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Untalented but Successful?
Rosen and Adler Superstar Pokemons*

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Abstract

When studying the reasons why and the conditions under which superstars emerge in some markets, scholars face difficulties in measuring talent, obtaining confidential data on earnings, and finding appropriate econometric techniques that cope with the presence of outliers (superstars). In this paper, we use a 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 various parametric or semi-parametric estimation techniques, we confirm that the relationship between talent and economic success is convex. On top of that, we document the existence of a different category of superstars with inferior talent and short-lived economic success.

Keywords: Superstars, Semi-parametric Estimation, Hedonic Prices, Quasi-experimental Data
JEL Classification: C4, D4, Z19

1 Introduction

Success stories are commonly believed to be related to talent. Following Rosen (1981) many economists believe that "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 has been challenged by other scholars such as Adler (1985) who suggest that superstars may even be found among less talented individuals. Their idea is that superstars are those artists who happen to be known by the group (possibly independently of their talent) and benefit from positive network effects induced by the need of consumers to interact and share a common culture (Adler, 2006). The phenomenon is now well-documented as we have accumulated a large body

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of empirical evidence since the late 90's in various market environments. While the first empirical tests were mostly focused on the link between talent and economic success (e.g. Mullin and Dunn, 2002), a second wave of applications has considered popularity measures (retrieved from the Internet) along with talent indicators to test for the presence of both Adler-type and Rosen-type superstars in some specific markets. Many studies, in very different fields including soccer, music, cinema[1] and even in artificial markets (trading card games) come to the conclusion that talent and popularity are factors that determine the income of superstars. But, this phenomenon has not been observed systematically in all creative industries and Gastronomy could be an exception. Indeed, studying this sector, Ehrmann, Meiseberg and Ritz (2009) find a mild effect of TV appearances on chefs' revenues (proxied by menu prices) which depend linearly on their level of talent summarized by the number of Michelin stars and Gault Millau points awarded to their restaurants. In this particular industry, where the influence of experts is non negligible, converting superior talent into superior quality requires however substantial investments in the setting of the restaurant (Gergaud, Montano and Verardi, 2007; Gergaud and Storchmann, 2014).

In this paper, we test if Rosen's predicted convex relationship holds. We then check if some individuals with inferior talent can also be vastly over-rewarded by the market as predicted by Adler (1985, 2006). Testing these assumptions is not trivial as talent is almost always impossible to measure objectively and success is generally only imperfectly quantified as, for example, in soccer as acknowledged by Lucifora and Simmons (2003). To cope with these issues, we collected data from the Pokemon Trading Card Game (TCG), in a similar way as Mullin and Dunn (2002) did for baseball player cards or Lucking-Reiley (1999) for the Magic Trading Card Game. While the idea of using trading cards is not new in economics, our approach contrasts with these studies as follows: Mullin and Dunn (2002) assume that star quality can be determined from a player's baseball card price as the residual value from a fit of card prices on their performance statistics. This measure is then used to compute the individual player's marginal revenue product that is compared to his/her salary using MLB data from 1990 to 1994. In our application, talent is directly measured objectively. Lucking-Reiley (1999), on the other hand, is interested in testing the equivalence or difference between various auction formats and therefore tackles a different research question.

In the Pokemon TCG, talent is fully observable, objective and printed on the card in a single variable called the card level; the supply of these cards is exogenously controlled by a single firm (Wizards of the Coast) that provides objective rarity indicators; trading prices are available and represent an adequate measure of economic success; no role is played by managers and, most importantly, Pokemons are well suited to analyzing the emergence of idols, given their worldwide commercial success. Indeed, Pokémon has sold over 27 billion cards as of March 2019.[2] We use data from 2000 and 2002 to deal with the initial market conditions of the game and a tractable, smaller, set of characters. Indeed, there exists now a much larger number of Pokemon cards available for purchase. As of September 2017, there were 6,959 cards in the Japanese sets and 9,110 cards in the English sets (source:

[1]See Hofman et al. (2017) for a meta analysis of the relationship between star power and movie success.
[2]https://www.pokemon.co.jp/corporate/en/services/

Wikipedia). Furthermore, the influence of social media was negligible at that time.

Our empirical strategy is to estimate a hedonic price equation coping with a possible convex earnings-talent relationship. This is done using flexible regression models. The convex relationship is detected in the data and some individuals are associated to a significantly larger commercial success than expected given their talent. These results obtained from a quasi-experimental setup are consistent with those observed in other creative or sports activities such as visual and contemporary art (Candela et al., 2016), soccer (Carrieri, Principe, and Raitano, 2017), cinema (Hofmann and Opitz, 2019).

The paper is organized as follows: section 2 reviews briefly the economics of superstars, section 3 presents the game and the data. Section 4, 5 and 6 introduce in turn the descriptive statistics, the results and some robustness checks. Section 7 concludes.

2 The Economics of Superstars

It is generally accepted that lower talent is an imperfect substitute for higher talent and that more talented individuals will attract a significant fraction of the market demand towards them. This will generate huge earnings for the best performers. Talent and earnings will therefore be linked by a convex relationship (Rosen, 1981).

