Demand for Rarity: Evidence from a Collectible Good

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Abstract

Markets for art, coins and other collectibles, culinary delicacies and eco-tourism suggest consumers value the rarity of many goods. While empirical evidence supports higher prices for rare goods, isolating the value of rarity has proven difficult. I analyze prices for a collectible card game and show goods that are designated as rare trade at higher prices than functionally-equivalent substitutes. Importantly, I use novel features of this market to account for scarcity, observed and unobserved product characteristics and separately identify rarity effects. These results have important implications for markets ranging from luxury goods to conservation of endangered species.

*The author thanks employees at Gamer's Guild, Matthew Butner, Kevin Starnes and seminar participants at the University of Colorado, Boulder for helpful comments. Samuel Hughes provided excellent research assistance.

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1 Introduction

There are many instances where consumers appear willing to pay a premium for uncommon goods or unique experiences. For example, rare stamps and coins routinely sell for high prices at auction (Beltran, 2018; Morris, 2018, 2019; Reaney, 2014). Luxury goods makers cultivate an aura of exclusivity to sell their products at premium prices relative to functionally equivalent substitutes (Catry, 2003; Kapferer, 2012). Safari's or other expeditions cater to tourists who wish to view and photograph exotic animals (Cong et al., 2014; Okello, Manka, and DAmour, 2008; Reynolds and Braithwaite, 2001).

The economic concept of rarity value is rooted in the notion that consumption value depends on the aggregate level of consumption across all consumers. Consumers' valuations of a good consist of an intrinsic component, *i.e.* typical product characteristics, and a rarity component that is inversely related to the total quantity of the good consumed. A number of authors have considered this possibility, most famously Veblen (1899). The first formal treatment was offered by Leibenstein (1950) who considered the behavior of "snobs," whose demand for a good increases with decreases in aggregate consumption. Further, rarity is closely related to the concept of conspicuous consumption where consumers purchase expensive goods to signal wealth and status (Bagwell and Bernheim, 1996; Leibenstein, 1950; Veblen, 1899). However in the case of rarity, consumers' valuations do not depend on any elevation of social status.

There are many reasons why understanding rarity value is important. Whether consumers value rarity is critical to understanding demand for luxury goods (Robinson, 1961) and collectibles (Stein, 1977; Krasker, 1979; Jaeger, 1981; Goetzmann, 1993; Pesando, 1993; Mei and Moses, 2002; Mandel, 2009). The value of rarity has implications for aggregation of consumer demand to market-level demand. Leibenstein (1950) shows the net result of demand for rarity, *i.e.* the "snob effect," is a steepening of the aggregate demand curve. More subtly, an interpretation of aggregate demand as on ordering of individuals from highest to lowest willingness to pay fails in the rarity context if a drop in price (increase in consumption) causes some individuals with high values of rarity to exit the market. Failure to account for rarity value, may lead to bias in environmental valuation. For instance, efforts to estimate the social cost of carbon may include the marginal external cost of changes in animal populations, *e.g.* polar bears or coral reefs. Benefits transfer estimates based on current populations will systematically underestimate marginal costs if climate change reduces future populations and if consumers' valuations increase as species become more rare (Fisher et al., 2008; Brander et al., 2012). Finally, conservation biologists have argued rarity effects could drive species extinction if willingness to pay for rare species increase faster than harvesting costs (Courchamp et al., 2006; Hall, Milner-Gulland, and Courchamp, 2008; Holden and McDonald-Madden, 2017; Lyons and Natusch, 2013) or if endangered species designations stimulate demand for harvesting rare species (Palazy et al., 2011; Prescott et al., 2012).

Despite the potential importance of these effects, there is little to no direct empirical evidence of demand for rarity. This is likely due to the many challenges of estimating rarity value in these settings. First, if the marginal value of consumption decreases in quantity, *i.e.* demand is downward sloping, inward shifts in supply result in higher prices due to scarcity. This can make it impossible to isolate rarity value. For instance, recent estimates of prices for rare coins (Dickie, Delorme Jr, and Humphreys, 1994; Koford and Tschoegl, 1998) cannot separately identify the rarity and scarcity components of high prices, since it is precisely the limited supply of certain coins that makes them more desirable. Second, increasing prices for rare goods could reflect increased production or harvest costs. Slone, Orsak, and Malver (1997) document higher prices payed to indigenous peoples who collect rare butterflies in New Guinea. Higher prices reflect increased costs if decreased abundance requires longer trips into the wilderness to collect specimens. Third, luxury goods may be more rare but may also have functional or quality differences relative to more abundant varieties.

Here, I exploit novel characteristics of a collectible goods market, "Magic: the Gathering," a trading card game, to estimate the value for rarity. In this market, the manufacturer labels goods according to four different rarity categories that approximate relative rarity. However, changes in product design combined with manufacturing technology constraints affect the market supply within and across rarity categories over time. Using these changes, I calculate the odds of obtaining a particular card in a retail pack, a proxy for quantity. Then, using two different empirical strategies I non-parametrically estimate the effect of odds on prices and separately identify the effect of rarity. To do this, I collect secondary market prices on thousands of unique goods (cards) from a popular online marketplace. I combine these data with detailed product-level information where I observe *every* characteristic appearing on each card. By comparing functionally equivalent and, in some cases otherwise identical cards, I isolate the effect of rarity designation from other factors such as scarcity and unobserved quality.

The two empirical approaches form upper and lower bounds on the rarity values. The first strategy leverages variation in prices and odds across different cards in each of the rarity categories. I collect data on approximately 3,600 recently-printed cards over a six-week period in 2019. I employ a cross-sectional hedonic framework using fixed-effects for observed product characteristics to flexibly model functional differences across cards. I show prices are inversely related to the odds of obtaining a particular card in a retail pack. However, conditional on these odds and product characteristics, prices are substantially higher for cards with rare designations. On average, prices for cards in the highest rarity category are between 70 and 90 times higher than cards in the common category, all else equal. I present several robustness checks investigating the salience of scarcity and the possibility of unobserved (to the econometrician) product differences across rarity categories. To the extent remaining unobserved quality differences are not captured by the model, these estimates are an upper bound on the true rarity values.

The second strategy uses variation in rarity designation *within* individual cards that are reprinted, many times more than once, at different rarity categories. I collect prices for approximately 600 cards that experienced these "rarity shifts." I account for observable and unobservable card characteristics with individual card fixed-effects. Since the rarity-shifted cards are identical other than the change in rarity designation, I attribute observed price differences to rarity value. I find prices are substantially higher for cards printed with rare designations relative to the same cards with common designations. For reasons discussed below, rarity values measured by these rarity shifts are likely biased downwards and therefore represent a lower bound on the true rarity values.

In both empirical approaches, I can easily rule out cost-based explanations for the observed price differences because manufacturing costs are equivalent across rarity categories. The observed price effects are also independent of scarcity value, as captured by the odds of obtaining a particular card in a retail pack, and do not seem to be driven by functional differences across cards. Since both empirical approaches yield large positive rarity values, these results are perhaps the best evidence to date in support of a demand for rarity.

2 Rarity

I first provide a simple model for consumers' valuations of rare goods. Assume a consumer's valuation of a rare good i can be written in terms of an intrinsic value for characteristics of the good $f(X_i)$ and a rarity value $V_r(Q_i)$ that depends on the total quantity of the good:

$$V_i = f(X_i) + V_r(Q_i),$$

where V_r is decreasing in Q_i. The intrinsic value term $f(X_i)$ captures functional differences across goods. The rarity term, $V_r(Q_i)$ captures the additional value consumers place on rare goods. The quantity Q_i, could be the actual total quantity of the good consumed or it could reflect a less precise measure of quantity, a perceived quantity $(\hat{Q}_i)$, for goods viewed as rare.

