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Learning Unethical Practices from a Co-worker: The Peer Effect of Jose Canseco

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Abstract

This paper examines the issue of whether workers learn productive skills from their co-workers, even if those skills are unethical. Specifically, we estimate whether Jose Canseco, a star baseball player in the late 1980's and 1990's, affected the performance of his teammates by introducing them to steroids. Using panel data, we show that a player's performance increases significantly after they played with Jose Canseco. After checking 30 comparable players from the same era, we find that no other baseball player produced a similar effect. Furthermore, the positive effect of Canseco disappears after 2003, the year that drug testing was implemented. These results suggest that workers not only learn productive skills from their co-workers, but sometimes those skills may derive from unethical practices. These findings may be relevant to many workplaces where competitive pressures create incentives to adopt unethical means to boost productivity and profits. Our analysis leads to several potential policy implications designed to reduce the spread of unethical behavior among workers.

Keywords: Peer Effects, Corruption, Crime, Externalities

JEL Codes: J24

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1 Introduction

There is a growing literature that stresses the importance of the environment in determining the outcomes of individuals. Most of this literature is concerned with examining how peers and environmental factors affect youth behavior regarding their educational achievements, health, criminal involvement, work status, and other economic outcomes.[1] This paper examines the issue of how workers affect the productivity of other workers. If workers learn valuable skills and work habits from their co-workers, then "peer effects" between workers should exist in many work environments. A peer effect across workers could also result from behavioral considerations such as group norms, peer pressure, shame, and guilt. Recent work suggests that peer effects between workers are empirically significant.[2]

The existing literature, however, has not examined whether workers sometimes learn unethical practices from their co-workers in order to boost their productivity. A high payoff to performance naturally creates incentives to adopt any means necessary to boost productivity. Given that there is heterogeneity in skill, risk aversion, and moral character, these incentives will sometimes be strong enough for at least some workers to adopt unethical practices which enhance productivity. Once one worker adopts questionable methods, another worker may consider it more socially acceptable (see Goldstein et al., 2008) and hence more likely to follow suit, perhaps with the help of (knowledge transfer from) the initial worker. In some cases, competitive pressures may lead others to follow in order to get ahead, or perhaps just to stay even with other workers who are adopting similar techniques.

This mechanism is a plausible explanation for the apparent widespread use of performance-enhancing drugs in baseball, cycling, and track and field. Outside the world of sports, this diffusion process could show up through the adoption of dubious accounting methods, questionable ethics by lawyers, unscrupulous practices by mortgage brokers, political cor-

[1] See Angrist and Lang (2004), Guryan (2004), Hoxby (2000), Sacerdote (2001), Zimmermann (2003), Katz, Kling, and Liebman (2001), Edin, Fredriksson, and Aslund (2003), Oreopoulos (2003), Jacob (2004), Weinberg, Reagan, and Yankow (2004), Gould, Lavy and Paserman (2004 and 2009).

[2] See Kandel and Lazear (1992), Ichino and Maggi (2000), Hanushek, Kain and Rivkin (2002), Falk and Ichino (2006), Winter (2004), Bandiera, Barankay and Rasul (2005, 2010), Mas and Moretti (2009), Guryan, Kroft and Notowidigdo (2009), and Gould and Winter (2009).

ruption, cheating by students, biased reporting by the media, falsification in academic research, or other ways of skirting legal or ethical requirements. The literature on crime has found that criminal activity does respond to economic conditions (see Gould, Weinberg, and Mustard, 2002). Here, we highlight the idea that in the absence of persistent monitoring and rigid enforcement of ethical and legal practices, competitive pressures may lead to a "rat race" among workers to learn unethical behavior from co-workers in order to boost their productivity. As such, this paper makes a contribution to the recent literature that has demonstrated that agents do respond to incentives to cheat or engage in corruption (Duggan and Levitt, 2002; Jacob and Levitt, 2003; Wolfers, 2006; Kuziemko and Werker, 2006; and Carrell et al., 2008).