Adler (1985) puts greater emphasis on network effects. Drawing on Stigler and Becker's (1977) notion of consumption capital, he states that a consumer's appreciation of an artistic good both depends on his/her past consumption and his/her interaction with other experienced consumers. Since popular artists have higher interaction potentials than non-popular artists, he concludes that networks can snowball an individual into becoming a superstar, even if s/he is not highly talented. In a more recent Handbook chapter, Adler (2006) states that this phenomenon explains why artists use appearances on talk shows and coverage in magazines to get known and enhance their popularity.

Empirical evidence on superstars are mostly found in the cultural and sports industries as suggested earlier by Rosen (1981). Common limitations are the subjective definitions of talent and the imperfect measurability of earnings. Many economists including Connolly and Krueger (2006), Franck and Nüesch (2012) acknowledge that testing these theories is particularly challenging.

Several authors have tackled these problems in very creative ways. As stated by Hamlen (1994, p. 399), "A proper test of the superstar phenomenon requires that the measure of "quality" ("ability") be an external measure". Hamlen (1991, 1994), for example, finds 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. 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. Salganik et al. (2006) adopted an experimental approach to the study of social influence in cultural markets and found that success in music is hardly predictable. Another important limitation is that quality/talent must be quantified independently of rarity. To deal with this, Franck and Nüesch (2008, 2012) use six indicators of talent to test the reliability of the measure in German soccer. Candela et al. (2016) used a factor analysis to come up with a single measure of talent for modern and contemporary visual artists. In Gastronomy, Ehrmann et al. (2009) relied on two popular cuisine awards (Michelin stars and Gault Millau points) to figure out differences in talent for a sample of German chefs.

In this paper, we use a unidimensional, objective and exogenous measure of talent to test the link between success and quality. Rosen (1981) argues there are two necessary conditions for a superstar phenomenon to emerge in a specific market: 1) inferior talent should not be a perfect substitute for superior talent, 2) the marginal cost of duplicating the artistic activity must be low such as in music or cinema nowadays. On top of these conditions, Rosen (1983) adds that such markets almost always require the attention of mass media. But as suggested by Perri (2013), the exact conditions under which this phenomenon may arise are still hotly debated.
In the present case, all three conditions hold. First, there are cards with different levels of strength in the game. Second, while the reproduction of Pokemon cards is strictly regulated by the cards supplier, a single card can be used in a large number of successive games which is equivalent to replicating the performance. At the same time, the maginal cost of printing/shipping additional cards, and therefore reaching a larger audience, is close to zero. Finally, these characters have been in the media since the game was launched throughout a succession of popular movies among others.

3 The Game and the Data

For Salonia (2017), the market for collectible card games is a dynamic market that can be modelled as a three-stage game as follows: 1) a firm produces and sells a certain amount of card packs at a given price, 2) the players buy the packs, and 3) they exchange some cards on the secondary market to create customized decks and challenge other players in tournaments. Players usually start by purchasing a starter deck. Additional cards are acquired either from randomized booster packs or online platforms such as https://www.cardmarket.com/.

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 causes some damage to the opponent's active "Defending Pokemon". If the attack does enough damage to knock-out the defending Pokemon, the winner scores 1 point. When a player has knocked out 6 of the opponent's active Pokemons, s/he wins the game. Pokemons with superior levels of talent have more chance to win the game.

In 2002, there were slightly more than 400 pokemon cards (and around 200 in 2000) for 152 documented Pokemon characters. Each creature has its own specificities. Each card has a rarity level (Rarity thereafter) which is exogenously determined by the cards supplier.

We collected data on prices and objective characteristics (printed on the card) for all 442 Pokemon cards available in the market as of April 2002. Our source of information for prices is SCRYE[3], a discontinued gaming magazine that was published monthly from 1994 to April 2009 and, back then, known to be the most accurate source of card prices among gamers. SCRYE used to provide the median price[4] charged by a sample of retail outlets (around 40) across the United States and Canada. These prices reflect actual market transactions. It is worth noting that SCRYE was not a card dealer itself. We used two different sets of prices for March 2000 and April 2002.

Pokemon cards possess different characteristics. The first is its strength: each Pokemon is associated with a given number of damage points that it can inflict to the opponent (ranging from 0 to 120). The second and equally important characteristic is its resistance to attacks, which is expressed in terms of health points (ranging from 30 to 120). Both indicators are summarized in the card level that is used as a measure of both strength and resistance. We call this aggregate measure Talent thereafter.

Pokemons have other characteristics that are not related to absolute quality. For example, each monster belongs to a particular element (Lightning, Fighting, Fire, Grass, Psychic, Water or Colorless). There is no best element but all creatures are weak or strong to some other elements (e.g. Fire is quite logically weak to Water, etc.). Elements are converted into zero-one dummies with Fighting as the reference category. There is no Condorcet winner in this setup. Accordingly, we do not expect any of these characteristics to be valued more than others by card buyers. Two additional dummies (Sophisticated 1 & Sophisticated 2) are used to control for the fact that some Pokemons (not all of them) can launch either one ortwo sophisticated attacks.