Figure 1 illustrates the effects of rarity on prices for two representative goods. Panel a.) shows the effect of rarity and panel b.) shows the effect of perceived rarity. First, consider supply of a "common" good, Q_C with inverse demand $D_C(P)$ that reflects the sum of individual valuations. Supply is shown as perfectly inelastic, for convenience and because it fits the empirical application.[1] Assume there is no rarity value for the common good such that $V_r(Q_c) = 0$. In equilibrium, the price of the common good is P_C. Now, consider a functionally equivalent, "rare" good with inverse demand $D_R(P)$, and supply Q_R, where $Q_R < Q_C$. Consumers have positive rarity value for the rare good such that $V_r(Q_R) > 0$. Note that in the absence of rarity value $D_C(P) = D_R(P)$, since the goods are assumed to be functionally equivalent and therefore have the same intrinsic value to each consumer.

[1]The intuition presented here readily extends to other models of supply.

The fact that the rare good is produced in lower quantity has two effects on price. First, because $Q_R < Q_C$, the price of the rare good is higher by the amount $P' - P_C$. However, when consumers value rarity the equilibrium price for the rare variety is higher by an additional $P_R - P'$. I define the first effect, $P' - P_C$, as the scarcity effect and the second effect, $P_R - P'$ as the rarity value.

The rarity effects can differ depending on whether or not consumers' valuations accurately reflect the quantity of the rare good. In panel a.) the rarity value reflects consumers' correct assessment of quantity such that $P_R - P' = V_r(Q_R)$. This yields a steeping of the demand curve relative to the functionally equivalent common variety with no rarity value. On the other hand, the rarity value could instead be based on imperfect information on the good's rarity, for instance, advertising, in the case of luxury goods, or rarity designations in the cases of collectibles or conservation. If the rarity value $V_r(\hat{Q}_R)$ does not strictly depend on Q_R, positive rarity value ($V_r(\hat{Q}_R) > 0$) would still yield an upward shift in D_R, though the magnitude would not necessarily have a functional relationship with Q_R. Because consumers may value real rarity, perceived rarity or both, I treat any positive effect of rarity on price as evidence of the existence of rarity value.

This simple conceptual model highlights several empirical challenges. First, estimating the rarity value requires accounting for the effect of scarcity $P' - P_C$ in the total price difference $P_R - P_C$. Second, if rare goods are functionally superior, as may be the case with luxury goods, some or all of the price difference ($P_R - P_C$) could be due to these characteristics. In other words, one must account for differences in the intrinsic value ($f(X_i)$) of each good. Third, while Figure 1 assumes perfectly inelastic supply, changes in marginal costs could contribute to higher observed prices for "rare" good. This seems most relevant for natural resource examples and in fact underlies most historical arguments against species extinction (Clark, 1976). If the marginal cost of a good shifts over time as it becomes more rare, for instance due to increased harvesting costs, the equilibrium price will rise, all else equal.

Overall, the empirical challenge for estimating rarity value requires understanding how consumer's perceptions of rarity affect prices accounting for differences in product characteristics, supply and marginal costs across goods. The following sections describe the novel features of this collectible good setting and the empirical approaches used to identify rarity value.

3 Data

I exploit detailed price and product data for the "Magic: the Gathering" (MTG) collectible card game. In many ways, the MTG market is an ideal setting for studying the existence of rarity value. First, the card manufacturer designates cards as being more or less rare than other cards, contributing to consumers' perceptions of rarity. Second, variation in the likelihood of obtaining a particular card in a retail pack can be used to separately identify scarcity effects. Third, the attributes of each good (card) are fully observable. Fourth, the common and rare varieties utilize the same production technology such that there are no differences in marginal costs across types.

MTG was created in 1993 and is played by approximately 20 million people worldwide (Wizards of the Coast, 2019). The game consists of individual cards that are assembled into decks used in recreational play and tournaments. Since 1993, thousands of unique card designs have been printed by the manufacturer "Wizards of the Coast Games," a subsidiary a Hasbro. Cards are produced as part of sets, *i.e.* the manufacturer does not, in general, sell individual cards.[2] New sets are released several times per year. Sets can include newly designed cards and reprinted versions of old cards. Cards are sold in pre-assembled decks or bundled into 15 card "booster packs." Primary sales are through online and retail stores. Importantly, there is an active secondary market that reveals the market value of individual cards. The secondary market includes traditional online retailers such as eBay and Amazon, but also online retailers specializing in collectible card games as well as brick-and-mortar gaming stores. The MTG market has previously been the basis for field experiments to study auction design (Lucking-Reiley, 1999; Reiley, 2006).

[2]Some promotional items will feature an individual card as part of a small bundle but the vast majority of cards are sold in sets. I exclude promotional cards from the data below.

From the outset, MTG has included both a gaming component and a collecting component. There are a large number of regional tournaments in the US and abroad. At the highest level, professional players in the *Magic* Pro League can earn prizes in the hundreds of thousands of dollars. Highly collectible cards earn high prices at auction. For instance, an original mint version of the "Black Lotus" card recently sold at auction for over $166,000 (Hall, 2019).

Each MTG card has unique attributes that make it more or less useful in game play. The supplementary appendix contains a schematic of the typical card layout and attributes. I collect detailed card attribute data from two sources: TCGplayer (2019b) and MTGJSON (2019). I observe *every* characteristic appearing on each card.[3,4] In addition to the detailed card attributes, each card is printed with a rarity designation. The manufacturer classifies cards into one of four rarity categories based on the *approximate* odds of obtaining a card of that type in a booster pack. The four categories from least to most rare are "common," "uncommon," "rare," and "mythic rare." Each card is labelled with a color-coded symbol and a letter C, U, R or M to denote its rarity category. Historically, a 15 card booster pack contains 10 common cards, 3 uncommon cards, one "basic land" and one rare, where approximately 1-in-8 rare cards is a mythic rare.[5]

I collect price data for the secondary market from TCGplayer, an online marketplace for the collectible gaming market used by over 2,500 local gaming stores. TCGplayer lists daily prices, calculated as average values across thousands of transactions (TCGplayer, 2019a). Prices were recorded once per week over a six-week period from March 14, 2019 through April 18, 2019 for cards from sixteen recent releases, ten "standard sets" consisting primarily of newly-designed cards and six "Masters" sets consisting mainly of reprinted cards.[6]

[3]These characteristics include; card type, power, toughness, mana cost, flavor text, oracle text and keyword abilities that are relevant for game play. I also observe characteristics such as artwork, artist, set name and card number that may be of value to collectors.

[4]While I observe every card attribute, modeling these features, and importantly interactions across features, in an econometric model is challenging. This suggests the possibility of omitted variable bias, an issue I address in the robustness checks below.

[5]I ignore basic lands because these are low value cards that do not vary substantially in design across sets.

[6]The sets were selected randomly from releases since 2015 and include: "Aether Revolt," "Amonkhet," "Dominaria," "Guilds of Ravnica," "Hour of Devastation," "Ixalan," "Kaladesh," "Ravnica Allegiance,"

Players and collectors obtain specific cards at random when they purchase retail packs. When individuals have heterogenous preferences, the secondary market reallocates cards based on individuals' willingness-to-pay for specific cards. Online platforms such as TCGplayer facilitate trades between large numbers of buyers and sellers. Therefore, I treat the market as competitive and assume transaction costs are small.[7] Under these conditions, trading in the secondary market achieves the efficient allocation of cards regardless of how the cards are initially distributed to individuals (Coase, 1960). Further, the equilibrium price recovers the price determined by the intersection of aggregate demand and the total supply of each card Q_i.

For my second specification, I collect prices on the approximately 600 cards that underwent "rarity shifts" and were reprinted in different rarity categories than initial printings. Cards can be "upshifted," where the reprinted version is in a more-rare category or "downshifted," where the opposite is true. I collect prices from TCGplayer (2019b), on a single day, for all versions of the reprinted cards but exclude any promotional versions that are not part of normal sets.

