Stock Market Anomalies and Baseball Cards *

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Abstract: Baseball cards exhibit anomalies that are analogous to those that have been documented in financial markets, namely, momentum, price drift in the direction of past fundamental performance, and IPO underperformance. Momentum profits are higher among active players than retired players, and among newer sets than older sets. Regarding IPO underperformance, we find newly issued rookie cards underperform newly issued cards of veteran players, and that newly issued sets underperform older sets. The results are broadly consistent with models of slow information diffusion and short-selling constraints.

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I. Introduction

Basic financial theory predicts that stock returns should be unpredictable after adjusting for risks. That is, any abnormal returns earned by trading strategies are either due to random chance or they are compensation for risks that investors care about that are not captured by the asset pricing model. However, financial economists have documented the existence of simple strategies that earn unusually high or low returns despite the fact that the strategies do not load heavily on common risk factors. For example, Jegadeesh and Titman (1993) document stock price "momentum," i.e., the tendency for stocks that have performed well in the past 3-12 months to continue outperforming stocks that have performed poorly in the past 3-12 months. In addition, Ritter (1991) documents that firms that have recently gone public underperform their peers over the three years after their public listing.

One of the most prominent explanations for momentum was developed by Hong and Stein (1999). In their model, momentum arises because information gradually diffuses across the investor population. That is, at each time *t* there is information that is released, but different portions of the population observe different pieces of the information at different times—it is only at a later date *s* (where s>t) that everyone has observed the information that was released at time *t*. Although Hong and Stein (1999) develop their model in the context of financial assets, its key features of gradual information diffusion and prices not fully reflecting available information should apply in other environments, too. A primary objective of this paper is to test Hong and Stein's (1999) explanation for price momentum in a new, non-financial environment. If we find support for their theory, we cannot rule-out alternative explanations for momentum in the stock market. However, if their predictions are not supported in non-financial environments, then we can safely conclude that it is unlikely their theory explains momentum in the stock market, where there are more sophisticated investors and arbitrageurs who should keep prices from diverging too far from fundamental values.

Our laboratory is the market for baseball cards. Baseball cards have a long history, dating all the way back to the late 1860's (Jamieson, 2011). By 1991, sales of baseball cards reached $1.2 billion annually (Jamieson, 2011). Although baseball cards produce no cash flows, their market values can be substantial. For example, the T206 Honus Wagner, which was produced from 1909-1911, has been sold for as much as $2.8 million.[1] Because there have been long periods of time over which their values have appreciated, baseball cards have often been perceived as investment vehicles. This perception has been fueled in part by the popular press: in 1988 the *New York Times* published an article on baseball cards noting that over the previous decade, cards' values had risen 32% per year.[2]

Most theories that financial economists have developed to explain stock price momentum do not apply in this market. There are no growth options, dividends, or mutual funds. Even within the class of behavioral theories, not all of the models apply to our setting. For example, Daniel, Hirshleifer and Subrahmanyam (1998) develop a model in which investors correctly interpret public information but overreact to private information. Since the vast majority of relevant information about baseball player performance and popularity is public, our setting is not naturally suited to testing their theory.[3] In contrast, Hong and Stein's (1999) model naturally applies to baseball cards. In the market for baseball cards, player performance is one of the primary determinants of card value, since performance has a strong effect on player popularity. Among active players, performance information is released almost daily since baseball teams play 162 games per year (plus playoffs). To the extent that collectors cannot immediately process all the performance information about all players in real-time (due to constraints such as limited attention), this information should diffuse through the population of collectors, and according to Hong and Stein (1999), baseball card prices should exhibit

[1] Source: http://www.latimes.com/sports/sportsnow/la-sp-sn-honus-wagner-card-20150427-story.html
[2] http://www.nytimes.com/1988/11/13/business/potpourri-a-grand-slam-profit-may-be-in-the-cards.html
[3] Consistent with this idea, we do not find any long run reversals, which Daniel, Hirshleifer and Subrahmanyam (1998) predict to exist in settings with non-trivial amounts of both public and private information.

momentum. We confirm that there is in fact momentum in the baseball card market, and that the momentum is actually much stronger than what is observed in financial markets: whereas momentum strategies earn less than 1% per month among stocks, momentum strategies of baseball cards earn up to 5.6% per month.

The substantial difference in momentum profits across markets should be expected, according to Hong and Stein (1999). There are many significant differences between the market for baseball cards and the stock market. One difference is the level of investor sophistication. In the stock market, there are many hedge funds that can arbitrage away inefficiencies and keep prices in line with fundamentals. In the baseball card market, there are dealers who are relatively sophisticated, but much of the activity in this market is driven by children. Moreover, whereas it is common to short stocks, there is little (if any) short selling of baseball cards. Hence, the opportunity for arbitrage is severely limited in the baseball card market. Because of these differences, we should expect momentum to be more pronounced in markets with lower levels of sophistication, such as the market for baseball cards.

Hong and Stein (1999) provide additional testable predictions in this market. Active players play up to 162 regular season games per year in addition to the postseason, whereas retired players do not play any games. If gradual information diffusion causes momentum, then momentum should be stronger among the cards of active players than retired players, because there is little to no new information released about the ability (or performance) of retired players. Consistent with this prediction, we find that when the 3 month momentum strategy is restricted to retired players, the strategy earns only 1.63% per month, but when the 3 month momentum strategy is restricted to active players, the strategy earns *9.42% per month*.

We can test Hong and Stein (1999) more directly by examining the relationship between the performance of active baseball players and their future card returns. If gradual information diffusion causes momentum, then we should find a positive relationship between the performance of a player in year t and the returns on his baseball cards in year t+1. To test this, we sort players into deciles each season based on common measures of player performance such as batting average, slugging percentage, etc. In the case of batting average, the cards of players within the top (bottom) decile in a given year have an average monthly return of 70 bps (-1.2%) in the following year. This return difference of 1.8% per month is statistically significant (t=4.35). In the case of slugging percentage, the cards of players within the top (bottom) decile in a given year have an average monthly return of 50 bps (-1%) in the following year. This return difference of 1.5% per month is statistically significant (t=3.22).

In addition to collecting individual cards, many people collect complete sets of cards, e.g., 1952 Topps. When a set is first produced, there is much uncertainty about the number of sets produced and the popularity of the set among other collectors. Over time, information should diffuse across the collector population. Hence, according to Hong and Stein (1999), we should expect to find momentum at the set level too. Consistent with this prediction, 3 month momentum strategies earn 4.34% per month. Moreover, according to Hong and Stein (1999), the profitability of momentum strategies should be greater among sets that were recently produced, since most of the information about older sets has likely already diffused among the collector population. This prediction is also confirmed: when the 3 month momentum strategy is restricted to sets that were released less than 10 years ago, the profits are 4.6% per month, but when the strategy is restricted to sets that are at least 10 years old the profits are 0.90% per month.