Each Pokemon card is a member of an expansion. There are nowadays 85 different expansions available in the US market[5]. In this paper, we only consider the first six expansions that were released in the following order: 1. Base set (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). Expansion dummies are created and allow us to control for the "age" of the character. The Base set is quite logically used as the reference category in all regressions. In this context, the regressions based on prices of March 2000 include two dummies (Jungle and Fossil) for three expansions while the second set of regressions, using prices of April 2002, concerns five dummies (Jungle, Fossil, Team Rocket, Gym Heroes, Gym Challenge) for six expansions.

The supplier provides a rarity (Rarity) index giving the frequency with which each card is distributed. This index is a categorical variable with four homogeneous rarity levels, level one being the rarest and also the reference category. After controlling for Rarity, the only message conveyed by the card level is its strength in the game. Finally, we control for the number of variants a card possesses (Variants). For example, there are 4 different cards for Pikachu, 2 cards for Squirtle and only one card for Chansey, etc.

[3]https://en.wikipedia.org/wiki/Scrye
[4]As well as the lower and upper prices.
[5]https://bulbapedia.bulbagarden.net/wiki/List_of_Pokémon_Trading_Card_Game_expansions

4 Descriptive statistics

Table 1 shows the main Pokemon characteristics of two samples of cards. We use here frequencies except for Talent which is a continuous variable. The first sample (column 1) corresponds to three different sets/expansions (Basic, Jungle and Fossil) and a total of 188 cards available in 2000 while the second sample (column 2) includes 442 cards contained in six different sets (the former sets plus Team Rocket, Gym Heroes and Gym Challenge) in 2002. The mean level of talent was lower in 2002 compared to 2000. The reason for this evolution is that the fraction of common cards has increased over time. There were about 24% (21%) of very rare cards, 20% (17%) of rare cards, 27% (28%) of uncommon cards and 29% (34%) of common cards in 2000 (2002). The large fraction of very rare cards is somewhat misleading as some cards, the most powerful ones (e.g. Charizard), were much harder to catch than others as testified by some players[6]. Only 2 to 4% of Pokemon cards possess two sophisticated attacks, while one sophisticated attack is a more common feature (28 to 32%). Some Pokemon types, such as Grass (24%) are more common than others like Fire (8 to 10%). The number of variants, i.e. the number of times the same card is found in different sets, ranges between 3 and 4.

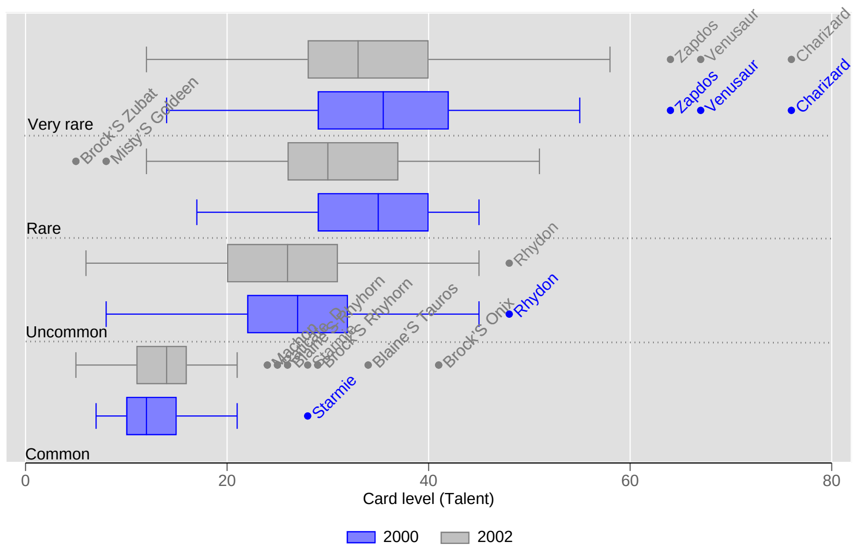
Table 1: Main Pokemon characteristics

Year	2000	2002
# of cards	188	442
Talent	26.85	24.66
Rarity		
Very rare	0.24	0.21
Rare	0.20	0.17
Uncommon	0.27	0.28
Common	0.29	0.34
# of variants	3.11	3.39
Attacks		
Sophisticated (1)	0.28	0.32
Sophisticated (2)	0.04	0.02
Type		
Lightning	0.10	0.09
Fire	0.08	0.10
Fight	0.13	0.14
Grass	0.24	0.24
Psy	0.10	0.12
Water	0.17	0.16
Colorless	0.18	0.16
Sets (expansions)		
Base	0.36	0.16
Jungle	0.34	0.14
Fossil	0.30	0.13
Team Rocket	NA	0.15
Gym Heroes	NA	0.21
Gym Challenge	NA	0.21

[6] https://www.huffpost.com/entry/how-far-my-father-went-to-find-a-charizard_b_10530074

In all theories of superstars it is assumed that Rarity and Talent are closely related. As can be seen in Fig. 1 where we plot the distribution of Talent (i.e. the level of the card in this setup) by Rarity groups, this relation holds in this dataset.

Figure 1: Rarity and Talent in the Pokemon Trading Card Game



As expected, Talent increases with Rarity but there are outlying individuals in each category. Of particular interest are those very rare cards with a superior level of Talent like Zapdos, Venusaur and, above all, Charizard who is in this framework the rarest, most sought-after Pokemon. As shown in Table 2, prices[7], Rarity and Talent clearly follow the same pattern.