The precise odds of obtaining a particular card in a booster pack are a function of the manufacturer's design of each set, *i.e.* how many unique cards of each type to include, and the printing technology used to manufacture cards. These odds are well-known to collectors and players.[8] For instance, in many recent standard sets there are 101 unique common cards, 80 unique uncommon cards, 53 rare cards and 15 mythic rare cards. In this configuration, the common cards are printed on a single print sheet to which 20 "basic land" cards are added, for a total of 121 cards per 11-by-11 print sheet. The 80 uncommon cards are printed on two sheets with all 80 cards appearing on each sheet plus duplicates of half the uncommon cards on the first sheet and duplicates of the remaining 40 cards on the second.[9] A rare print sheet contains two copies of each rare card plus one copy of each mythic rare, for a total

"Rivals of Ixalan," "Battle for Zendikar," "Eternal Masters," "Iconic Masters," "Masters 25," "Modern Masters 2015," "Modern Masters 2017" and "Ultimate Masters."

[7] I.e. TCGplayer and local gaming stores are treated as low cost intermediaries who facilitate trades between individual collectors.

[8] Odds are widely discussed on internet forums, posted on web pages and other online media.

[9] Each sheet also contains a filler (blank) card.

of 121. A typical print run will include 10 common sheets, 3 uncommon sheets, 1 basic land sheet and 1 rare/mythic rare sheet. The individual cards are then cut from each sheet, pseudo randomized and one card from each sheet is inserted into a booster pack.

While the configuration above characterizes many recent sets, from time to time Wizards of the Coast designs sets that vary the number of cards of each type. For instance, in the "Ixalan" set, there are 10 additional rare cards, *i.e.* 63 total, plus 15 mythic rares. Because booster packs are assembled from cards cut from print sheets, this change alters the odds of opening a rare or mythic rare. Specifically, in a set of 53 rare cards and 15 mythic rares, the odds of obtaining a particular mythic rare card in a booster pack are 1 in 121. In a set with 63 rare cards and 15 mythic rares, the odds drop to 1 in 141.[10] I calculate the odds of obtaining a particular card in a booster pack using data on print sheet and set configuration. Because the manufacturer sells sets and not individual cards, potential endogeneity between rarity designation and individual card price is less of a concern.[11] Further, several specifications below use set fixed effects to account for design choices that affect mean price differences across sets. Table 1 in the appendix details the different configurations and card odds for each set.

An additional source of variation comes from premium "foil" versions of each card in a set. Foil cards are functionally identical to the normal versions of each card but use a special printing technology that gives the cards a metallic glossy finish. For standard sets, the odds of opening a foil card is 1 in 67, and is printed on each booster pack wrapper. For Masters sets, each pack contains one foil card, for odds of 1 in 15 cards. The inclusion of foil cards has two effects. First, since foil versions are essentially copies of cards in the set, they alter the odds of opening any given card in a pack. This effect is different in magnitude for standard sets where foil odds are much lower compared with Masters sets where one foil is guaranteed in each pack. The odds presented in Appendix Table 1 take into account the additional

[10] In other words, while there are the same number of mythic rares in the set, there are more total cards on each print sheet such that when that sheet is divided into packs, the odds of obtaining a mythic rare are lower.

[11] Specifically, while the overall set design choices do affect the prices a manufacturer receives for a retail booster box, the use here of individual card prices from the secondary market limits the possibility of endogeneity. Further, the empirical results below are robust to the inclusion of set fixed-effects that account for mean differences in design features and prices across sets.

effect of foil on category odds. Second, foils may act as an additional rarity category that is valued by collectors.

Both empirical strategies exploit variation in odds, independent of the rarity designation, to identify the effect of scarcity on card prices. Figure 2 plots the odds z_i of opening card in a MTG booster pack for the four rarity categories. Panel a summarizes data used in the cross-sectional hedonic approach. We see that there is variation in odds within categories across sets coming from different set configurations. Introducing foil versions increases the variation in odds, both within and across rarity categories. Panel b presents data for the rarity-shift sample. Because there are over 60 sets included in this sample spanning many years, there is substantially more variation in odds within rarity categories. The odds of opening a particular uncommon in some sets is greater than opening a common in other sets, for instance. Overall, this suggests that while odds are correlated with the rarity categories, there is sufficient variation in odds to separately identify both effects.

Table 1 presents summary statistics for cards in the two samples. The top panel summarizes prices for data used in the cross sectional-hedonic approach. There are approximately 3,600 unique cards, consisting of approximately 1,400 common cards, 1,200 uncommon cards, 800 rare and 200 mythic rare cards.[12] Since every card is printed in a non-foil and foil version, including foil prices doubles the number of cards to approximately 7,200. Mean prices for normal cards range from \$0.07 for common cards to \$2.76 for rare and \$12.29 for mythic rare cards. Mean prices are higher for foil versions, ranging from \$0.28 for common foil cards to \$22.59 for mythic rare foils. The maximum price is \$393.06 for a foil mythic rare, "Force of Will." Overall, the unconditional summary statistics indicate higher prices for premium foil versions and for cards in the more rare categories. The empirical models below isolate the effects of rarity from other factors that contribute to higher prices for these cards.

The middle panel summarizes prices for data used in the rarity-shift fixed-effect approach.[13] There are two trends worth noting. First, mean prices are higher in the rarity

[12]Here, I consider a unique card as an individual card in a set. Cards are often reprinted and may appear in multiple sets, a feature I exploit in an alternate specification below.

[13]Because reprinted cards may be reprinted several times and rarity shifted more than once, I include every version of each rarity-shifted card. Each version appears once in the data. Rarity is classified according to each versions designation.

shift sample. Since the sets covered in this sample span many more years than the recent sets included in the cross-sectional hedonic approach, and because cards for older sets are valued more by collectors, the mean prices are higher across all rarity categories. Second, the mean prices for non-foil versions of rare cards are higher than for mythic rare cards. This is because the the mythic rare category did not exist prior to 2008. Because cards in older sets are worth more, all else equal, mean prices for older rare cards are higher than for mythic rare cards that were only produced recently. The effect is more pronounced for non-foil cards because premium cards were not introduced until 1999 and card prices are substantially higher for sets from the first few years of production. The rarity-shift specification below uses set fixed-effects to account for mean differences in prices across sets produced in different years.

The final panel summarizes the proportions of different rarity shifts. Upshifts and downshifts occur with approximately equal probabilities. The most common shifts are from common to uncommon (34%) and from uncommon to common (31%). Shifts from rare to mythic rare make up about 5% of rarity shifts and shifts from mythic to rare about 2% of shifts. About 3% of shifted cards move more than one rarity category.

4 Value of rarity

The fundamental empirical challenge in estimating rarity value is one of estimating demand while separating out the effects of intrinsic value, scarcity and rarity value. Both identification strategies employ a hedonic approach. Following the definition in Section 2, an individual's utility for good i depends on an intrinsic component and a rarity value such that $V_i = V(X_i, \beta, V_r) + \epsilon_i$. Under standard assumptions, integrating over the distribution of the error term (ϵ_i) yields a market-level relationship between market shares and prices that can be interpreted as a hedonic price function (Allcott and Wozny, 2014; Rosen, 1974). Below I describe the details involved in implementing this approach in the two samples as well as interpretation of the rarity effect estimates.

