corrected MAD. The MAD was used in the formula of the CI (instead of the standard deviation of the residuals) to reduce the influence of outliers (i.e. individuals with large residuals such as Pikachu and Squirtle). Nevertheless, using the latter would only inflate the confidence interval without affecting the generality of the results.

[INSERT FIGURE 1 HERE]

Figure 1 clearly highlights that the relation between the log of prices and talent is increasing, convex and with a gradient increasing sharply for top individuals. It therefore goes in the same direction as Rosen. In contrast, we observe two large positive residuals among the less talented individuals. This was clearly not predcited by Rosen but could be explained by Adler's theory.

Adler (2006) states that "artists use publicity such as appearances on talk shows and coverage in tabloids and magazines to signal their popularity". In doing so, they strive to increase their fame in hopes of winning over new consumers as these will prefer popular artists. In the case of Pikachu this exposure comes from its predominant role in the movie "Pokemon: The First Movie". This initial advantage (Arthur, 1989) has contributed to building up its popularity and prompted a large fraction of consumers to purchase this card (inducing a higher demand and large overpricing). The same mechanism prevails with Squirtle. This is more evidence backing up 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 three superstars: Pikachu, Squirtle and Charizard. For Pikachu and Squirtle, the Alder superstars, we plot the level of overpricing and its evolution over time (i.e. the actual price over the price predicted by the semiparametric model). The reference vertical axis is the left-hand one. For Charizard, the Rosen superstar, we plot the slope of the tangent near the best individual and the reference axis is the right-hand one.

For Charizard we observe that the convex relation holds for most periods and only disappears during the last one. By contrast, when we look at the other two characters, the degree of "network-generated" overpricing appears to decrease quickly and vanishes for all the "non-Rosen" superstars in one year. 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 revive their popularity through some very original merchandizing, while superstars *à la Rosen* could last longer.

[INSERT FIGURE 2 HERE]

7 Conclusion

Adler (2006) raised the following question: "Is stardom the reward for superior talent or does stardom arise because consumers need to share a common culture?". The previous empirical findings point in several directions and, as stated by this author, 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. Proxies are frequently used to tackle this issue, but they are generally imperfect (or even endogenous) measures. Furthermore, the success of a performer mostly depends on the talent of his/her 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. 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 economic success. Finally, the talent of the cards does not depend on a manager's. As far as we know, this is the first paper that deals with all of these issues at the same time. To estimate the relation between economic success as proxied by prices and talent, we use a semiparametric regression model. 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 ones.

We show that the Adler phenomenon is the prerogative of individuals who have been given a clear initial advantage in terms of public exposure (here by the game conceptor), i.e. a high level of visibility in the successive movies associated with the TCG. This particular type of fame, which is not talent but network based is shown to be more fragile as it vanishes faster when the promoting activity winds down or ceases.

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8 Appendix

8.1 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 the best "monster" trainer is. A player picks these 60 cards out of all the cards s/he has with the restriction that all characters should be different. Each player draws randomly a start-off hand of 7 cards from his/her deck (this is called the active hand). Among these s/he chooses a so-called "Active Pokemon". The objective of both players is to knock out the opponent's active monster while keeping theirs 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, the player must pick a card from the deck at each turn until s/he gets one. Players take turns 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/her active hand the energy cards needed to launch the specific assault and discard them at the end of his/her 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 s/he has in his/her 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, Team Rocket, Blaine, Koga, Lt. Surge, Brock, Giovanni, Sabrina and Misty) that have different empowering effects. A player can also strengthen his/her 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/her deck and sets them aside without revealing them. Each time a player knocks out one of the opponent's Pokemons, s/he randomly selects one of his/her own prizes (not the opponent's) and put it into his/her hand. The first player who manages first to take his/her 6 prizes wins the game.

8.2 Appendix 2: Partial linear regression estimator

Let us assume that the model is as follows:

$$y_i = z_i\theta + f(x_i) + \varepsilon_i \text{ for } i = 1, ..., N \tag{2}$$

where y_i is the value taken by the dependent variable for individual i, z_i is the vector of characteristics of individual i and x_i is the value taken by the explanatory variable of interest for individual i. The latter variable is supposed to be drawn from a distribution with finite support and measured without error. The relation between y and x is supposed to be non-linear and of an unknown form. However, let us assume that the first derivative of f is bounded by a constant L. The errors ε_i are i.i.d with mean 0 and variance σ_ε^2.