[7] Defined as median prices charged by a sample of retail outlets (around 40) across the United States and Canada

Table 2: Descriptive Statistics

Rarity	Statistics	Prices (2000)	Prices (2002)	Talent (2000)	Talent (2002)
Very Rare (1)	Minimum	12	3.36	14	12
	Mean	14.63	7	37.57	35.24
	Median	13	6.1	35.5	34
	Maximum	50	36.85	76	76
Rare (2)	Minimum	5	1.9	17	5
	Mean	6.1	2.75	33.7	31.36
	Median	6	2.25	35	31.5
	Maximum	8	4.5	45	51
Uncommon (3)	Minimum	1	0.25	8	6
	Mean	1	0.61	27.02	25.46
	Median	1	0.5	27	26
	Maximum	1	0.8	48	48
Common (4)	Minimum	0.25	0.15	7	5
	Mean	0.26	0.22	12.85	14.11
	Median	0.25	0.25	12	13
	Maximum	0.5	0.5	28	41

An interesting feature is that the mean level of Talent is stable within Rarity groups over time (the maximum difference found is at around 2 units of Talent only) while the distribution is slightly higher in 2002 compared to 2000. Indeed, in 2000 (2002) the min-max range is 62 (64) for very rare, 28 (46) for rare, 40 (42) for uncommon and 21 (36) for common cards. The price dispersion seems to follow that of Rarity. Indeed, in 2000 the min-max range is 0.25 for common, 0 for uncommon, 3 for rare and 38 for very rare cards. In 2002, prices dropped but the relative dispersion across Rarity categories remains comparable to 2000.

One may wonder whether the level of the card is a relevant univariate measure of strength and resistance in this game. To test this hypothesis, we run a linear regression of *Level* on the number of health points (*HP*) and the series of damages inflicted by the card (*Damage#1* and *Damage#2*)[8]. It turns out that *Level* is a linear combination of strength in attacking and defense ability as follows:

$$Level_i = 0.46HP_i - 0.07Damage\#1_i + 0.19Damage\#2_i$$

The R-squared value of this regression being close to one (0.95) and all of its estimated coefficients significantly different from 0 at the 1% level, we can reasonably conclude that the card level is a relevant univariate measure of Talent and therefore utility in the Pokemon TCG. If we decompose the R-squared using Shapley's decomposition, we find that 46% of variations in levels are due to *HP*, 30% to *Damage#1* and 24% to *Damage#2*. This informs us that strength in attacking and defense ability more or less have the same importance in the game. We tested this hypothesis using different alternative specifications, considering all available characteristics, allowing for more flexible forms, with or without interaction terms, but we failed to find a significantly better model that the parsimonious one presented above.

[8]This regression does not have a constant term as we assume that a card with no health points and that would not trigger any damage would have no value (*Level = 0*).

5 Estimations

In this section, we estimate a partially linear regression model where the dependent variable is the log of the median price of the card and the set of explanatory variables includes the characteristics of the card that enter the model linearly and Talent for which the functional form is estimated empirically.

We estimate three different models: i) a parametric model where Talent is modeled quadratically, ii) a semiparametric model as proposed by Robinson (1988) where the non-parametric part is estimated using a kernel regression with Epanechnikov kernel and bandwidth selected through cross-validation and iii) a penalized spline semiparametric model. The last model is known as the best linear unbiased predictor of a mixed model as described by Ruppert et al. (2003, p.108).

Table 3 summarizes the results obtained using these different estimation techniques for March 2000[9]. As expected, the results are similar.

[9]Only three expansions (Basic, Jungle and Fossil) were available at that time. Basic, the first expansion ever released, is omitted is serves as the reference category.

Table 3: Hedonic Regressions (March 2000) - Parametric Part

	Parametric Quadratic	Semiparametric Kernel	Penalized spline
Talent	-0.002***		
	(0.003)		
Talent²	0.0004***	See graph	See graph
	(0.00004)		
Lightning	0.048	0.054	0.059
	(0.040)	(0.039)	(0.037)
Fire	0.037	0.011	0.006
	(0.038)	(0.038)	(0.035)
Grass	-0.001	0.005	-0.001
	(0.029)	(0.028)	(0.027)
Psy	-0.002	0.013	-0.000
	(0.037)	(0.037)	(0.035)
Water	0.027	0.026	0.028
	(0.030)	(0.029)	(0.028)
Colorless	0.015	0.016	0.023
	(0.031)	(0.031)	(0.029)
Sophisticated (1)	0.011	0.023	0.012
	(0.019)	(0.019)	(0.018)
Sophisticated (2)	-0.012	0.000	-0.004
	(0.045)	(0.044)	(0.042)
Jungle	-0.026	-0.046**	-0.041**
	(0.022)	(0.021)	(0.020)
Fossil	0.008	-0.007	-0.009
	(0.022)	(0.022)	(0.020)
Rarity (2)	-0.768***	-0.767***	-0.774***
	(0.025)	(0.024)	(0.023)
Rarity (3)	-2.575***	-2.570***	-2.586***
	(0.026)	(0.025)	(0.024)
Rarity (4)	-3.994***	-3.982***	-3.969***
	(0.037)	(0.039)	(0.037)
# of Variants	-0.011	-0.005	-0.009
	(0.009)	(0.009)	(0.008)
Constant	2.872***		2.780***
	(0.075)		(0.227)
Observations	188	188	188
R-squared	0.996	0.990	0.990