In addition to testing Hong and Stein (1999), the other major objective of our study is to use a non-financial environment to test Miller (1977). Miller (1977) argues that assets' prices are determined not by the average investor's valuation, but rather, the most optimistic investor's valuation, especially when there are short sale constraints. If investors are right on average, and in the long run, investors' beliefs converge, then returns should be lower for assets in which there are high levels of disagreement than for those with lower levels of disagreement. This theory has been used to explain the tendency for IPO firms to underperform their peers in the first three years after their public listing (Ritter and Welch, 2002). We test Miller (1977) by analyzing the performance of rookie cards and new sets. A card is a considered a "rookie card" if it is the player's first appearance on a regular issue card from a major card company. Players often have rookie cards before they play in the major leagues, and some players with rookie cards never make it to the major leagues. Like young firms, there is less information about rookies so it is more difficult to determine their quality/ability. Moreover, when sets are first released, there is a lot of uncertainty over the number of sets produced and how other collectors will value the sets. Hence, according to Miller (1977), we should expect rookie card prices to be initially overvalued compared to the cards of veteran players, and for rookie cards to underperform veteran cards over their first few years. Similarly, newly issued sets should underperform older sets. Consistent with these predictions, we find that rookie cards and new sets have cumulative abnormal returns of –6.6% and –5.7% (respectively) over the 12 months following their release, both of which are statistically significant (t = 2.8 and 2.8 respectively).

The paper is organized as follows. We discuss our data on baseball card prices in Section 2. In Section 3, we analyze momentum, and in Section 4, we discuss IPO underperformance. Section 5 concludes.

II. Data

Card Price Data

Our card price data come from *Beckett Baseball Card Monthly* (henceforth "Beckett Monthly"). *Beckett Monthly* was established by James Beckett, a statistics professor. In 1976, Beckett began polling dealers and collectors about transaction prices of cards. In 1979, he released a price guide that was updated at an annual frequency. In November, 1984, Beckett released the first issue of *Beckett Monthly*. To provide card price information at a monthly frequency, Beckett employed a team of full-time baseball card analysts to travel to card shows and shops and examine auction data (Jamieson, 2011). At its peak, *Beckett Monthly* had a circulation of around one million (Jamieson, 2011).

We scanned the price data contained in the 72 issues of *Beckett Monthly* issued between January 1991 and December 1996. We converted the scanned images to a machine-readable format using optical character recognition (OCR) software.

For each set, Beckett individually lists the prices of the more valuable cards, and the rest of the cards' values are listed by a single entry: "COMMON PLAYER." For a card to enter our sample, it must be listed in at least one of the 72 monthly issues. For each of these cards, we only consider its prices *after* the first date it is listed.[4] If a card is listed in one month but not in a later month, we assign the card's value to equal the value of "COMMON PLAYERS" in the later month (in which the card is unlisted).

For each card (including common players), Beckett provides two prices: a low price and a high price. These prices should not be interpreted as bid-ask spreads. Rather, they represent "the range within which the card is currently selling."[5] The magazine further elaborates that the prices represent the 10th and 90th percentiles of the transacted prices. We define a card's price as the average of its high (90th percentile) and low (10th percentile) price. This measure of price has been shown to be closely correlated with the actual closing prices of cards in eBay auctions (Highfill and O'Brien, 2008).

[4] We follow this methodology because it is often difficult to determine whether a card is of a "COMMON PLAYER" prior to the first date it is listed. The reason is that many of the sets are released in "series"—i.e., some of the cards in the set are released early in the baseball season ("SERIES 1"), while others in the set are released later in the season ("SERIES 2" or "SERIES 3"). These later series often contain star players whose cards are valuable, so if we treated them as "COMMON PLAYERS" prior to the series release, we would falsely assign those cards as having extremely high returns over the month prior to the series' release.
[5] Source: *Beckett Monthly* Issue #70 (January 1991), page 66.

Our sample consists of 37,116 distinct cards that were released between 1948 and 1996. We have 1,662,273 price observations for these cards across the 72 months of *Beckett Monthly*.[6] Cards' values exhibit a lot of cross-sectional variation, even within a given set. Star players' cards trade at higher prices than ordinary players' cards. Across our entire sample, the average card value is $8.87, and the distribution is heavily skewed: the median is just $0.37, and the 75th percentile is $2.40.[7] The most valuable card in our sample is the 1952 Mickey Mantle Topps card, whose value averaged $19,733 over our 6 year sample.

[Insert Table 1 here]

As in other markets such as housing (Pope et al, 2015), prices cluster on round numbers. For example, there are 7,215 instances in which a low or high card price equals $0.90 and 69,317 instances in which a low or high card price equals $1.00. However, there are no instances in which a card's low or high price is strictly between $0.90 and $1.00.

[Insert Figure 1 here]

Such clustering likely increases the probability that a card's price in one month exactly equals its price in the previous month. In our sample, this happens frequently: 78.2% of the

[6] This is less than 37,116*72 because we do not have prices for the 1992-1996 sets in our 1991 issues of *Beckett Monthly*, etc. In other words, our sample of cards is larger in our last issues of *Beckett Monthly* than in our first issues.

[7] To compute these statistics, we first compute the time series average value of each card, leaving us with a distribution of 37,116 observations (one observation for each card). We report the characteristics of this distribution.

time, a card's price is the same as it was in the prior month. The 5^{th} percentile of returns is −14.3%, while the 95^{th} percentile is 9.1%.

Player Performance and Career Length Data

Our player performance data come from the website *Baseball Reference*.[8] We collect the batting performance of every MLB player in every MLB regular season game between 1991 and 1996. We also collect when players begin their MLB careers and when they retire from *Baseball Reference*.

III. Hong and Stein (1999)

Momentum

Jegadeesh and Titman (1993) document that over short horizons, stocks that have recently performed well outperform those that have recently performed poorly, which is referred to as "momentum." Momentum strategies entail sorting stocks into deciles each month based on their cumulative returns over the prior J months and going long (short) the stocks that are in the highest (lowest) decile. Each month, the strategy unwinds the positions that it took K months ago. J is referred to as the "formation period" and K is referred to as the "holding period."

In financial markets, momentum profits are positive when the holding and formation periods are between 3 and 12 months. In terms of economic significance, the strategies earn between 6-9% annually on average (Asness et al, 2014). Economists have proposed many different explanations for momentum. In the realm of financial markets, it is difficult to isolate one theory's predictions from the others' because they all predict momentum in financial markets. One of the most prominent explanations for momentum is Hong and Stein's (1999)

[8] URL: http://www.baseball-reference.com.

theory that information gradually diffuses across the investor population, and prices do not fully reflect the information until it has fully diffused across the investor population. An objective of this study is to directly test Hong and Stein's (1999) theory in an environment where its predictions should hold, but the alternative theories of momentum should not apply. Verifying the theory's predictions in a non-financial environment would not prove that Hong and Stein (1999) explains momentum in the stock market (or disprove "rational" theories of momentum), but it would provide additional support for their theory.

We begin by establishing that Hong and Stein (1999) predicts momentum in the baseball card market. We hypothesize that a player's on-field performance is a significant determinant of the value of his cards. To test this, we take the set of players that retired before 1991, and we regress their card values onto the following hitting performance measures: batting average, on-base percentage, slugging percentage, OPS, home runs, runs, RBIs, and steals.[9] See the appendix for a definition of these performance measures. Our unit of observation is (card, date), e.g., "1952 Topps #24, March 1992), and we include (card set, date) fixed effects, e.g., "1952 Topps, March 1992." Because some players are popular for non-performance reasons (e.g., they played for a popular team like the Yankees), we do not expect the errors to be independent, so the standard errors are clustered by player. The results of these regressions are reported in Table 2.

[Insert Table 2 here]

As predicted, players' card values are positively correlated with their on-field performance. Of the eight performance measures, all of them except stolen bases are statistically significant. Because baseball teams play 162 games per year (plus playoffs) over the course of the year, information about (non-retired) players' abilities is released almost daily. If

[9] Since hitting is not an important component of a pitcher's contribution to a team, we exclude pitchers in this analysis.