To examine the empirical relevance of this issue, we estimate whether Jose Canseco, one of the leading baseball players in the 1980's and 1990's, affected the productivity of his fellow teammates. In 2005, Canseco wrote a highly controversial book in which he not only admits to taking steroids throughout his playing career, but also claims to have personally ignited a contagion of drug use in professional baseball by educating dozens of teammates on the benefits and proper use of steroids.[3] In addition, he specifically named six famous power-hitters that he personally injected with steroids when they were teammates.[4] Naturally, these claims were treated with skepticism, especially since Canseco's reputation was tarnished even in his playing days, and he was particularly known for doing just about anything for money. As a result, no one really knows whether his claims are true or whether they were part of a publicity stunt to help promote his book.[5]

[3]Indeed, taking steroids is not simple. According to Canseco, steroids are effective only if they are used correctly in conjunction with appropriate doses of human growth hormone, lifting weights, a proper diet, abstinence from recreational drugs, and cycling on and off the various types of drugs. He writes in his autobiography that he obtained his human capital on steroid use from extensive reading, talking to bodybuilders, and years of experimenting on himself. He writes (page 135), "I was the first to educate others about how to use them, the first to experiment and pass on what I'd learned, and the first to get contacts on where to get them. I taught which steroid has which effect on the body, and how to mix or "stack" certain steroids to get a desired effect."

[4]Canseco claimed that he shared his knowledge not only with other players, but also with trainers who would transmit the knowledge throughout the league. He writes (page 211) that: "As soon as the trainers I talked to started getting involved, the steroid floodgates burst. The players started doing them right there in the locker room, so openly that absolutely everybody knew what was happening."

[5]Even the Mitchell Report (2007) did not give much credence to his testimony, despite the fact that Canseco was one of the only current or former players who agreed to cooperate with the investigation. Three of the seven players that Canseco claimed in his book that he personally injected with steroids were

This paper analyzes whether there is any empirical evidence to support the notion that Jose Canseco affected the performance of his teammates by turning them on to steroid use. The hypothesis is tested using panel data on the performance of baseball players from 1970 to 2009. After controlling for the individual fixed-effect of each player and a rich set of other control variables (experience, year effects, home ballpark characteristics, division effects, and managerial quality), the empirical analysis shows that a player's performance significantly increases after playing on the same team with Jose Canseco. This result is especially true for measures of performance like power hitting which are typically affected by physical strength. However, the results are significant for simple batting performance as well, where baseball folklore maintains that physical strength is not a dominant factor. In addition, we find that Canseco had a positive effect on the number of innings played by pitchers, which suggests that Canseco improved the endurance of pitchers on his team. We also examined wither 30 other comparable players from the same era generated similar positive effects on their teammates. This analysis reveals no evidence of similar effects from any other player – thus indicating that Jose Canseco had an unusual influence on the productivity of his teammates. Furthermore, the positive effect of Canseco disappears after 2003, the year that drug testing was implemented.

It is important to note that our main results are not driven by a common shock to all players on the same team, which is always a potential problem in the identification of peer effects. There are several reasons for this. First, Canseco played on seven different teams throughout his career. In fact, the seven players that Canseco claimed to have injected played on three different teams with him.[6] Second, the positive effect of Canseco on his peers shows up after they no longer play with him, and therefore, are playing for various teams in the league. So, the results could not come from a common shock to all players on one team. Third, as stated above, we found no evidence of peer effects for six power-hitters

not even mentioned in the report (Ivan Rodriguez, Wilson Alvarez, and Dave Martinez). Three of the other players were cited by the report, but not for evidence provided by Canseco. Canseco also named other players that he did not personally inject as users, and these players were not mentioned in the report either (Bret Boone, Tony Saunders, and Brady Anderson).

[6] McGwire played with Canseco on the Oakland A's in the late 1980's; Palmeiro, Gonzalez, and Rodriguez played with Canseco on the Texas Rangers in the early 1990's; Giambi played with Canseco on the Oakland A's in 1997; and Alvarez and Martinez played with Canseco on the Tampa Bay Devil Rays in the late 1990's.

who played with Canseco and shared the same coaches and team characteristics, which refutes the idea that the effect is coming from the team rather than Canseco himself.

Although it is theoretically possible that teams endogenously chose players who would improve their performance after playing with Canseco, it is difficult to explain why teams would do this regarding Canseco and no other player in the league. In addition, it is difficult to understand why Canseco's team would systematically trade a player away at the point where the player's performance is expected to improve. For all these reasons, the evidence points strongly in favor of Canseco's claims that he improved his teammates by introducing them to steroids.[7] It is possible that his teammates benefited from his other qualities (workout habits, batting technique, work ethic, etc.) rather than his human capital in steroids, but again, it is hard to explain why Canseco is the only player who affected his teammates through these channels. Overall, the evidence points to the strong contagion effect of improper behavior which can be generated by one worker when the incentives to keep up with fellow workers are very strong.