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

For all models, the quality of the fit is extremely high as expected, since we control in this setup for all existing objective characteristics. The most important variables in explaining the price are Rarity and Talent. If we decompose the R^2 using a Shapley decomposition in the parametric model, it turns out that 66.93% of the explained variance is due to Rarity while the contribution of Talent is at around 28.82%. Only 4.26% of the explained variance is due to the other factors.

Figure 2: Pokemon TCG: Price and Talent in March 2000

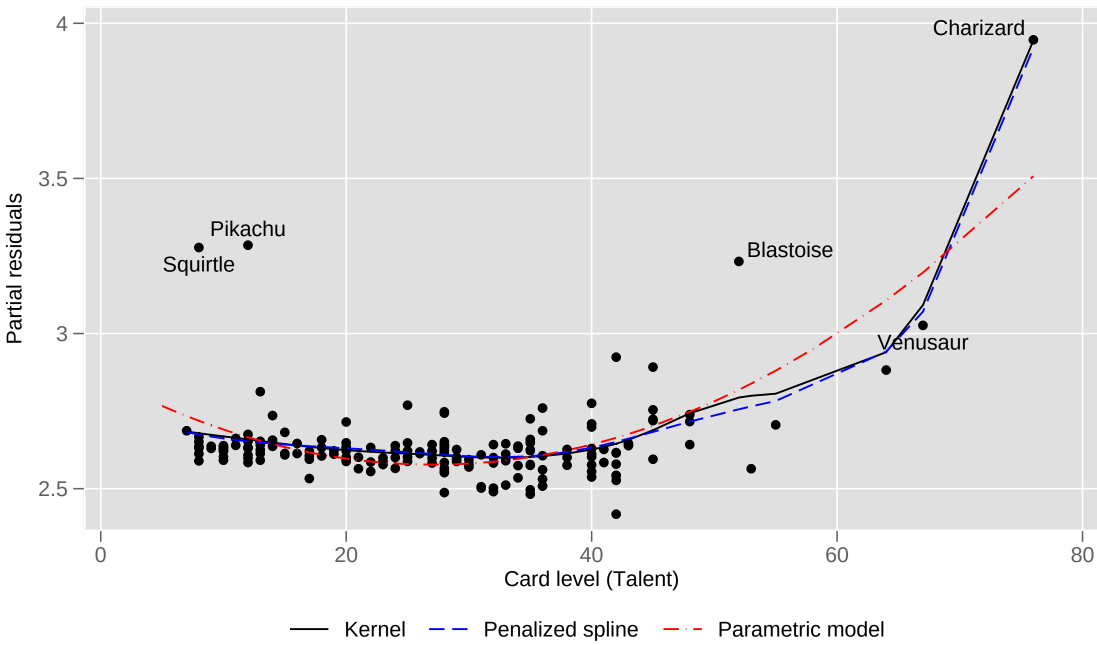


Figure 2 clearly highlights that the relationship between the log of price and Talent is increasing, convex with a gradient increasing sharply for top characters. Interestingly, two Pokemon cards among the least talented individuals, Pikachu and Squirtle, stand out from the crowd with large positive residual values. Their prominent role in “Pokemon: The First Movie”[10], a highly successful movie released on November 10, 1999 in the United States[11], seem to have risen them to fame. Indeed, the movie trailer features Pikachu and Squirtle beside Ash Ketchum, the main protagonist of this anime film. In the case at hand, the popularity that the film gave to certain characters led to an elevated interest among collectors but not for the purpose of using the cards in the game but rather for owning a character about which more information had become available. This economic effect is in line with Adler’s argumentation, according to which an individual ’snowballs’ into a superstar (over time) when followers (i.e. fans) economize on transaction costs while accumulating consumption capital. It could, however, be argued that only two characters is not a sufficient number to conclude that Alder type superstars exist among Pokemons. Despite its low level of talent, Pikachu has become the most recognized Pokémon all over the world and was ranked, for instance, as the "second best person of the year" by Time in 1999. Pikachu and ten other Pokémon were also chosen as Japan’s mascots in the 2014 FIFA World Cup, etc. This is, we believe, enough to qualify Pikachu as a superstar with no specific talent (interest for the purpose of the game) and therefore as an Adler type superstar.