Hong and Stein's (1999) theory is valid, this information should gradually diffuse across the card collector population, and the information should not be fully incorporated in the card prices. In other words, Hong and Stein (1999) predict that baseball card returns will exhibit price momentum.

Of course, there are many differences between financial markets and the market for baseball cards. While there are many highly sophisticated traders and investors with large amounts of capital that can exploit mispricing in the stock market, the overall level of sophistication in the baseball card market should be expected to be much lower: most of the collectors are children and/or hobbyists. Hence, if Hong and Stein's (1999) theory really explains the momentum that is observed in various markets, we should expect to find momentum profits that are *much higher* in the market for baseball cards compared to what we see in financial markets.

To test these hypotheses, at each month t we sort cards based on their returns between months t-J and t (for J = 3, 6, 9, 12). We analyze the profitability of the strategy that is long (short) the cards in the highest (lowest) decile in months t+1 through t+K (for K = 3, 6, 9, 12). When testing these strategies, we restrict attention to cards whose value is at least $1.[10] We report the average monthly profits from this strategy in Table 3.

[Insert Table 3 here]

As predicted, the strategy is profitable at all horizons. The strategy is most profitable for short formation and holding periods: when the formation and holding periods are equal to 3 months, the average monthly returns are *5.6% per month*. For comparison, momentum

[10] We impose this restriction because a change from $20 to $35 seems more significant than a change from $0.01 to $0.02. However, our qualitative results are not sensitive to this filter.

strategies earn less than 1% per month in equities. Hence, momentum is much stronger among baseball cards than among stocks, as predicted.

In addition to its economic significance, another striking feature of the momentum is its consistency. Consider the strategy with a 3 month formation period and 3 month holding period that earns 5.6% per month. In the 68 months that this strategy has positions, its returns are positive in 66 months, i.e., 97% of the time.

Cross-Sectional Differences in Momentum

If momentum is driven by gradual information diffusion, then it should be strongest among the cards of players for which the most information is being released. By definition, retired players' careers are over, so there is little new information that is released about their performance ability. In contrast, active players play up to 162 games per year, plus playoffs, so there is an almost continuous release of information about their performance ability. If gradual information diffusion causes momentum, then momentum profits should be significantly higher among the cards of active players than it is among the cards of retired players.

To determine whether there are differences in momentum profits between active players and retired players, we collected data on the years that each MLB player was active.[11] At each portfolio formation date, we consider a player to be "active" if his playing career extended to the portfolio formation date or beyond, and we consider the player to be "retired" if his career ended prior to the portfolio formation date.

We report momentum profits for active and retired players in Table 4. Consistent with the predictions of Hong and Stein (1999), momentum strategies earn significantly higher abnormal returns among active players than among retired players: Three-month momentum strategies of active players' cards earn 9.42%, compared to 2.66% for retired players.

[11] Source: http://www.baseball-reference.com/

[Insert Table 4 here]

Post-Fundamental Performance Drift

We can also test Hong and Stein (1999) by directly examining the relationship between the on-field performance of active baseball players and their future card returns. If prices fully reflect available public information, then future card price movements should be unpredictable based on past on-field performance. Hong and Stein (1999), on the other hand, predict that prices will not fully reflect players' past on-field performance, and that prices will drift in the direction of players' past on-field performance. These tests are closely related to one of the most puzzling anomalies in capital markets research: "Post-earnings announcement drift" (PEAD) . PEAD refers to the tendency of stock returns to drift in the direction of earnings surprises. Since a player's on-field performance is the most natural measure of his "fundamental performance," these tests are a natural analogue of PEAD within our environment.

While we know the month of each issue of *Beckett Monthly* (e.g., "March 1993"), we do not know the exact date each issue was actually published, and more importantly, we do not know when the card price information was actually observed by Beckett's staff. Due to this complication, we take a conservative approach by examining the monthly card returns in year t as a function of the player's fundamental performance during the regular season in year t-1. Since regular seasons end in late September or early October, this ensures that there is sufficient time between the fundamental performance that we observe and the subsequent price changes that we examine (in the subsequent calendar year).

We restrict attention to non-pitchers, and we examine their offensive production based on the eight statistics that were demonstrated to affect players' card values in Table 2: batting average, on base percentage, slugging percentage, on base plus slugging (OPS), home runs, runs, runs batted in (RBIs), and stolen bases. We provide formal definitions for these performance statistics in the appendix. Among all players with at least 300 at bats over the course of the season, we sort players into deciles based on their performance in each of these eight statistics. We then compute the average monthly returns in the subsequent year for the cards of the players in each of the ten deciles. This generates a time series of monthly returns for each of the deciles. We then compute the average monthly return for each of the deciles for each of the performance measures. These returns are reported in Table 5.

[Insert Table 5 here]

For each of the eight performance measures, the following year's monthly returns are greater for the players in the top decile than for those in the bottom decile. In terms of economic significance, the drift is most pronounced for batting average, slugging percentage, and OPS: for each of these statistics, the drift is at least 1.5% per month, yielding annual returns of at least 18%. Though these returns are smaller than for the 3 month momentum strategies, it is worth noting that our post-fundamental performance strategies trade on much staler information (up to almost two years) and has a longer holding period (12 months versus 3 months). In terms of statistical significance, the drift is significant for five of the statistics.[12]

Set-Level Momentum

Collectors often buy and sell baseball cards by *the set*. In addition to posting the prices of individual cards, *Beckett Monthly* also includes the values of complete sets of cards.

At the individual card level, player performance is a primary source of information that should affect the player's card value. This motivated our hypothesis that momentum would be stronger among active players than among retired players. At the set level, the information that

[12] Three are significant at the 1% significance level, one is significant at the 5% level, and one is significant at the 10% level. It is worth noting that these measures are not independent of one another. For example, OPS is the sum of on base percentage and slugging percentage.

should diffuse across the collector population consists of the design of the cards, the number of sets that the manufacturers likely produced, and the relative popularity of the set among the population of card collectors. Hence, according to Hong and Stein (1999), we should expect to find momentum at the set level too.

Consistent with our prediction, there is momentum at the set level. The average return of the 3 month formation and 3 month holding momentum strategy is 4.34% per month, which is reported in Table 6.

[Insert Table 6 here]

If momentum at the set level is driven by information diffusion, momentum should be most pronounced among sets that were recently produced, as these sets should have the most information diffusion.[13] When we restrict attention to the sets that were released less than ten years before the portfolio formation date, momentum returns are equal to 4.6% per month, whereas when we restrict attention to the sets that were released at least ten years before the portfolio formation date, momentum profits are just 0.90% per month.

[Insert Table 7 here]

IV. Miller (1977)

[13] For older sets, most of the information should have already diffused across the population of collectors.

Miller (1977) posits that assets' valuations are not determined by the average investor's assessment, but rather, by the most optimistic investor's assessment, particularly when there are short sale constraints. If investors are correct on average, and if investors' beliefs eventually converge, then returns should be lower for assets with the highest levels of disagreement. Ritter and Welch (2002) argue that Miller (1977) explains the tendency for IPO firms to underperform their peers in the first three years after their public listing, because IPOs firms are young and generally difficult to value. There are two obvious analogs to IPOs in the baseball card market: rookie cards and the releases of new sets of cards. Applying a similar logic as Ritter and Welch (2002), we predict that these types of cards will exhibit poor returns, as we elaborate below.