Overall, these findings highlight the need for firms and trade organizations to develop policies designed to contain the spread of unethical practices among workers. These policies could attack the phenomenon from two angles. First, policies could be developed in order to prevent individual workers from engaging in dubious behavior. One way to achieve this is through stricter monitoring of workers, and raising the severity of the punishment for those that are caught. The second way to combat the phenomenon is to create policies that restrict the flow of information about unethical behavior between workers. Incentives to share information about such practices with other workers could be reduced by inflicting severe penalties on the sharing of information. Other alternatives include rewarding workers for reporting on the unethical behavior of other workers, and

[7] Two years after Canseco's book, the Mitchell Report (2007) also made accusations of widespread use of steroids and human growth hormone in professional baseball. The two main sources of information for the report came from two trainers (Kirk Radomski and Brian McNamee) who provided evidence that they supplied 53 players with steroids and human growth hormone. McNamee is directly linked to Canseco, since they both worked for the Toronto Blue Jays in 1998. McNamee later went on to inject many other players during his tenure with the New York Yankees, and thus, Canseco has a direct link to the contagion outlined in the Mitchell Report. In addition, McNamee admits in the report that he consulted with Canseco on the use of steroids and considered him a knowledgeable expert. See footnote 387 on page 170 of the Mitchell Report.

to use a form of group punishment – such as punishing the whole firm for the behavior of individual workers. Group punishment on the whole firm would increase the incentives for firms to monitor their workers, while producing peer pressure among workers to stay away from dubious practices. These policy implications are discussed further in the concluding section.

2 The Data and Background

The data was obtained from the "Baseball Archive" which is copyrighted by Sean Lahman, and is a freely available on the Internet for research purposes. The data contains extensive personal and yearly performance information on players, coaches, and teams for every season of professional baseball. The sample is restricted to the seasons between 1970 and 2009. Pitchers are included in the sample if they pitched at least 10 games in a season, while non-pitchers are included if they batted at least 50 times in a season. The unit of observation is the person-year, so all variables are measured at the annual level.

Table 1 presents summary statistics for the sample. The upper portion of the table presents the means and standard deviations for standard measures of performance by non-pitchers: home runs, strikeouts (which typically are high if you are trying to hit home runs), RBIs (runs batted in), batting average (number of hits per time at-bat), slugging percentage (which is similar to the batting average but takes into consideration the quality of the hit), intentional walks (which are typically high if you are a dangerous batter), base on balls (typically high if you are a dangerous batter), steals (typically related to speed, but Canseco claims that steroids helped him steal by making him faster), errors (in fielding), number of times at-bat, and number of games played. The sample of non-pitchers is divided into "power hitters" (those that played a majority of their career at first base, catcher, in the outfielder, or designated hitters) and "position players" (those that played a majority of their career at second base, third base, or short-stop). The former category emphasizes batting with power (home runs, slugging percentage, etc.) while the second one emphasizes fielding skills at the expense of hitting prowess. This pattern is exhibited in Table 1 which shows that power hitters hit 9.83 home runs per year versus 6.87 for position players. The slugging percentage is also considerably higher for power hitters.

Table 1 also shows the means for variables which concern the extent to which players interacted with Canseco throughout his career. The variable "ever with Canseco" is a dummy variable for ever playing on the same team with Canseco, while "currently with Canseco" is a dummy variable for currently being on the same team as Canseco in a given year. Table 1 indicates the 11 percent of the players in the sample played with Canseco at some point in their careers, while 1.7 percent were currently playing with him in a given year.[8]

The bottom panel of Table 1 presents summary statistics for pitchers. The standard indicator of a pitcher's performance is called the ERA (Earned Run Average).[9] A higher ERA reflects poorer performance. The average ERA is 4.26, while 12 percent of the pitchers played at some point with Canseco and 1.8 percent play concurrently on the same team with him.

Table 2 presents summary statistics for a list of individual players. The list includes Jose Canseco, the six power-hitters named by Jose Canseco as players that he personally injected with steroids (Rafael Palmeiro, Jason Giambi, Mark McGwire, Juan Gonzalez, Ivan Rodriguez, and Dave Martinez), Ken Caminiti (who admitted that he took steroids but was not implicated by Canseco and never played with Canseco), and three leading power hitters from the 1990's that have never been implicated in any scandal and never played with Jose Canseco (Ken Griffey Jr., Ryne Sandberg, and Cecil Fielder).[10] Like Canseco, most of these other players were voted "most valuable player" at some point in their career (Canseco in 1988, Sandberg in 1984, Caminiti in 1996, Gonzalez in 1996 and 1998, Griffey in 1997, Rodriguez in 1999, and Giambi in 2000).