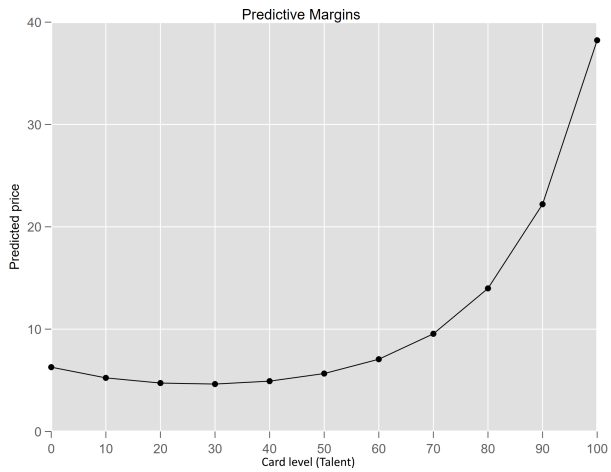
[10] https://en.wikipedia.org/wiki/Pokémon:_The_First_Movie

[11] “Pokemon: the first movie” was the highest-grossing anime film in the United States once adjusted for ticket-price inflation ($152 million): https://www.boxofficemojo.com/franchises/chart/?id=pokemon.htm

This is also in line with Moshe Adler's view that some media exposure is needed for individuals with less talent to become superstars.

In the graph here below, we plot the predictive margins for values of Talent ranging from 0 (theoretical minimum) to 100 (theoretical maximum) by increments of 10 level points while averaging the remaining covariates. For simplicity, we used the quadratic parametric model. As shown above, results would not differ dramatically using any alternative specification.

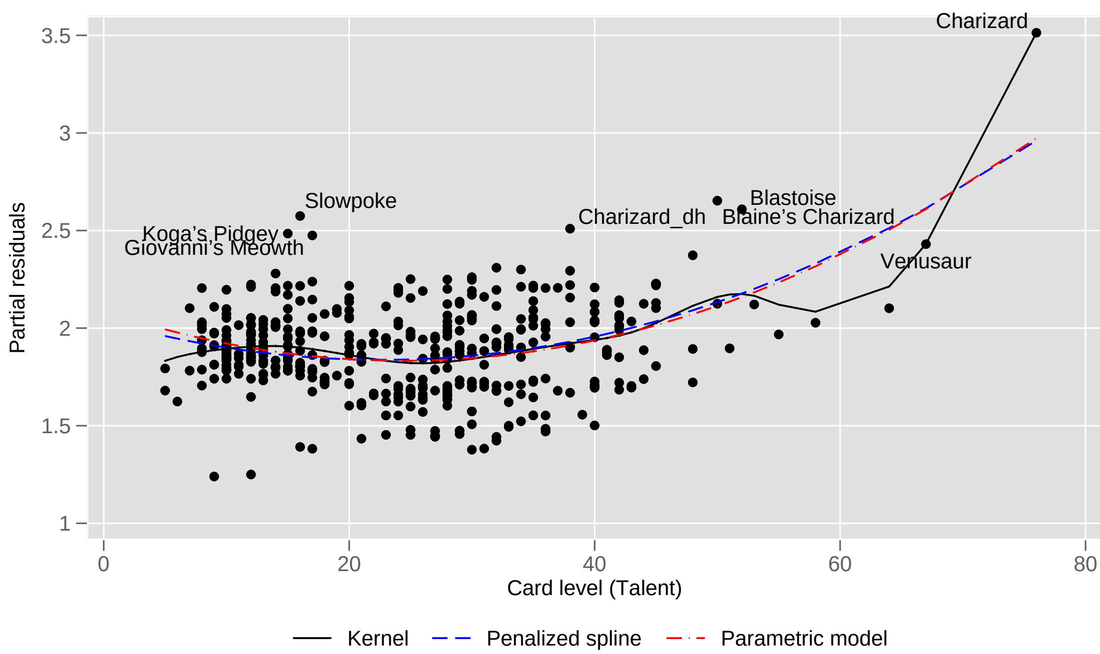
Figure 3: Predictive margins



Up to a Talent level of 50, the price hardly changes with the card level. From that point onwards, the gradient increases sharply. For example, moving from 50 to 60 translates into a price premium equivalent to \$1.40 from \$5.66 to \$7.06 or 24.7%. The price premium is even more sizeable between 70 to 80. In this range, card prices increase from \$9.54 to \$13.98 or 46.5%. For higher card levels, the impact on the price is even larger.

An interesting feature is how superstars have evolved over time. To test for it, we run the same set of regressions with median prices collected in April 2002. By that time, the number of cards had raised to 441. We plot the flexible part of the model in Figure 4. The parametric part is not reproduced but remains similar to that of year 2000.

Figure 4: Price and Talent in April 2002



Interestingly, Pikachu and Squirtle's economic advantage acquired in 2000 had faded away in just 2 years while the convex relationship still holds. Some new "low-quality" superstars such as Slowpoke, Koga's Pidgey and Giovanni Meowth have replaced them in the arena. It is interesting here to note that this class of superstars, with inferior talent, enjoy a more short-lived economic success. This is illustrative of a more general movement nowadays in the media, on TV and internet in particular, where strong superstars, who are then quickly forgotten, manage to differentiate from the crowd.