Rookie Cards

Beckett Monthly formally defines a rookie card as a "player's first appearance on a regular issue card from one of the major card companies (presently [January 1991] Topps, Donruss, Fleer, Score, or Upper Deck)."[14] We rely on *Beckett Monthly's* classification of rookie cards—each rookie card is designated by the letters "RC" following the player's name in the price listing.

Card manufacturers often produce rookie cards for players who have been drafted by a major league organization but have not yet reached the major leagues.[15] Recall from Table 2 that there is a strong relationship between retired players' on-field playing performance and their card values. When forecasting the expected long term value of rookie player's cards, collectors must predict the long-run on-field performance of the rookie. This is a difficult task. Collectors must rely on scouting reports and their performance in college baseball and/or the minor leagues. Even major league baseball teams—who have the strongest incentives to

[14] Source: *Beckett Monthly* Issue #70 (January 1991), page 66.
[15] The term "major leagues," or "majors," refers to the National League and the American League. Players seldom begin their careers in the major leagues. Rather, they begin their playing careers in the "minor leagues," which are leagues composed of teams that are affiliated with major league teams.

accurately evaluate players' abilities—have difficulty analyzing the available information: only 66% of players who are drafted in the first round of the MLB draft ever make it to the major leagues.[16] Because it is so difficult to evaluate the ability of these players, we expect there to be more disagreement among collectors about rookies' abilities than about veteran players' abilities. According to Miller (1977), this should result in rookie cards underperforming relative to cards of players who have a longer history of professional baseball experience.

Because our price data begin in 1991 and we are interested in the initial performance of rookie cards, we restrict attention to rookie cards issued in 1991 or later. One complication that arises is that some rookie cards are initially unlisted, so their value in the first year is given by the value of a "COMMON PLAYER" (or "COMMON ROOKIE"), but later, the player becomes popular and his rookie card is listed individually. Because we are interested in the *initial* performance of rookie cards, we require that the rookie card be listed individually by *Beckett Monthly* in the year of the rookie card's set year.[17] For example, B.J. Wallace's 1992 Bowman RC (card number 554) does not enter our sample because it was not individually listed until the March 1993 issue of *Beckett Monthly*. After applying these filters, we obtain a sample of 2,778 distinct rookie cards in 93 distinct sets. Throughout this paper, we consider different years of the same set manufacturer to be distinct sets. For example, "1991 Topps" and "1992 Topps" are considered distinct sets.

To analyze the initial performance of rookie cards, we follow standard event study methodology. Each month, we define a rookie card's "benchmark return" as the average return of all non-rookie cards within the RC's set that month. A rookie card's abnormal return in a given month is defined as the difference between the card's return and its benchmark's return. We compute cumulative abnormal returns by summing abnormal returns in event time.

[16] Source: http://bleacherreport.com/articles/1219356-examining-the-percentage-of-mlb-draft-picks-that-reach-the-major-leagues/page/2

[17] This does not create a "look-ahead" bias because we are not conditioning on future information. In contrast, including the RC's that go from unlisted to listed *would* create a look-ahead bias: we would be conditioning on future information, and we are unable to analyze the RC's that remain unlisted because we do not have any data on such RC's.

Following Kothari and Warner (2006), we compute the test statistic as cumulative abnormal returns divided by the standard errors, which are the square roots of the variance of abnormal returns times the number of days in the event windows. We plot the CARs and 95% confidence interval in Figure 2.

[Insert Figure 2 here]

As predicted, new rookie cards significantly underperform their non-rookie peers by 8.6% (t=2.8) over their first 12 months, which supports Miller (1977).

New Sets

Because many collectors collect *complete sets* of cards, *Beckett Monthly* also reports the values of complete sets of cards. When sets are first released, collectors have little information about the number of sets that the manufacturer produced, the quality of the cards within the set, how other collectors will value the set, etc. Hence, there should be more disagreement about the value of new sets compared to older sets, and Miller (1977) therefore predicts that new sets will perform poorly relative to older sets.

To test this prediction, we analyze the returns of the sets that were released during our sample period (1991-1996). We define the sets' benchmark return as the average return of all sets that were released prior to 1991. Each set's abnormal return in a given month is the difference between its return and the benchmark return. CARs are computed by adding ARs in the event time windows. Standard errors are computed as described above. We report the CARs and 95% confidence intervals in Figure 3.

[Insert Figure 3 here]

As predicted by Miller (1977), new set issuances underperform older sets.

V. Conclusions

Financial markets exhibit puzzling price patterns, and financial economists have developed an array of theories to explain these puzzling patterns. Although the motivation for all of these theories is to explain the behavior of financial markets, some of the theories naturally generate predictions in non-financial markets, too. By testing the theories in non-financial settings, we can gain a better understanding of the validity of these theories. If the theories' predictions cannot be supported in non-financial markets, the theories' validity should be called into question. Conversely, if the theories' predictions are confirmed in a wide variety of environments, then the theories should be given more credence.

We used the theories of Hong and Stein (1999) and Miller (1977) to generate testable predictions for baseball card prices. Consistent with our predictions, baseball cards exhibit some of the same anomalous patterns as the stock market, including price momentum, price drift in the direction of past fundamental performance, and poor performance of new issuances. Although our evidence supports the theories of Hong and Stein (1999) and Miller (1977), it does not "disprove" any of the alternative explanations for the stock market anomalies that have been developed by financial economists. Nevertheless, we document that it is possible for the anomalous price patterns to arise naturally in environments without all the bells and whistles of financial markets on which some alternative theories rely.

Appendix: Baseball Performance Statistics

Statistic	Definition
Plate Appearances (PA)	The number of times a player goes to bat and is either declared out or gets on base
At Bats (AB)	The number of plate appearances (PA) excluding base on balls, hit by pitch, sacrifice fly/bunt, or awarded first base due to obstruction by catcher
Batting Average (BA)	The number of hits divided by the number of at bats (AB)
On Base Percentage (OBP)	The sum of {hits, base on balls, and hit by pitch} divided by the sum of {at bats, base on balls, hit by pitch, and sacrifice flies/bunts}
Total Bases (TB)	The total number of bases earned through hitting, where singles, doubles, triples, and home runs are worth one, two, three, and four bases, respectively. TB = 1*num_singles + 2*num_doubles + 3*num_triples + 4*num_home_runs.
Slugging Percentage (SLG)	Total bases (TB) divided by at bats (AB)
On Base Plus Slugging (OPS)	On base percentage (OBP) plus slugging percentage (SLG)
Runs	The number of times that a player safely crosses home plate after safely crossing first, second, and third base
Runs Batted In (RBI)	The number of times another player safely crosses home plate due to the player's at bat, excluding double plays and errors
Stolen Bases	The number of times that a player safely advances to the next base without the batter completing his plate appearance, excluding balks

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Figure 1: Price Clustering

Beckett Monthly provides two values for a card's price: a low price and a high price, representing the 10th percentile and 90th percentile of the transacted prices. We aggregate the low and high prices across the 72 issues of *Beckett Monthly*, and we plot the number of times that the prices equal a given value.