4.1 Cross-sectional hedonic approach

The first approach uses a cross-section hedonic framework to estimate the value of rarity in the MTG market. The price of card i is modeled as:

$$lnP_{it} = \delta_r + \beta X_i + \lambda(z_i) + \epsilon_{it} \tag{1}$$

where δ_r is a set of dummy variables corresponding to the different rarity categories, common, uncommon, rare and mythic rare. X_i is a vector of characteristics of card i, $\lambda(z_i)$ is a flexible function of the odds of opening card i in a booster pack and ϵ_{it} is a well-behaved error-term.[14,15]

A novel feature of this setting, and a point of departure from prior attempts to measure rarity, is the ability to separately identify the scarcity and rarity value effects. In settings such as rare stamps or coins, it is precisely the relatively low quantities of these goods, i.e. scarcity, that leads to a rarity designation. Here, while the rarity designations are correlated with relative quantities, there is meaningful variation in the odds of obtaining rare cards within categories such that both effects can be identified. The scarcity effect, $P' - P_C$ in Figure 1, is modeled as a non-parametric function of the odds of obtaining a particular card in a booster pack, $\lambda(z_i)$. Here, the odds relationship is used as a proxy for the unobserved quantity Q_i. The odds z_i accurately measures relative quantity *within* a set and measures Q_i in models with set fixed effects.[16] In this approach, the demand curve is identified from cross-sectional variation in the inelastic supply of different individual cars via the odds ratio.

I estimate the partial linear model, Equation 1, using Robinson's two-step differencing estimator (Robinson, 1988).[17] The main variables of interest are the dummy variables for

[14] I use a log specification because the mean prices for foil cards presented in Table 1 suggests a proportional relationship. However, results with prices in levels are qualitatively similar.

[15] Price data for each card (i) are collected once a week (t) for six weeks. While technically a short panel, this is little time-series variation in prices within cards relative to cross-sectional variation across cards.

[16] In other words, the number of cards is simply the pack odds times the number of packs (Q_s) produced in each set, $Q_i = z_i \times Q_s$.

[17] In this approach, the parameters are estimated by first, kernel regressing the dependent variable and each independent variable on z, then regressing residuals for the dependent variable on the residuals for the independent variables. The non-parametric function $\lambda(z_i)$, is estimated by kernel-regression of z on the parametric residuals.

each of the main rarity categories in δ_r. Conceptually, these capture the rarity value in each category, *i.e.* the shifts leading to $P_R - P'$ in Figure 1. The advantage of not restricting the functional form of $\lambda(z_i)$, which may be highly non-linear, is that strong assumptions about the form of the odds relationship could bias the estimated rarity effects. However, the cost of this flexibility is that if consumers accurately perceive variation in odds, then the odds function $\lambda(z_i)$ may capture some of the rarity value. In this case, the estimated rarity values δ_r will be smaller than the true rarity values. However, if consumers' perceptions of quantities differ from the true quantities, the estimated rarity values will reflect perceived rarity across the different rarity designations. In either case, the estimated parameters are conservative in the sense they are biased toward finding no rarity effect.

The vector of card attributes X_i includes observable characteristics, apart from the rarity designation, to account for functional differences across cards. These attributes are flexibly modeled using sets of categorical variables for the presence or intensity of different attributes.[18] A limitation of the hedonic approach outlined here is that the value of certain attributes may be difficult to capture in an empirical model either because the attribute has a complex effect on game play or because the value of the attribute is enhanced or diminished by the other cards a player possesses. Therefore, while the main specification models observable card attributes, there is still the possibility of omitted variable bias. I address this possibility in an alternate specification below by including measures of card i's popularity in tournament play, a proxy for unobserved card quality. In Section 4.2, I account for unobserved card characteristics using card-specific fixed-effects.

Table 2 presents estimates of Equation 1 and several alternate specifications. I focus on the rarity category mean-effects. Estimates for other observable card characteristics are presented in the supplemental appendix. Column 1 shows the preferred specification including the main card attributes. Column 2 adds fixed effects for card sub-types. We see that relative to common cards, the omitted category, cards with more rare designations sell

[18]Specifically, X_i includes mana cost, power, toughness and "keyword abilities." Mana cost, power and toughness are modeled using sets of indicator variables for levels zero through five and a separate indicator for levels greater than five. Keyword abilities are modeled as indicator variables equal to one if a particular card is printed with this ability. See Table 2 of the supplementary appendix for means of card characteristics by rarity category.

at substantially higher prices. In particular, moving from common to rare increases log price by about 2.6 and increases price by about 13 times. Moving from common to mythic rare increases log price between 4.2 and 4.5, about 70 to 90 times the price in dollars.[19] Similarly, log prices for foil versions are on average 0.83 to 0.85 higher, about 130 percent higher, than non-foil versions. To see the effect of changes in odds on prices, Figure 3 plots the parametric residuals and the fitted non-parametric function $\lambda(z_i)$ against odds z_i for model 1. The slope is negative, indicating that prices fall as the odds of obtaining a particular card in a pack increase. The largest effects are for the rarest cards, *i.e.* foil versions, mythic rare and rare cards with odds < 0.02. The slope decreases in magnitude as the odds increase.

The results of the base model suggest prices respond to both odds and the rarity designations. Holding constant odds, cards with more rare designations transact at higher prices. Figure 1 provides two potential explanations for this result. First, it could be the case the rarity-value function $V_r(Q)$ is different for cards with different rarity designations, for instance, $V_r(Q_R) > V_r(Q_C)|Q_R = Q_C$. In this case, cards with more rare designations would be valued more highly even if card quantities are the same and consumers accurately perceive these quantities. Second, the rarity designations may cause consumers to perceive cards with rare designations as more rare, i.e. $\hat{Q}_R > Q_R$. This is the perceived rarity case. Empirically, I do not believe I can distinguish between these two case. However, I interpret the existence of either effect as evidence of rarity value.

The results in models 1 and 2 indicate consumers value rarity as conveyed by the rarity designations beyond the scarcity effects captured by the odds relationship. However, one concern is that the rarity designations are proxying for differences in odds across card types. In model 3, I indirectly test the salience of odds beyond the changes in rarity signified by the rarity designations. I exploit features of two sets in the sample. First, in the set "Ixalan," Wizards of the Coast slightly altered the ratio of mythic rare to rare cards on the rare print sheet. This decreased the odds of opening a mythic rare in a booster pack. Comments in online forums suggest this change was salient to collectors and players.[20] If the rarity

[19]Referring back to Table 1, the mean price for a non-foil uncommon is about 4 times the mean price of a common card. Mean prices for rare and mythic cards are approximately 40 and 170 times as large as the mean common card price.

[20]For instance, MTG head designer Mark Rosewater discussed the implications of the Ixalan design change

designation is simply proxying for the odds of obtaining a particular card, the lower mythic odds in this set would increase the mythic rare fixed-effect relative to other sets. Similarly, in the set "Ultimate Masters," Wizards of the Coast increased the odds of obtaining a mythic rare. Here, we would expect a decrease in the estimated effect of the mythic rare designation if the rarity categories are proxying for the actual odds. Column 3 explores these hypotheses by interacting indicator variables for the Ixalan and Ultimate Masters sets with the mythic rare effect. I find mythic rare cards in Ixalan are valued relatively less than mythic rare cards in other sets. The negative effect means these cards are less desirable, perhaps because set designers focused on the novel features of this set instead of the mythic cards, and does not support the hypothesis buyers are using the rarity category as a proxy for odds. Further, Ultimate Masters mythic rare cards are valued relatively more than other rare cards, again contrary to the hypothesis the rarity category is capturing changes in odds.

Another potential threat to identification relates to omitted variables, or the possibility combinations of card attributes are more or less valuable to players in ways that are difficult to model. For instance, certain cards are combined based on themes or play styles. To the extent these themes vary systematically, this can increase demand for certain types of cards based on characteristics that unobserved to the econometrician. This may bias my results if themes are correlated with rarity designations or if collectors view rarity categories as indicators of unobserved quality.[21] To account for this possibility, I leverage data from MTG tournaments. Most tournaments require players to register the cards used in their decks. The "deck lists" of tournament winners are reported and aggregated at several online sources. When certain cards or groups of cards become more or less popular due to unobserved attributes, this will show up as a change in the popularity of those cards in tournament play. Column 4 includes a measure of tournament popularity, the expected number of copies of a particular card in a tournament deck, as an additional regressor.[22] Tournaments fall into several types and have different rules for which cards may be used. I focus on three

in his popular blog (Rosewater, 2017).