6 Robustness checks

While the results are interesting, a series of robustness checks is needed for different reasons. A first potential concern is the strong collinearity between Rarity and Talent. A second issue relates to the fact that we use the median price and not the mean price as a dependent variable. Indeed, given the substantial variations in such price distributions, one may reasonably think that using the median price might shrink artificially the distribution and therefore be misleading. In this section, we will use, in the absence of the mean price, the available minimum and the maximum prices observed to check whether the results are affected or not. A third problem is the assumed additive separability of Rarity and Talent. We indeed control for Rarity assuming that this is a sufficient condition to identify the effect of Talent on Price but this will not be the case if Rarity and Talent interact with each other in a significant way. Our last concern is the natural presence of outlying individuals in such distributions who require a specific, robust, econometric treatment. Our goal here is to ensure that the convexity of the price-talent distribution is not simply driven by a single outlier. Here, we will follow a parametric approach but comparable results have been obtained using semiparametric models.

6.1 Collinearity issues

To check for the presence of severe collinearity we calculate the variance inflation factor (VIF) associated to each variable.

Table 4: Variance Inflation Factor

	VIF
# of Variants	1.69
Lightning	1.75
Fire	1.29
Grass	1.41
Psi	1.48
Water	1.41
Sophisticated (1)	1.14
Sophisticated (2)	1.09
Jungle	1.52
Fossil	1.44
Rarity (2)	1.51
Rarity (3)	2.03
Rarity (4)	3.65
Talent	2.54

This statistic informs us by how much the variance of the coefficient of a given explanatory variable is inflated due to collinearity. A rule of thumb is that if $VIF > 5$ then multicollinearity is severe. As can be seen in Table 4 here above, collinearity is never above this threshold but is still not negligible for both Talent and Rarity. To cope with it we consider two strategies: i) we run a LASSO estimator that will automatically look for a parsimonious model and discard uninformative variables and ii) orthogonalize Talent and Rarity before estimating the model.

6.1.1 LASSO estimator and collinearity

LASSO (Least Absolute Shrinkage and Selection Operator) minimizes the residual sum of squares subject to a constraint on the absolute size of coefficient estimates. For large enough penalty λ, some coefficients will be equal to 0. The LASSO will hence perform the model selection. The choice of λ is highly discussed in the literature. In this paper, we estimate it by minimizing the bayesian information criterion (see Table 5, column 1). Note that minimizing other information criteria lead to very similar results. Relying on Ridge regression or Elastic Net regression do not change the results either.

6.1.2 Partialling-out orthogonalization

Dealing with collinearity is all but straightforward when collinear relations exist among many variables in the regression context. From Table 4 it is evident that the problem is mild here except for Talent and Rarity. To separate the two effects, we orthogonalize these variables. To do so, we regress Talent on Rarity dummies and fit the residuals. These residual values correspond to the fraction of Talent not explained by Rarity. We then re-run the original quadratic parametric model by replacing the original Talent variable with the new one. Obviously, the scale of the variable has been modified but a positive and significant coefficient associated to Talent squared still points towards a convex relationship between Price and Talent (see Table 5, column 2).

6.2 Price dispersion

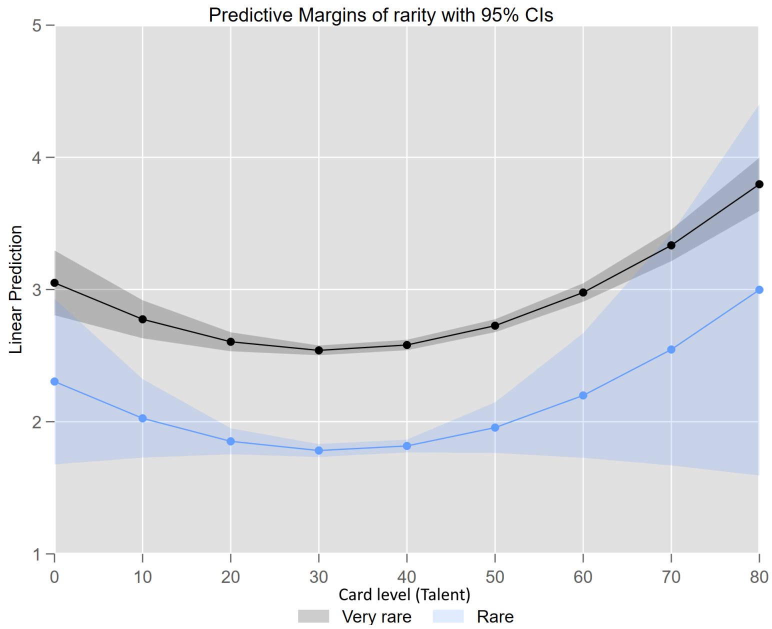
In the previous section, we considered the median price as the reference price. However, by doing so, we neglected the fact that prices might be more stable for some cards than for others. To deal with this issue, we run an interval censored regression using both the lowest observed price (lower bound) and the highest observed price (upper bound) that were also available from SCRYE. Results for this regression are reproduced in Table 5, column 3.

6.3 Additive separability

Up to now, we assumed additive separability between Rarity and Talent. However, it is possible that these effects interact with each other and that considering them separately might be misleading. We hence relax the additive separability assumption between Rarity and Talent by considering a full model with all possible interactions between Talent, Talent^2 and Rarity dummies. By doing so, we test whether all these interactions drive our results or not (see Table 5, column 4). We present here below the marginal effects associated to the set of interaction terms. For the sake of clarity, we only present the marginal effects and the confidence intervals for the two higher rarity levels for which the convexity is observed. As expected, the convex relationship clearly prevails among the rarest cards but does not hold for lower rarity levels[12]. To summarize, Talent and Rarity are clearly intertwined but the convexity of the relationship between Talent and Price is not entirely due to Rarity.