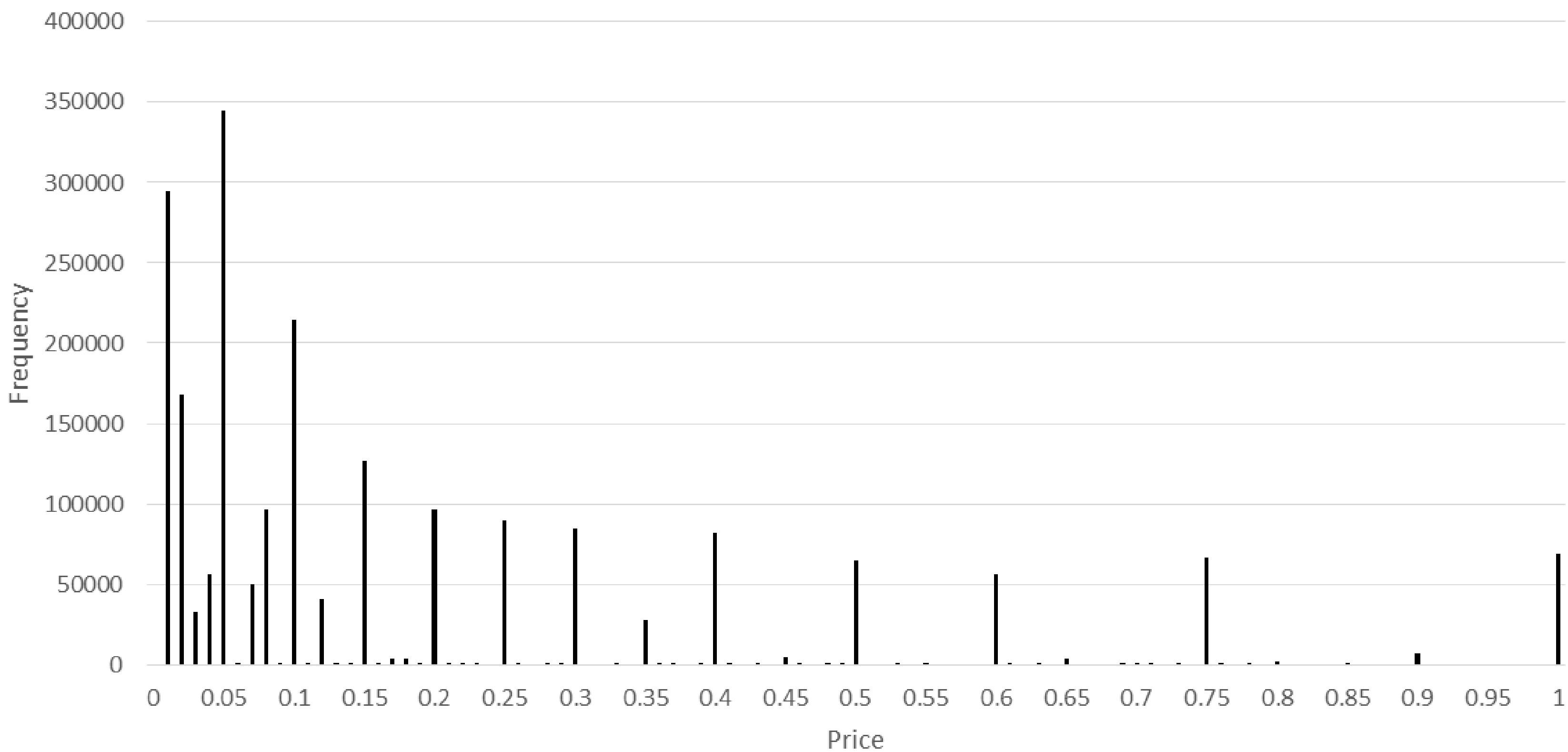

Figure 2: Rookie Card Underperformance

The figure plots the cumulative abnormal returns (CAR) by month following the release of rookie cards (RC) issued during our sample period (1991-1996). Each month, the benchmark return is computed as the average return of non-RC's within the RC's set. For example, the benchmark return for a 1993 Upper Deck RC in a given month is the average return of all non-RC's in the 1993 Upper Deck that month. Abnormal returns (AR) are computed as the difference between the RC's return and the benchmark return. CARs are computed by adding ARs in event time, where t=0 corresponds to the first month that the RC is listed in *Beckett Monthly*. Standard errors are computed as the square roots of the variance of abnormal returns times the number of days in the event windows (Kothari and Warner, 2006).

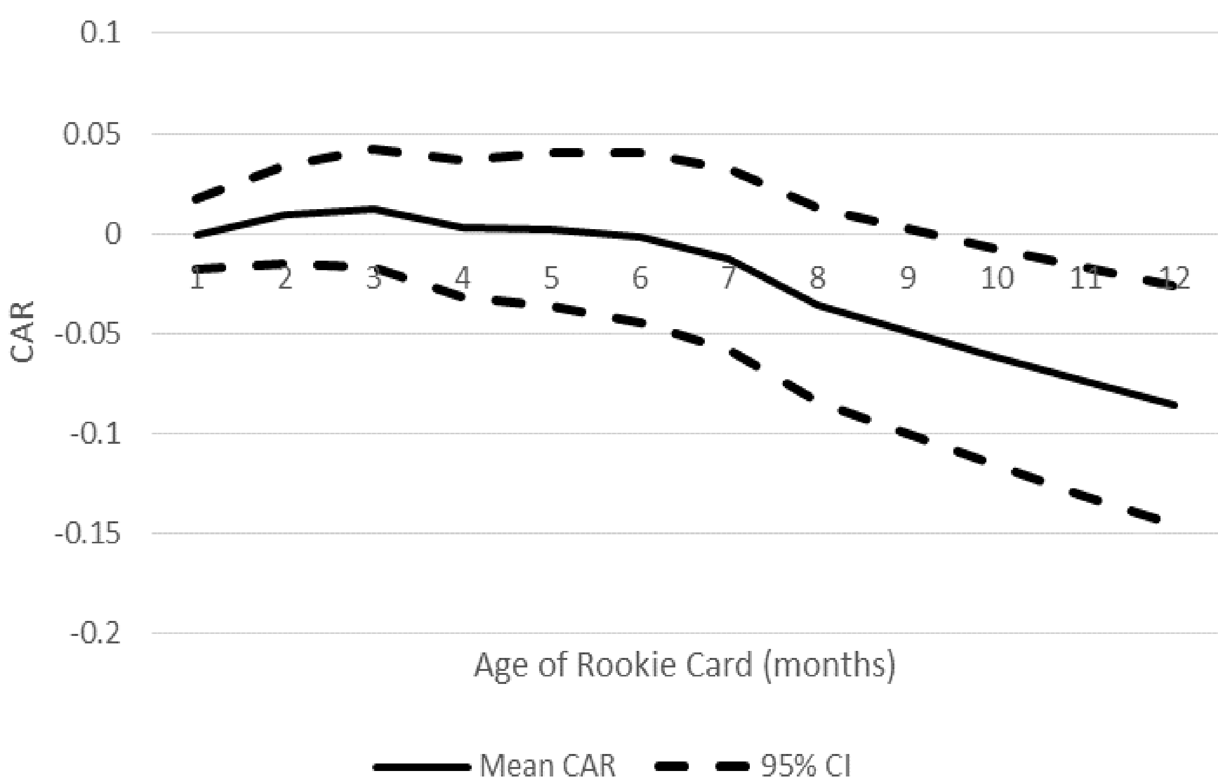

Figure 3: New Set Underperformance

The figure plots the cumulative abnormal returns (CAR) by month following the release of new sets issued during our sample period (1991-1996). Each month, the benchmark return is computed as the average return of card sets issued prior to 1991. Abnormal returns (AR) are computed as the difference between the set's return and the benchmark return. CARs are computed by adding ARs in event time, where t=0 corresponds to the first month that the set is listed in *Beckett Monthly*. Standard errors are computed as the square roots of the variance of abnormal returns times the number of days in the event windows (Kothari and Warner, 2006).