Suppose that we rearrange the observations by sorting them in increasing order according to variable x (i.e. $x_1 \leq x_2 \leq ... \leq x_N$). By first differencing, we get:

$$y_i - y_{i-1} = (z_i - z_{i-1})\theta_{diff} + [f(x_i) - f(x_{i-1})] + (\varepsilon_i - \varepsilon_{i-1}) \text{ for } i = 2, ..., N \tag{3}$$

Increasing the number of observations (which broadly means filling the finite support interval of x with new values) will cause the difference $x_i - x_{i-1}$ to shrink at a rate of about $1/N$. Since the first derivative of f is assumed to be bounded, we have that $|f(x_i) - f(x_{i-1})| \leq L\,|x_i - x_{i-1}|$. The shrinkage of $(x_i - x_{i-1})$ will therefore induce $f(x_{i-1})$ to cancel out with $f(x_i)$. This means that reordering and differencing makes it possible to estimate the θ parameter consistently whatever the functional form of f as soon as $\partial f/\partial x$ is bounded. In order to visually assess the relation between y and x, it is now possible to run a nonparametric estimation of the fitted residuals $\tilde{\varepsilon}_i = y_i - z_i\hat{\theta}_{diff}$ and x. Note that this simple estimator is inefficient (it has a Gaussian efficiency of only 66.7%). To increase efficiency, Yatchew (1997) suggests using higher order differences and considers a generalization of (3) which can be written as:

$$\sum_{j=0}^{m} d_j y_{t-j} = \left(\sum_{j=0}^{m} d_j z_{i-j} \right) \theta_{diff} + \sum_{j=0}^{m} d_j f\left(z_{i-j}\right) + \sum_{j=0}^{m} d_j \varepsilon_{i-j} \text{ for } i = m+1, ..., N \tag{4}$$

where m is the order of differencing. Two conditions are imposed on the differencing coefficients $d_0, ..., d_m$. The first, which guarantees that the nonparametric effects disappear, is that $\sum_{j=0}^{m} d_j = 0$; the second, that guarantees that the residual in (4) has variance σ_ε^2, is that $\sum_{j=0}^{m} d_j^2 = 1$. With m sufficiently large, the estimator approaches asymptotic efficiency.

In this paper, the nonparametric estimator used is Nadaraya-Watson. Several alternative estimators are available but our results turned out to be insensitive to the choice of the nonparametric estimator.

As far as inference is concerned, Yatchew (1998) shows that $\hat{\theta}_{diff}$ has the approximate sampling distribution:

$$\hat{\theta}_{diff} \,\tilde{}\, N\left(\theta, \frac{1}{N}\frac{1.5\sigma_\varepsilon^2}{\sigma_u^2}\right) \tag{5}$$

where σ_u^2 is the conditional variance of z given u. It is then straightforward to compute the standard errors of the estimated parameters in the differenced equation. As far as the inference associated with variable x is concerned, Yatchew (1998) developed a simple test based on the comparison of the residuals scale of the differenced equation (s_{diff}^2) with that of the OLS regression where the function f is supposed to be constant (s_{res}^2).

More precisely the test statistic is:

$$V = \frac{N^{1/2}(s_{res}^2 - s_{diff}^2)}{s_{diff}^2} \,\tilde{}\, N(0,1)$$

If the null is rejected, it means that the effect of the variable x on y is statistically different from 0.

Note that Yatchew (1998) developed some more efficient estimators by considering higher order differencing. However, since the results are insensitive to this variation in our setup, we will not concentrate on these here.

TABLES

Table 1: Descriptive Statistics

				Prices in $US (March-00)		
Rarity	Level	Hit Points	Damage	Actual	IQR4	IQR10
Rare - Holofoil	35.54	75.54	47.28	14.63	3	6
Rare	31.36	70	41.05	6.1	0	1.5
Uncommon	25.46	61.71	37.64	1	0	0
Common	14.11	45.79	21.32	0.26	0	0

Table 2: PLR results for the Hedonic Price Equation - Parametric part

Variables	Log of the price level
Number of variants	0.005 (0.012)
Rarity:	
Rare	-0.777^{***} (0.028)
Uncommon	-2.600^{***} (0.030)
Common	-3.974^{***} (0.045)
Pokemon type:	
Elec	-0.005 (0.0428)
Fire	0.042 (0.041)
Grass	-0.018 (0.028)
Psi	-0.015 (0.043)
Water	0.027 (0.032)
No weakness	0.005 (0.023)
No resistance	0.001 (0.055)
Deck:	
Jungle	-0.039 (0.025)
Fossil	-0.015 (0.028)
Observations	186
R^2	0.987