[21]For instance, Hilger, Rafert, and Villas-Boas (2011) show labels containing "expert" opinions serve as indicators of quality.

[22]Calculated as the percent of registered decks containing card i times the average number of copies of card i in a deck.

popular tournament formats, "standard tournaments" that only allow cards from recently released sets, "modern" tournaments that allow most cards from sets going back many years and "legacy" tournaments that focus on older sets. These formats capture a large share of competitive play. In column 4, we see prices are higher for cards that are more popular in tournament play. The largest effects are for the "modern" format, each time a particular card is included in a deck, in expectation, log price increases by approximately 4.9. Importantly, the point estimates for the rarity categories remain large and statistically significant, though the point estimates are slightly smaller in magnitude compared to the base model. This suggests the rarity designations still have value apart from unobserved card quality.

Finally, column 5 adds set fixed-effects. Recall that while the odds relationship captures the likelihood of obtaining a particular card in a pack, the *total* number of cards (packs) produced by Wizards of the Coast is unobservable and varies by set. However, the product of set fixed-effects and card odds captures the total card quantity. In addition, because each set is printed once, set effects act like year effects, capturing the loss or destruction of cards over time, reduced quantity and the associated effects on prices.[23] Unobserved quality may also vary by set if certain sets are more or less desirable. In column 5 we again see the estimated effects for the rarity categories are quite similar to the base specification, column 1. The estimated premium for foil cards is smaller, but still positive and statistically significant.

4.2 Rarity-shift fixed-effect approach

The results above strongly support consumer demand for rarity. Here, I exploit an additional feature of MTG to estimate the value of rarity using an alternate identification strategy. Card sets contain newly designed cards and a few cards reprinted from earlier sets. Masters sets are composed entirely of reprinted cards. Typically, reprinted cards are identical to earlier versions. However, cards are occasionally reprinted in a different rarity category. Apart from the rarity designation, these rarity-shifted cards are otherwise identical to the earlier version. Therefore, the effect of rarity on price for rarity shifted cards can be estimated using panel methods, exploiting card fixed-effects to account for both observable and unobservable

[23]Estimates with print year fixed-effects are very similar to those show in column 5.

characteristics. Unfortunately, the manufacturer's decision to rarity-shift cards likely biases downward the estimated rarity value for two reasons. First, reprinted cards decrease the value of prior versions due to an increase in supply. Since cards with more rare designations are printed in smaller quantities in a print run, the price impact of a reprint on prior versions is smaller for an upshifted card than for a downshifted card. This reduces the price gap between the original and reprinted cards, for both types of rarity shifts. Second, if cards that are upshifted are relatively "better" within-category, or if the upshifting itself increases collectors' subjective assessments of the original card's value, they will be priced relatively higher within the lower rarity category so that the difference in price between the original and upshifted version will be smaller. The opposite logic holds for downshifted cards. So, while the rarity shift approach has the advantage of accounting for unobserved card characteristics, it likely suffers from downward bias that works against finding a positive rarity value. In light of this, I interpret these estimates as lower bounds on the true rarity values.

Using the data on reprinted cards with rarity shifts I estimate the fixed-effect model:

$$lnP_i = \delta_r + \lambda(z_i) + \epsilon_s + \epsilon_n + \epsilon_i \tag{2}$$

where ϵ_n is a fixed-effect for card of name n reprinted at least once with a rarity shift.[24] As in the main results, δ_r is a set of indicator variables corresponding to the different rarity categories. The parameters are now identified from within-card variation in price and rarity designation. $\lambda(z_i)$ is a non-parametric function of the odds of obtaining a particular card in a booster pack, which also varies from set (printing) to set. I use set fixed-effects ϵ_s to account for differences in the sizes of print runs across sets and the survival rate of cards over time. As before, Equation 2 is estimated using Robinson's method.

The bottom panel of Figure 3 plots the estimated non-parametric relationship between odds and prices for Equation 2. The relationship is comparable to the estimated function in panel (a) for the main specification and suggests a strong relationship between odds and prices. However, conditional on this relationship buyers still pay higher prices for reprinted

[24]There is one observation for each card i from each printing. The number of printings varies from card to card. I omit subscripts for printing to simplify notation.

cards with more rare designations, as shown in column 6 of Table 2.

Estimates for the rare and mythic rare designations as well as for foil cards are positive and statistically significant, consistent with the existence of rarity value. The estimated values for the rarity categories and premium foil cards are smaller in magnitude compared with the other results in Table 2 and the point estimate for the uncommon designation is essentially zero and not statistically significant. These results are not surprising given the potential bias described above. Since the ratio of average uncommon to common odds is the largest and because cards in these categories are most similar in terms of overall design, the bias is likely largest for rarity-shifts between uncommon and common. For the more rare categories, the effects are economically significant. Moving from common to rare increases log price by 0.445 or about 56 percent. Moving from common to mythic rare increases log price by 0.726 or about 107 percent. The effect for foil cards is similar in magnitude. These results, namely that variation in rarity designation *within-card* yields significant price effects, are quite remarkable and provide further evidence of rarity effects.

5 Conclusions

The existence of rarity value has important implications for understanding the demand for luxury and collectible goods. Whether consumers place higher value on rare goods may also hasten the depletion of natural resources and complicate efforts to protect endangered species. However despite these important implications, empirical challenges have prevented credible estimates of rarity value. Here I surmount many of these challenges by exploiting the novel characteristics of a collectible goods market to estimate the market value of rarity. I find that the odds of obtaining cards of a particular type, a proxy for quantity, and manufacturer created rarity designations, positively affect prices. In other words, conditional on the likelihood of obtaining a particular card, cards designated as more rare are worth more to collectors. The higher prices for goods designated as rare do not appear to be driven by unobserved quality or differences in costs across goods of different rarity categories, confounding factors that are difficult to rule out in earlier studies in other markets. Overall, these results strongly support consumer demand for rarity in this setting.

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Figures

Figure 1: Conceptual model for rarity value.