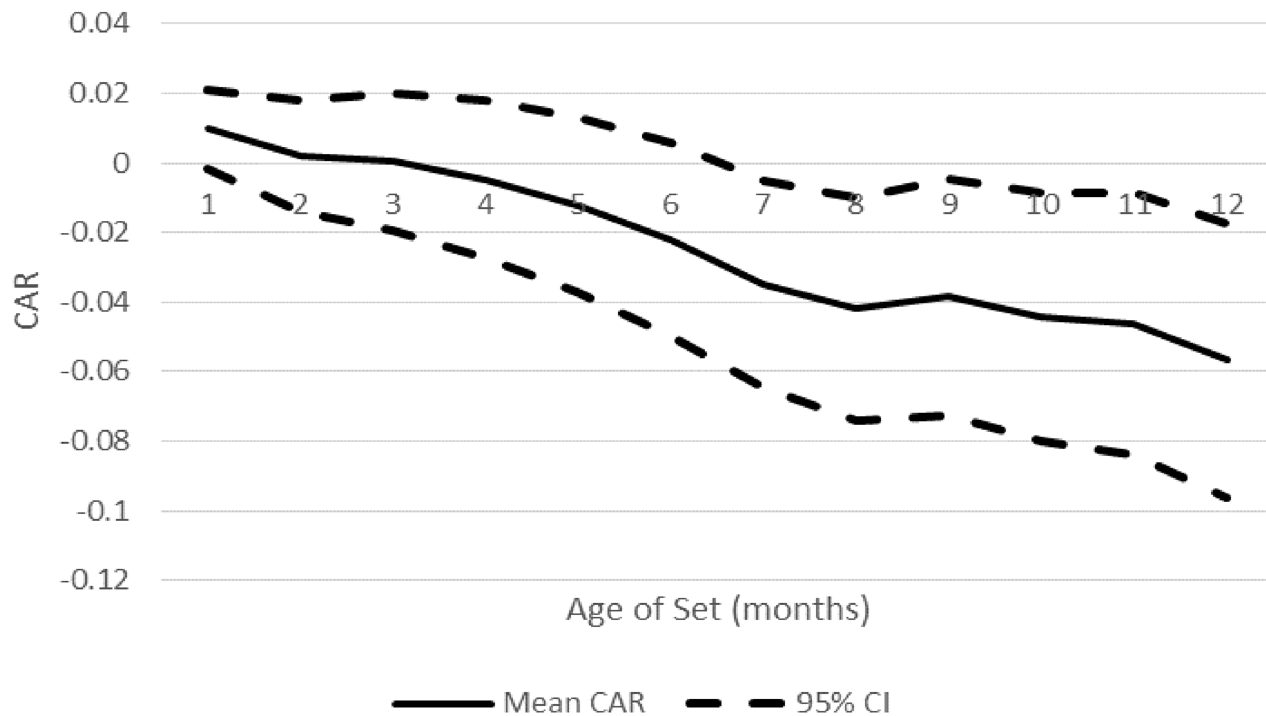

Table 1: Summary Statistics

The table reports summary statistics for baseball prices and returns taken from Beckett guides between 1991 and 1996. Prices are the midpoint of the Beckett high and low price and returns are calculated as the percentage change in monthly prices.

PANEL A: Individual Baseball Cards

		PRICES									RETURNS								
Year	N	Mean	Std	1st	5th	25th	50th	75th	95th	99th	Mean	Std	1st	5th	25th	50th	75th	95th	99th
1991	135,181	12	79	0	0	0	0	2	45	205	0.00	0.12	-0.29	-0.17	0.00	0.00	0.00	0.13	0.32
1992	181,626	12	93	0	0	0	0	2	41	205	0.00	0.12	-0.40	-0.20	0.00	0.00	0.00	0.17	0.30
1993	218,384	11	94	0	0	0	0	2	38	193	0.00	0.14	-0.40	-0.17	0.00	0.00	0.00	0.17	0.38
1994	270,017	9	83	0	0	0	0	2	32	163	-0.01	0.15	-0.58	-0.19	0.00	0.00	0.00	0.14	0.35
1995	312,589	9	77	0	0	0	0	2	28	140	-0.01	0.15	-0.50	-0.17	0.00	0.00	0.00	0.00	0.27
1996	349,063	9	77	0	0	0	0	2	33	143	0.00	0.15	-0.39	0.00	0.00	0.00	0.00	0.00	0.27

PANEL B: Baseball Card Sets

		PRICES									RETURNS								
Year	N	Mean	Std	1st	5th	25th	50th	75th	95th	99th	Mean	Std	1st	5th	25th	50th	75th	95th	99th
1991	1,296	1765	4416	6	9	20	93	1800	8250	23000	0.01	0.04	-0.08	-0.05	0.00	0.00	0.01	0.06	0.13
1992	1,637	1769	5383	5	8	15	70	950	7800	23250	-0.01	0.05	-0.16	-0.09	-0.02	0.00	0.00	0.06	0.14
1993	2,817	1059	4228	1	3	13	30	125	6250	17375	-0.01	0.07	-0.20	-0.11	0.00	0.00	0.00	0.06	0.21
1994	4,177	736	3404	2	4	12	28	95	4200	12000	-0.01	0.07	-0.21	-0.14	0.00	0.00	0.00	0.08	0.22
1995	5,805	583	2968	2	4	12	28	100	3250	11000	-0.01	0.05	-0.20	-0.12	0.00	0.00	0.00	0.00	0.15
1996	7,679	507	2683	3	5	15	38	120	2400	10250	-0.01	0.05	-0.22	-0.11	0.00	0.00	0.00	0.00	0.13

Table 2: Relationship between Retired Players' On-Field Performance and their Card Values

We regress card prices onto various measures of a player's performance during his career. The sample is restricted to players who retired before 19991. Card prices are taken from 1991-1996. The unit of observation is (card, month). Standard errors are clustered by player.

	Dependent Variable: Price							
Batting Average	1461.55***							
	(521.64)							
On Base Percentage		1465.22**						
		(565.99)						
Slugging Percentage			758.11***					
			(257.06)					
OPS				606.98***				
				(203.35)				
Home Runs					0.272***			
					(0.093)			
Runs						0.104***		
						(0.033)		
RBIs							0.098***	
							(0.0296)	
Stolen Bases								0.103
								(0.063)
Observations	187186	187186	187186	187186	187186	187186	187186	187186
Card Set*Month Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
R-Squared	0.0821	0.1017	0.1088	0.1156	0.1112	0.1108	0.1057	0.0682

Table 3: Momentum Portfolio Returns

The table reports the average monthly portfolio return and associated t-statistic for a variety of momentum strategies among individual baseball cards. Strategies vary according to the formation period (3, 6, 9 and 12 months) by row and holding period (3, 6, 9, and 12 months) by column. Winner (Middle, Loser) portfolios are constructed monthly by ranking cards according to their return during the formation period and selecting the top 10% (middle 80%, bottom 10%). Returns are calculated using overlapping portfolios held for the length of the holding period. Only cards whose prior month price is at least $1 are used to construct the portfolio returns.