Standard errors in parentheses robust to heteroskedasticity ; *** p<0.01, ** p<0.05, * p<0.1

FIGURES

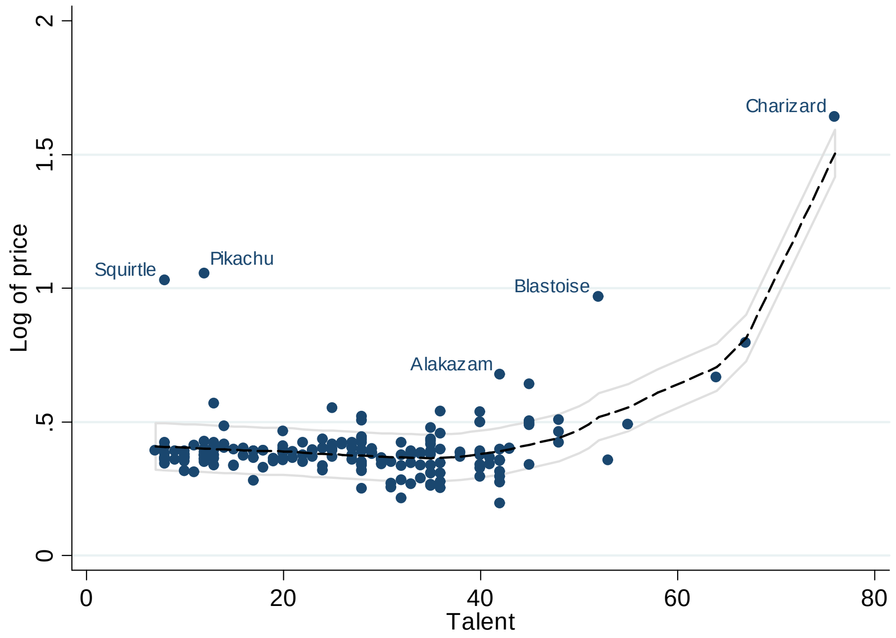

Figure 1: Price-Talent Relationship

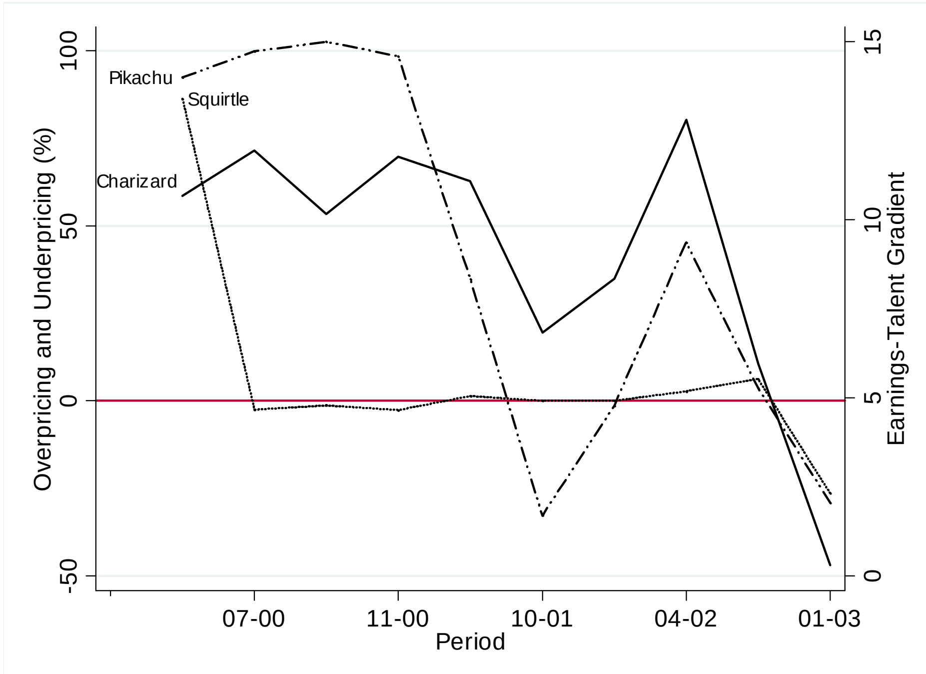

Figure 2: Superstar Phenomenon Over Time