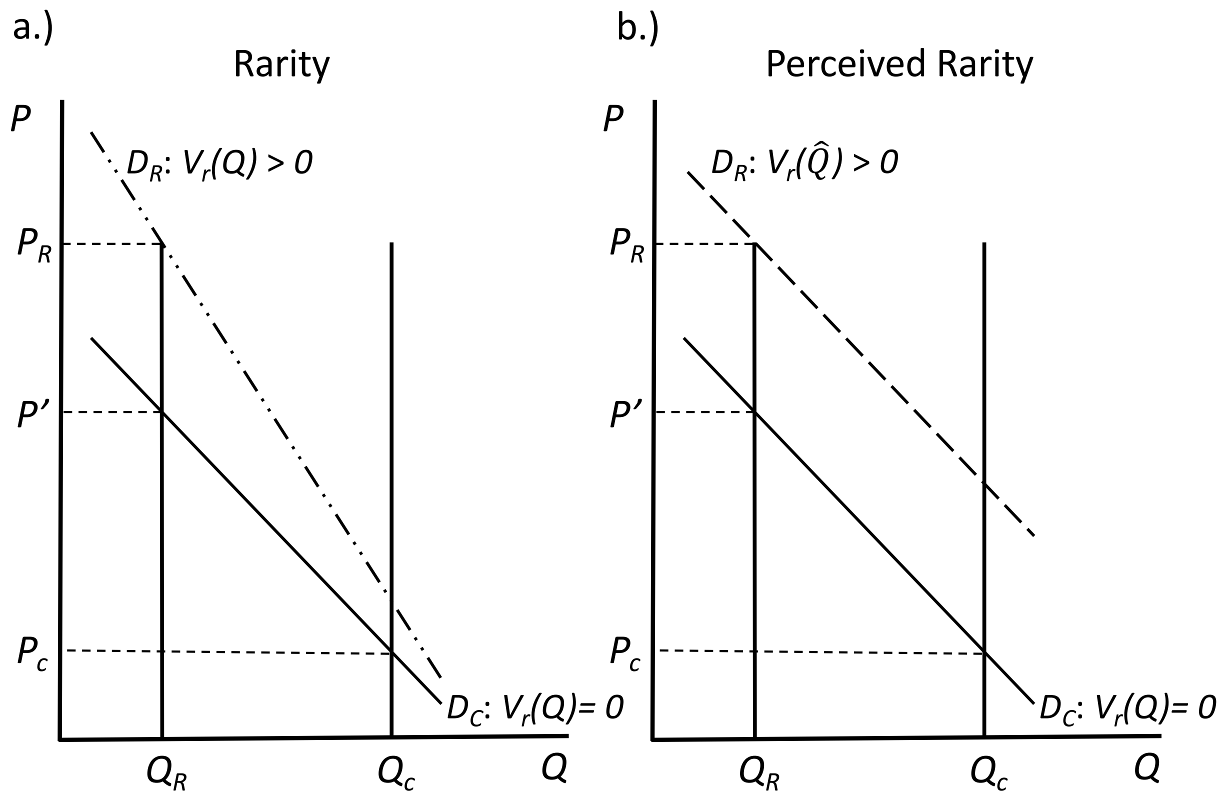
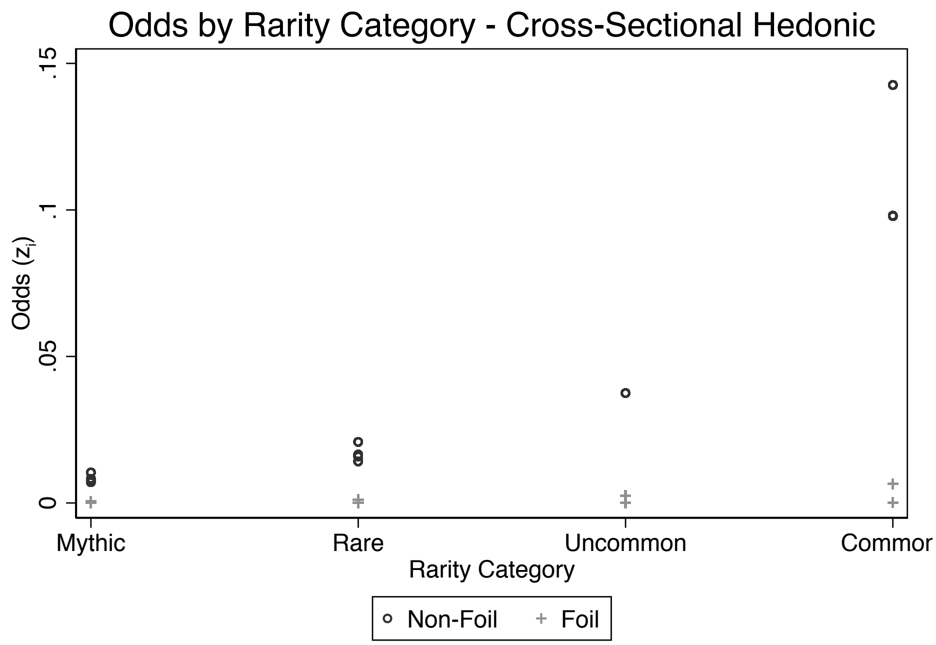


Figure 2: The odds of obtaining a particular card in a MTG booster pack (z_i). Odds depend on the rarity category, the total number of unique cards in a set, the number of cards from each rarity category in a given set and whether the card is a premium (foil) card.

(a) Main specification



(b) Rarity shifts

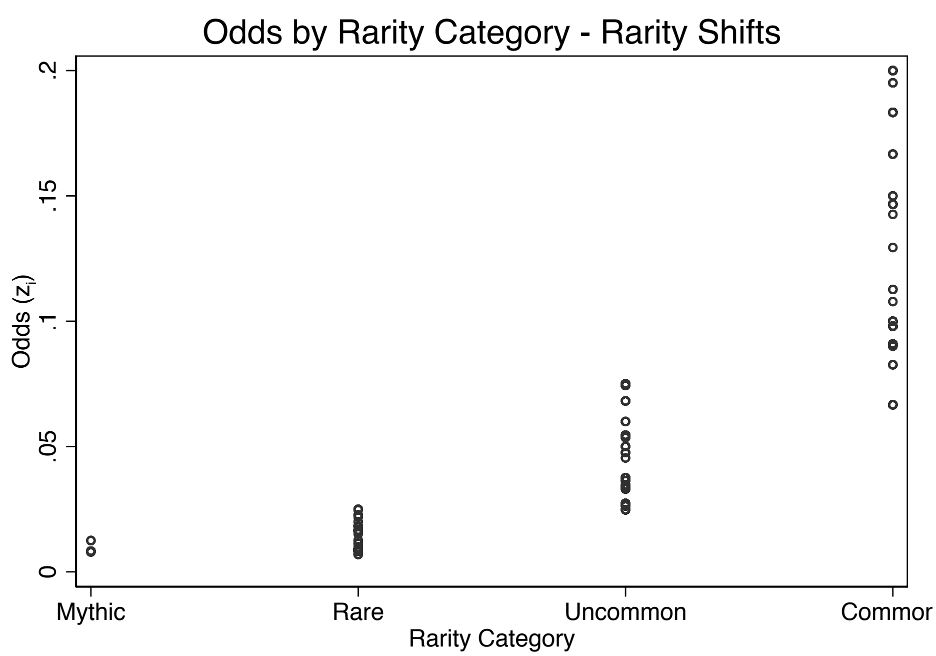
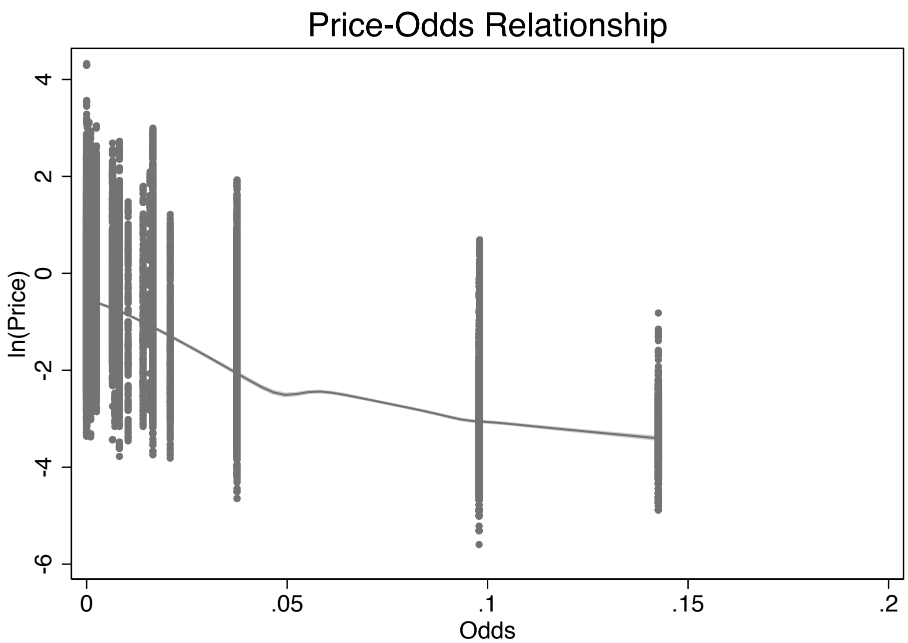
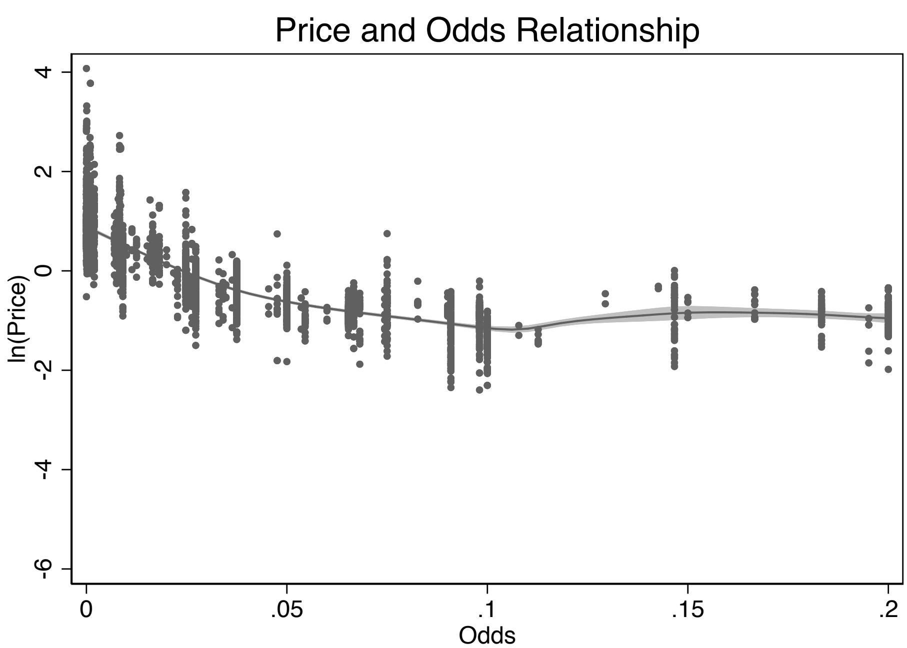