	Holding	3 Months		6 Months		9 Months		12 Months	
Formation		Ret	t-stat	Ret	t-stat	Ret	t-stat	Ret	t-stat
3 Months	Loser	-2.91%	-13.52	-2.57%	-10.99	-2.29%	-9.33	-2.09%	-8.50
	Middle	0.17%	1.21	0.18%	1.26	0.17%	1.26	0.18%	1.33
	Winner	2.69%	10.48	2.33%	8.98	2.04%	7.65	1.75%	6.46
	W - L	5.60%	19.46	4.91%	16.58	4.33%	13.40	3.84%	11.34
6 Months	Loser	-2.45%	-11.21	-2.20%	-9.94	-1.91%	-8.10	-1.78%	-7.29
	Middle	0.22%	1.65	0.22%	1.69	0.22%	1.68	0.22%	1.69
	Winner	2.16%	8.88	1.87%	7.51	1.60%	6.18	1.44%	5.41
	W - L	4.61%	17.08	4.08%	14.64	3.51%	10.94	3.21%	9.47
9 Months	Loser	-2.30%	-11.21	-2.01%	-9.66	-1.76%	-7.84	-1.68%	-7.12
	Middle	0.24%	1.84	0.25%	1.93	0.24%	1.87	0.25%	1.96
	Winner	2.18%	8.17	1.85%	6.85	1.64%	5.93	1.46%	5.14
	W - L	4.48%	15.09	3.86%	12.62	3.40%	10.08	3.14%	8.81
12 Months	Loser	-2.17%	-10.36	-1.91%	-9.34	-1.73%	-7.74	-1.60%	-6.71
	Middle	0.27%	2.10	0.28%	2.14	0.28%	2.16	0.28%	2.18
	Winner	2.19%	8.13	1.91%	7.11	1.70%	6.23	1.56%	5.59
	W - L	4.37%	13.59	3.82%	12.04	3.43%	10.09	3.17%	8.83

Table 4: Momentum among Active and Non-Active Players

The table reports the average monthly portfolio return and associated t-statistic for a variety of momentum strategies among individual baseball cards as in Table 3. The top panel only considers the baseball cards of "active" players, i.e. those who are still playing in the major leagues as of the date of the Beckett monthly price guide. The bottom panels considers the set of players that are not currently active.

PANEL A: Momentum among Cards of Active Players

Formation	Holding	3 Months		6 Months		9 Months		12 Months	
		Ret	t-stat	Ret	t-stat	Ret	t-stat	Ret	t-stat
3 Months	Loser	-4.61%	-11.44	-3.82%	-9.90	-3.12%	-7.44	-2.73%	-6.47
	Middle	-0.61%	-2.70	-0.61%	-2.74	-0.60%	-2.66	-0.56%	-2.50
	Winner	4.82%	10.01	4.24%	8.59	3.42%	6.89	2.77%	5.61
	W - L	9.42%	15.48	8.07%	13.53	6.55%	10.55	5.50%	8.51
6 Months	Loser	-3.70%	-9.55	-3.10%	-8.09	-2.59%	-6.20	-2.28%	-5.40
	Middle	-0.52%	-2.40	-0.51%	-2.41	-0.50%	-2.29	-0.48%	-2.17
	Winner	3.98%	8.32	3.48%	7.05	2.85%	5.81	2.37%	4.91
	W - L	7.68%	13.80	6.58%	11.69	5.44%	8.95	4.65%	7.43
9 Months	Loser	-3.50%	-9.60	-2.96%	-8.10	-2.48%	-6.69	-2.17%	-5.70
	Middle	-0.42%	-1.93	-0.40%	-1.85	-0.40%	-1.80	-0.37%	-1.69
	Winner	4.04%	7.54	3.45%	6.43	2.94%	5.54	2.47%	4.64
	W - L	7.54%	12.41	6.42%	10.38	5.42%	8.62	4.64%	7.07
12 Months	Loser	-3.49%	-8.61	-2.97%	-7.52	-2.49%	-6.20	-2.20%	-5.38
	Middle	-0.31%	-1.42	-0.30%	-1.39	-0.29%	-1.35	-0.26%	-1.22
	Winner	4.25%	7.92	3.74%	7.02	3.22%	6.03	2.70%	5.08
	W - L	7.74%	11.50	6.71%	10.43	5.70%	8.68	4.90%	7.16

PANEL B: Momentum among Cards of Non-Active Players

Formation	Holding	3 Months		6 Months		9 Months		12 Months	
		Ret	t-stat	Ret	t-stat	Ret	t-stat	Ret	t-stat
3 Months	Loser	-1.03%	-9.85	-0.88%	-7.06	-0.82%	-6.46	-0.74%	-5.60
	Middle	0.40%	3.28	0.40%	3.31	0.42%	3.41	0.42%	3.38
	Winner	1.63%	7.43	1.50%	7.44	1.34%	7.38	1.34%	7.01
	W - L	2.66%	10.53	2.38%	10.03	2.17%	9.67	2.08%	9.00
6 Months	Loser	-0.97%	-9.65	-0.81%	-7.26	-0.71%	-6.48	-0.64%	-5.53
	Middle	0.42%	3.49	0.42%	3.49	0.43%	3.52	0.43%	3.51
	Winner	1.34%	7.93	1.29%	7.47	1.18%	6.97	1.13%	6.67
	W - L	2.31%	11.71	2.10%	10.25	1.88%	9.36	1.77%	8.70
9 Months	Loser	-0.93%	-9.43	-0.69%	-6.18	-0.58%	-5.17	-0.54%	-4.62
	Middle	0.42%	3.56	0.42%	3.55	0.42%	3.54	0.43%	3.54
	Winner	1.33%	7.82	1.25%	7.17	1.15%	6.73	1.10%	6.36
	W - L	2.26%	11.39	1.94%	9.46	1.72%	8.22	1.64%	7.56
12 Months	Loser	-0.87%	-8.80	-0.63%	-5.76	-0.49%	-4.45	-0.39%	-3.27
	Middle	0.44%	3.56	0.44%	3.56	0.44%	3.60	0.43%	3.49
	Winner	1.29%	8.05	1.20%	7.19	1.09%	6.13	1.11%	6.26
	W - L	2.16%	11.14	1.84%	9.30	1.58%	7.50	1.50%	7.02

Table 5: Fundamentals and Predictable Returns

The table reports the average monthly returns for baseball cards sorted into deciles based on prior year performance metrics. Performance metrics are for hitters with at least 300 at-bats. Performance metrics are listed in the first column and the difference between returns in the top and bottom decile for each performance metric is listed in the second to last column along with the associated t-stat in the final column. *, **, *** represent statistical significance at the 10%, 5% and 1% level respectively.