[12]Given the confidence interval, we cannot reject a linear relationship for the second highest level of talent and, even if not repoduced here, it is even more obvious for lower levels

Figure 5: Predictive margins, additive separability



6.4 Robust regression

Theories around the emergence of superstars all assume that a very limited number of individuals (potentially with a superior talent) will exist. These atypical individuals will get much higher rewards than their competitors. To deal with the influence these outliers might have on estimated coefficients we fit the model using an outlier-resistant estimator (more precisely an S-estimator with a 10% break-down point[13]). If the convexity of the earnings-talent relation holds, this means that the results were not driven exclusively by a limited number of atypical individuals (see table 5, column 5).

[13]The estimator will hence resist if there are up to 10% of outlying individuals

Table 5: Robustness Checks

	LASSO	Orthogonalized partialling-out	Interval censored	Non-additive separable	Robust BDP(10%)
Talent	-0.021***	0.003*	-0.017***	-0.033***	-0.010***
	(0.003)	(0.002)	(0.003)	(0.006)	(0.002)
$Talent^2$	0.004***	0.000488***	0.000333***	0.000527***	0.000198***
	(0.000)	(0.00018)	(0.000044)	(0.000068)	(0.000039)
Lightning		0.058	-0.001	0.037	0.038*
		(0.057)	(0.048)	(0.039)	(0.023)
Fire	0.014	0.043	0.141***	0.019	0.012
	(0.030)	(0.039)	(0.047)	(0.037)	(0.014)
Grass	-0.014	0.015	0.022	-0.016	0.008
	(0.019)	(0.020)	(0.034)	(0.029)	(0.012)
Psy		0.004	0.042	-0.018	-0.006
		(0.030)	(0.041)	(0.037)	(0.016)
Water		0.037	0.008	0.026	-0.004
		(0.036)	(0.034)	(0.030)	(0.013)
Colorless		0.028	-0.005	0.006	0.024*
		(0.022)	(0.036)	(0.031)	(0.014)
Sophisticated (1)		0.009	-0.015	0.012	0.001
		(0.022)	(0.022)	(0.019)	(0.008)
Sophisticated (2)		-0.019	0.034	-0.004	0.007
		(0.024)	(0.061)	(0.044)	(0.020)
Jungle	-0.027	-0.039*	-0.050**	-0.035	-0.011
	(0.010)	(0.022)	(0.025)	(0.021)	(0.010)
Fossil		-0.008	0.020	-0.010	0.025**
		(0.025)	(0.025)	(0.022)	(0.011)
Rarity (2)	-0.768***	-0.783***	-0.784***	-0.747**	-0.768***
	(0.025)	(0.027)	(0.029)	(0.340)	(0.018)
Rarity (3)	-2.570***	-2.60***	-2.57***	-3.10***	-2.560***
	(0.024)	(0.029)	(0.025)	(0.170)	(0.016)
Rarity (4)	-3.980***	-3.940***	-3.670***	-4.330***	-3.960***
	(0.035)	(0.033)	(0.157)	(0.177)	(0.020)
Rarity (2)*Level				-0.000204	
				(0.021)	
Rarity (3)*Level				0.036***	
				(0.010)	
Rarity (4)*Level				0.026	
				(0.018)	
Rarity (2)*$Level^2$				-5.53e-06	
				(0.00032)	
Rarity (3)*$Level^2$				-0.000577***	
				(0.000164)	
Rarity (4)*$Level^2$				-0.000482	
				(0.000567)	
# of Variants		-0.000	-0.011	-0.005	-0.009**
		(0.008)	(0.0104)	(0.009)	(0.004)
Constant	2.830***	2.570***	2.790***	3.070***	2.690***
	(0.059)	(0.044)	(0.083)	(0.128)	(0.043)
Observations	188	188	188	188	188
R-squared	0.996	0.995	0.993	0.996	0.999

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

As it is evident in all five regressions, the convex relationship holds strongly and the quality of the fit is very high in all setups.[14]

7 Conclusion

In this paper, using Pokemon trading card game data, we contribute to the economic literature on superstars by showing that the role of talent is crucial in explaining the emergence of the phenomenon as success and talent exhibit a robust, convex relationship. However, superstars with inferior talent might also emerge in the short run due to the need of consumers to share a common culture. These empirical evidence are in line with the results of previous studies both in the arts sector and the sports sector. This phenomenon seems to be the prerogative of individuals who have been given, or managed to get, a clear initial advantage in terms of public exposure in the media as recognized in many papers mentioned above. This particular type of fame, which is not talent but network driven seems to vanish faster when the promoting activity winds down or ceases. Last, this paper shows that the phenomenon may develop in environments different from these initially imagined by Sherwin Rosen and Moshe Adler.

Compliance with Ethical Standards

Conflict of Interest: Olivier Gergaud declares that he has no conflict of interest. Vincenzo Verardi declares that he has no conflict of interest. Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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