Figure 3: Price-Odds relationship for the cross-sectional hedonic (a) and rarity-shift (b) approaches. Plotted are the parametric residuals ($ln(price) - X\beta$) and the non-parametric function $\lambda(z_i)$. The gray-shaded regions are 95-percent confidence bands.

(a) Main specification



(b) Rarity shifts



Tables

Table 1: Summary statistics by rarity category for the cross-sectional hedonic and rarity shift samples.

	Cross-Sectional Hedonic Approach				
	Num. Cards	Mean	Std. Dev.	Min.	Max.
Non-Foil					
Common	1,442	$ 0.07	$ 0.14	$ 0.01	$ 2.84
Uncommon	1,159	$ 0.28	$ 0.69	$ 0.01	$ 10.25
Rare	808	$ 2.76	$ 7.43	$ 0.07	$ 98.81
Mythic Rare	226	$ 12.29	$ 21.98	$ 0.21	$ 185.64
Foil					
Common	1,442	$ 0.28	$ 0.73	$ 0.01	$ 17.86
Uncommon	1,159	$ 0.89	$ 1.70	$ 0.02	$ 18.20
Rare	808	$ 5.22	$ 10.44	$ 0.15	$ 123.01
Mythic Rare	226	$ 22.59	$ 39.14	$ 0.68	$ 393.06

	Rarity-Shift Fixed-Effect Approach				
	Num. Cards	Mean	Std. Dev.	Min.	Max.
Non-Foil					
Common	605	$ 3.48	$ 26.65	$ 0.14	$ 532.23
Uncommon	804	$ 16.84	$ 94.70	$ 0.20	$1,200.00
Rare	334	$ 52.39	$270.48	$ 0.30	$3,500.40
Mythic Rare	65	$ 22.31	$ 28.60	$ 0.80	$ 130.00
Foil					
Common	335	$ 4.86	$ 23.91	$ 0.24	$ 296.49
Uncommon	430	$ 3.08	$ 9.11	$ 0.27	$ 116.18
Rare	147	$ 30.26	$ 96.53	$ 0.73	$ 800.00
Mythic Rare	53	$ 35.31	$ 45.43	$ 2.70	$ 234.95

Rarity Shifts	% of Cards
Common to Uncommon	34%
Uncommon to Common	31%
Uncommon to Rare	11%
Rare to Uncommon	14%
Rare to Mythic Rare	5%
Mythic Rare to Rare	2%

Table 2: Estimated relationships between rarity designations and card prices accounting for relative scarcity (odds) and card attributes.

Card Prices and Rarity Designations

	(1) Base Model	(2) Type Effects	(3) Rarity as Odds Proxy	(4) Controls for Unobserved Quality	(5) Set Effects	(6) Identification from Rarity Shifts
Uncommon	0.985***	0.969***	0.984***	0.913***	0.955***	-0.008
	(0.0385)	(0.0390)	(0.0385)	(0.0357)	(0.0383)	(0.0599)
Rare	2.599***	2.534***	2.595***	2.487***	2.486***	0.445***
	(0.0492)	(0.0518)	(0.0492)	(0.0477)	(0.0453)	(0.0914)
Mythic Rare	4.492***	4.242***	4.513***	4.223***	4.273***	0.726***
	(0.0866)	(0.1026)	(0.0910)	(0.0795)	(0.0786)	(0.1134)
Foil	0.849***	0.843***	0.843***	0.828***	0.302***	0.794***
	(0.0478)	(0.0477)	(0.0476)	(0.0453)	(0.0519)	(0.0648)
Ixalan Mythic Rare			-0.958***			
			(0.2647)			
Ultimate Masters Mythic Rare			0.929***			
			(0.2537)			
Standard Tournament Popularity				1.351***		
				(0.2781)		
Legacy Tournament Popularity				1.879***		
				(0.3316)		
Modern Tournament Popularity				4.879***		
				(0.6667)		
Card Attribute Effects	Yes	Yes	Yes	Yes	Yes	No
Keyword Ability Effcts	Yes	Yes	Yes	Yes	Yes	No
Sub Type Effects	No	Yes	No	No	No	No
Card Effects	No	No	No	No	No	Yes
Set Effects	No	No	No	No	Yes	Yes
Observations	43613	43613	43613	43613	43613	3008
Adjusted R Sq.	0.53	0.53	0.53	0.58	0.57	0.90

Notes: Dependent variable is the natural logarithm of TCGPlayer "Market Price." Tournament popularity refers to the expected number of copies of a particular card registered in a tournament deck. Card effects are fixed effects by card name. Standard errors clustered at the card-level in parentheses. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Supplemental appendix

Appendix figures

Figure 1: Schematic depicting MTG card design and attributes, adapted from MTGWiki (2019).

Appendix tables

Table 1: Individual card odds by set and rarity category for normal (non-foil) and premium (foil) cards.

Individual Odds for Foil and Non-Foil Versions by Set and Rarity Category

	Non-Foil				Foil			
Series	C	U	R	M	C	U	R	M
Aether Revolt	0.14264	0.03750	0.02083	0.01042	0.000151	0.000033	0.000018	0.000009
Amonkhet	0.09789	0.03750	0.01653	0.00826	0.000103	0.000033	0.000015	0.000007
Battle for Zendikar	0.09789	0.03750	0.01653	0.00826	0.000103	0.000033	0.000015	0.000007
Dominaria	0.09789	0.03750	0.01653	0.00826	0.000103	0.000033	0.000015	0.000007
Eternal Masters	0.09804	0.03750	0.01653	0.00826	0.006920	0.002206	0.000972	0.000486
Guilds of Ravnica	0.09789	0.03750	0.01653	0.00826	0.000103	0.000033	0.000015	0.000007
Hour of Devastation	0.14264	0.03750	0.02083	0.01042	0.000151	0.000033	0.000018	0.000009
Iconic Masters	0.09804	0.03750	0.01653	0.00826	0.006920	0.002206	0.000972	0.000486
Ixalan	0.09789	0.03750	0.01418	0.00709	0.000103	0.000033	0.000013	0.000006
Kaladesh	0.09789	0.03750	0.01653	0.00826	0.000103	0.000033	0.000015	0.000007
Masters 25	0.09804	0.03750	0.01653	0.00826	0.006920	0.002206	0.000972	0.000486
Modern Masters 2015	0.09804	0.03750	0.01653	0.00826	0.006920	0.002206	0.000972	0.000486
Modern Masters 2017	0.09804	0.03750	0.01653	0.00826	0.006920	0.002206	0.000972	0.000486
Ravnica Allegiance	0.09789	0.03750	0.01653	0.00826	0.000103	0.000033	0.000015	0.000007
Rivals of Ixalan	0.14264	0.03750	0.02083	0.01042	0.000151	0.000033	0.000018	0.000009
Ultimate Masters	0.09804	0.03750	0.01587	0.00794	0.006920	0.002206	0.000934	0.000467

Notes: Individual card probabilites are adjusted for the number of cards of each type contained in a standard booster pack of each series.