	Average Returns by Decile											
Performance Metric	Bottom	2	3	4	5	6	7	8	9	Top	Top - Bottom	t-stat
Batting Average	-0.012	-0.004	0.004	-0.007	0.003	-0.009	-0.003	0.004	-0.005	0.007	0.018***	4.35
On Base Percentage	-0.003	-0.009	-0.007	0.012	0.004	-0.002	-0.010	-0.005	0.000	0.002	0.005	0.85
Slugging Percentage	-0.010	-0.005	-0.016	-0.003	0.001	0.016	-0.012	-0.007	-0.002	0.005	0.015***	3.22
OPS (On Base + Slugging)	-0.014	-0.014	0.004	-0.014	0.020	0.000	-0.008	-0.009	0.002	0.004	0.018***	4.38
Home Runs	0.001	-0.007	-0.009	-0.006	0.000	0.002	-0.004	0.000	0.000	0.002	0.001	0.26
Runs	-0.007	-0.007	-0.016	-0.007	-0.004	0.001	0.003	-0.003	0.007	0.000	0.007*	1.59
RBIs	-0.013	-0.006	-0.004	-0.001	-0.007	-0.003	0.000	0.002	0.006	-0.001	0.011**	2.21
Stolen Bases	-0.005	0.025	-0.003	-0.011	-0.003	-0.002	0.002	-0.006	-0.007	-0.001	0.004	1.01

Table 6: Set-level Momentum

The table reports the average monthly portfolio return and associated t-statistic for a variety of momentum strategies among baseball card sets (rather than individual cards as in Table 3). Strategies vary according to the formation period (3, 6, 9 and 12 months) by row and holding period (3, 6, 9, and 12 months) by column. Winner (Middle, Loser) portfolios are constructed monthly by ranking sets according to their return during the formation period and selecting the top 10% (middle 80%, bottom 10%). Returns are calculated using overlapping portfolios held for the length of the holding period. Only sets whose prior month price is at least $1 are used to construct the portfolio returns.

	Holding	3 Months		6 Months		9 Months		12 Months	
Formation		Ret	t-stat	Ret	t-stat	Ret	t-stat	Ret	t-stat
3 Months	Loser	-2.60%	-9.69	-2.29%	-8.80	-2.02%	-8.11	-1.68%	-6.44
	Middle	-0.62%	-5.59	-0.67%	-5.98	-0.69%	-6.08	-0.72%	-6.34
	Winner	1.75%	6.19	1.59%	6.22	1.45%	5.68	1.37%	5.69
	W - L	4.34%	13.18	3.88%	11.90	3.47%	10.86	3.05%	9.69
6 Months	Loser	-2.24%	-8.94	-2.06%	-8.47	-1.79%	-7.38	-1.53%	-6.25
	Middle	-0.62%	-5.64	-0.65%	-5.94	-0.67%	-6.07	-0.70%	-6.24
	Winner	1.44%	5.48	1.29%	5.37	1.21%	5.04	1.15%	4.97
	W - L	3.67%	11.92	3.35%	11.88	3.00%	10.24	2.69%	9.40
9 Months	Loser	-2.19%	-9.94	-1.99%	-8.87	-1.75%	-8.12	-1.52%	-6.99
	Middle	-0.58%	-5.42	-0.60%	-5.58	-0.63%	-5.72	-0.65%	-5.86
	Winner	1.33%	4.85	1.17%	4.87	1.10%	4.60	1.05%	4.42
	W - L	3.51%	13.20	3.16%	12.39	2.85%	10.79	2.57%	9.51
12 Months	Loser	-2.22%	-10.37	-1.94%	-8.97	-1.78%	-8.73	-1.54%	-7.18
	Middle	-0.56%	-5.10	-0.59%	-5.45	-0.61%	-5.48	-0.63%	-5.67
	Winner	1.32%	5.02	1.16%	4.92	1.15%	4.96	1.09%	4.76
	W - L	3.54%	12.45	3.10%	11.87	2.94%	11.15	2.64%	9.67

Table 7: Set-level Momentum and Age

The table reports the average monthly portfolio return and associated t-statistic for a variety of momentum strategies among baseball card sets as in Table 6. The top panel only considers sets which are less than 10 years old while the bottom panel considers sets which are at least 10 years old.

PANEL A: Momentum among Sets Less than 10 Years Old

Formation	Holding	3 Months		6 Months		9 Months		12 Months	
		Ret	t-stat	Ret	t-stat	Ret	t-stat	Ret	t-stat
3 Months	Loser	-2.67%	-9.07	-2.48%	-8.79	-2.02%	-7.46	-1.76%	-6.34
	Middle	-1.02%	-7.79	-1.04%	-7.82	-1.09%	-8.24	-1.11%	-8.25
	Winner	1.93%	5.14	1.70%	4.91	1.60%	4.64	1.46%	4.40
	W - L	4.60%	10.90	4.18%	10.51	3.62%	9.62	3.22%	8.38
6 Months	Loser	-2.36%	-8.84	-2.13%	-8.17	-1.84%	-7.15	-1.61%	-6.50
	Middle	-1.02%	-7.76	-1.04%	-7.87	-1.08%	-8.06	-1.09%	-8.02
	Winner	1.59%	4.44	1.40%	4.30	1.34%	4.24	1.20%	3.83
	W - L	3.94%	10.18	3.53%	10.02	3.17%	9.27	2.82%	8.13
9 Months	Loser	-2.32%	-9.40	-2.13%	-8.77	-1.83%	-8.01	-1.57%	-7.00
	Middle	-0.98%	-7.63	-0.99%	-7.49	-1.03%	-7.76	-1.05%	-7.78
	Winner	1.59%	4.28	1.38%	4.28	1.31%	4.04	1.19%	3.71
	W - L	3.91%	10.86	3.51%	11.04	3.14%	10.14	2.76%	8.45
12 Months	Loser	-2.32%	-9.61	-2.09%	-9.04	-1.82%	-8.02	-1.63%	-7.39
	Middle	-0.96%	-7.47	-0.97%	-7.48	-1.01%	-7.76	-1.02%	-7.61
	Winner	1.64%	4.45	1.44%	4.39	1.42%	4.29	1.26%	3.95
	W - L	3.96%	10.61	3.53%	10.61	3.23%	9.80	2.89%	8.61

PANEL B: Momentum among Sets At Least 10 Years Old

Formation	Holding	3 Months		6 Months		9 Months		12 Months	
		Ret	t-stat	Ret	t-stat	Ret	t-stat	Ret	t-stat
3 Months	Loser	-0.48%	-1.98	-0.42%	-1.48	-0.49%	-1.73	-0.37%	-1.36
	Middle	-0.03%	-0.22	-0.05%	-0.37	-0.05%	-0.38	-0.05%	-0.41
	Winner	0.49%	2.38	0.57%	3.45	0.59%	3.29	0.54%	3.03
	W - L	0.90%	3.36	0.95%	3.36	1.04%	3.60	0.86%	3.17
6 Months	Loser	-0.62%	-3.41	-0.40%	-1.43	-0.46%	-1.61	-0.42%	-1.58
	Middle	-0.01%	-0.07	-0.03%	-0.21	-0.03%	-0.21	-0.03%	-0.21
	Winner	0.47%	2.50	0.56%	3.40	0.54%	3.23	0.49%	3.08
	W - L	1.04%	5.09	0.92%	3.54	0.96%	3.35	0.87%	3.27
9 Months	Loser	-0.51%	-2.52	-0.28%	-1.04	-0.43%	-1.57	-0.45%	-1.61
	Middle	0.01%	0.10	-0.01%	-0.07	0.00%	-0.01	0.01%	0.09
	Winner	0.41%	2.42	0.39%	2.57	0.43%	2.78	0.32%	2.03
	W - L	0.86%	4.25	0.62%	2.27	0.82%	3.04	0.72%	2.70
12 Months	Loser	-0.47%	-2.45	-0.30%	-1.06	-0.52%	-1.80	-0.39%	-1.43
	Middle	0.01%	0.09	-0.01%	-0.06	0.01%	0.05	0.00%	-0.03
	Winner	0.41%	2.21	0.42%	2.68	0.41%	2.70	0.40%	2.50
	W - L	0.82%	3.43	0.68%	2.39	0.89%	3.24	0.74%	2.79