Table 2: Means for card characteristics by rarity category in the cross-sectional hedonic data.

Cross-Sectional Hedonic Sample Means	Common	Uncommon	Rare	Mythic Rare
Foil	0.500	0.500	0.500	0.500
Mana Cost	2.719	4.665	3.468	3.135
Power	2.303	4.447	3.103	2.563
Toughness	2.512	4.682	3.172	2.734
Ascend	0.003	0.009	0.011	0.008
Deathtouch	0.015	0.013	0.010	0.015
Defender	0.017	0.004	0.004	0.016
Destroy	0.017	0.022	0.010	0.017
Double Strike	0.006	0.018	0.011	0.008
Enchant	0.041	0.000	0.007	0.023
Enrage	0.003	0.009	0.004	0.007
Exile	0.065	0.173	0.137	0.096
First Strike	0.024	0.027	0.017	0.014
Flash	0.022	0.044	0.025	0.030
Flying	0.119	0.247	0.129	0.130
Haste	0.034	0.097	0.061	0.047
Hexproof	0.007	0.013	0.010	0.013
Indestructible	0.007	0.058	0.014	0.012
Lifelink	0.017	0.040	0.028	0.019
Meance	0.017	0.018	0.015	0.009
Reach	0.015	0.009	0.005	0.004
Trample	0.031	0.106	0.043	0.045
Vigilance	0.022	0.071	0.033	0.028
Standard Pop.	0.007	0.037	0.038	0.020
Legacy Pop.	0.004	0.033	0.009	0.009
Modern Pop.	0.004	0.025	0.010	0.009

Notes: Foil is an indicator variable equal to one if the card is a premium foil card. Mana cost, power and toughness are non-negative, integer variables. Standard Pop., Legacy Pop. and Modern Pop. are measures of tournament popularity defined as the expected number of cards in a tournament deck. The remaining variabilities are indicator variables equal to one if the card contains a given "keyword ability."

Table 3: Expanded results including main card characteristics.

	Card Prices and Rarity Designations				
	(1)	(2)	(3)	(4)	(5)
	Base Model	Type Effects	Rarity as Quality Proxy	Controls for Unobserved Quality	Series Effects
Uncommon	0.985***	0.969***	0.984***	0.913***	0.955***
	(0.0385)	(0.0390)	(0.0385)	(0.0357)	(0.0383)
Rare	2.599***	2.534***	2.595***	2.487***	2.486***
	(0.0492)	(0.0518)	(0.0492)	(0.0477)	(0.0453)
Mythic Rare	4.492***	4.242***	4.513***	4.223***	4.273***
	(0.0866)	(0.1026)	(0.0910)	(0.0795)	(0.0786)
Foil	0.849***	0.843***	0.843***	0.828***	0.302***
	(0.0478)	(0.0477)	(0.0476)	(0.0453)	(0.0519)
Ixalan Mythic Rare			-0.958***		
			(0.2647)		
Ultimate Masters Mythic Rare			0.929***		
			(0.2537)		
Standard Tournament Popularity				1.351***	
				(0.2781)	
Legacy Tournament Popularity				1.879***	
				(0.3316)	
Modern Tournament Popularity				4.879***	
				(0.6667)	
Mana Cost = 1	-0.382***	-1.150***	-0.381***	-0.571***	-0.385***
	(0.0981)	(0.3700)	(0.0981)	(0.0923)	(0.0912)
Mana Cost = 2	-0.740***	-1.507***	-0.740***	-0.720***	-0.721***
	(0.0840)	(0.3665)	(0.0841)	(0.0835)	(0.0796)
Mana Cost = 3	-0.933***	-1.699***	-0.928***	-0.852***	-0.896***
	(0.0828)	(0.3658)	(0.0829)	(0.0834)	(0.0783)
Mana Cost = 4	-1.178***	-1.940***	-1.170***	-1.084***	-1.152***
	(0.0859)	(0.3667)	(0.0860)	(0.0863)	(0.0816)
Mana Cost = 5	-1.289***	-2.041***	-1.281***	-1.171***	-1.243***
	(0.0917)	(0.3677)	(0.0919)	(0.0921)	(0.0862)
Mana Cost > 5	-1.403***	-2.184***	-1.373***	-1.251***	-1.386***
	(0.0984)	(0.3688)	(0.0981)	(0.0990)	(0.0927)
Power = 1	-0.102	-0.128	-0.1050	-0.02	-0.11
	(0.1608)	(0.1627)	(0.1608)	(0.1374)	(0.1501)
Power = 2	-0.134	-0.164	-0.141	-0.137	-0.14
	(0.1554)	(0.1577)	(0.1554)	(0.1333)	(0.1438)
Power = 3	-0.321**	-0.345**	-0.326**	-0.329**	-0.294**
	(0.1571)	(0.1591)	(0.1570)	(0.1347)	(0.1454)
Power = 4	-0.407**	-0.417***	-0.413***	-0.389***	-0.400***
	(0.1594)	(0.1613)	(0.1593)	(0.1380)	(0.1483)
Power = 5	-0.169	-0.172	-0.1970	-0.158	-0.187
	(0.1705)	(0.1710)	(0.1704)	(0.1506)	(0.1589)
Power > 5	-0.125	-0.154	-0.137	-0.131	-0.165
	(0.2024)	(0.2016)	(0.2020)	(0.1854)	(0.1990)
Toughness = 1	-0.115	-0.16	-0.112	-0.101	-0.156
	(0.1654)	(0.1994)	(0.1653)	(0.1407)	(0.1547)
Toughness = 2	-0.042	-0.114	-0.037	-0.024	-0.031
	(0.1581)	(0.1947)	(0.1581)	(0.1357)	(0.1462)
Toughness = 3	-0.119	-0.193	-0.113	-0.095	-0.059
	(0.1551)	(0.1905)	(0.1551)	(0.1330)	(0.1438)
Toughness = 4	0.094	0.004	0.099	0.089	0.125
	(0.1618)	(0.1953)	(0.1618)	(0.1386)	(0.1495)
Toughness = 5	0.076	-0.037	0.063	0.092	0.102
	(0.1622)	(0.1946)	(0.1621)	(0.1424)	(0.1510)
Toughness > 5	0.199	0.113	0.189	0.200	0.200
	(0.1935)	(0.2201)	(0.1933)	(0.1767)	(0.1909)
Card Attribute Effects	Yes	Yes	Yes	Yes	Yes
Keyword Ability Effcts	Yes	Yes	Yes	Yes	Yes
Sub Type Effects	No	Yes	No	No	No
Series Effects	No	No	No	No	Yes
Observations	43619	43613	43613	43613	43613
Adjusted R Sq.	0.53	0.53	0.53	0.58	0.57

Notes: Dependent variable is the natural logarithm TCGPlayer "Market Price." Tournament popularity refer to the expected number of copies of a particular card registered in a tournament deck. Standard errors clustered at the card-level in parentheses. ***, ** and * denote significance at the 1 percent, 5 percent