[8] Only 1.7 percent of the players played with Canseco in a given year because there are 30 teams in professional baseball (as of 2000), and Canseco played in less than half of the seasons in our sample.

[9] This measure takes the number of runs that a pitcher allows the opposing team to obtain, and scales it by the number of innings played, so that it represents the average number of runs which would have been scored off the pitcher in a full game. The ERA is calculated by: (number of earned runs/innings pitched)*9. Runs due to defensive errors by other players are not counted, hence the name "earned" run average.

[10] In Canseco's book, he also named pitcher Wilson Alvarez, who is not included in the table because he is not a hitter. Ken Caminiti was the most valuable player in the National League 1996, but later admitted that he took steroids throughout his career. He ended his 15 year career in 2001 and died in 2004 of a heart attack. In an interview with Sports Illustrated in 2002, Caminiti estimated that half of the players in baseball are on steroids. (See *Associated Press*, May 28, 2002)

Comparing these players to the overall average, Table 2 reveals a pattern which is very typical for excellent power hitters: many home runs, very high slugging percentage, a little better than average batting average, many RBIs, and many strikeouts (since going for home runs often results in strikes). Also, these players have higher than normal intentional walks and "base on balls" since the opposing teams often "pitch around" dangerous hitters to prevent them from getting a home run.

Overall, Table 2 demonstrates that this list of players includes some of the best power hitters of their generation, although Dave Martinez is perhaps not quite at the same level as the others. The statistics for Jose Canseco certainly show that he belongs in this elite group, but he does not stand out among the group as being the absolute best. In the next section, we examine whether Jose Canseco affected the performance of his peers, and then we compare the results for Canseco to those obtained by estimating the peer effect of players who had similar careers and played during the same era (the 10 players listed in Table 2 plus 20 other players who are among the best home run hitters of all-time).

3 The Empirical Analysis

This section examines how the performance of individual players is affected by coming into contact with Jose Canseco. Figure 1 presents a naive analysis by showing the mean home runs for three mutually exclusive categories of power hitting players from 1995-2000 (as a crude control for year effects): those that never played with Canseco, those that were playing concurrently with Canseco, and those that played with Canseco in the past. Figure 1 shows that players who played with Canseco in the past have much higher home runs than those who played with him concurrently, and both of these groups have much higher home run production than those that never played with him. Figure 2 displays a similar pattern regarding the slugging percentage – those that played with him are much better sluggers than those that did not.

This stark pattern could be due to the higher ability levels of players who happened to play with Canseco in the present and past, or it may be due to the causal effect of Canseco on his peers. To control for the non-random allocation of players who might have played with Canseco over time, all regressions will include individual fixed-effects. Furthermore, Figures 1 and 2 suggest that the effect of Canseco on his peers may be different between current and former teammates. Therefore, to allow for the possibility that it may take a period of time for Canseco to affect the performance of his teammates, the analysis examines whether there is evidence for an immediate effect of Canseco on the output of current teammates and whether there is a lingering effect of Canseco on former teammates. The basic regression equation is the following:

$$\begin{aligned} performance_{it} = \; & \beta_0 + \beta_1 (playing\ with\ canseco)_{it} + \beta_2 (after\ canseco)_{it} \\ & + \mu_i + \delta_t^{league} + \beta_3 (other\ controls)_{it} + \varepsilon_{it} \end{aligned}$$

where the performance of player i in year t is a function of a dummy variable for whether he plays on the same team as Jose Canseco in year t (*playing with canseco*), a dummy variable for having played with Canseco in the past but not during year t (*after canseco*), the fixed-effect of player i represented by μ_i, the year effect for each league δ_t^{league} (a year dummy for each year for each of the two leagues), other observable control variables, and the error term, ε_{it}.[11] Separate regressions are run for each performance measure listed in Table 1. The other control variables include: the slugging percentage in player i's division (excluding his own team) in year t which controls for the quality of the pitching and batting in the team's division in the same year, the team manager's lifetime winning percentage which is an indicator for the quality of the team's coaching, the ballpark hitting factor which control for whether the team's ballpark is easy or difficult for batters in year t, and the player's years of experience and experience squared.[12] It is worth noting that the inclusion of a fixed-effect for each year in each league controls for several common explanations for why hitting power has increased over time – namely, the dilution of pitching talent due to the addition of expansion teams into professional baseball and other structural changes.

[11] If a player played with Canseco in non-consecutive years, the variable for "playing with Canseco" is equal to 1 for every year starting in the first year that the player played with Canseco until the last year that he played with Canseco. The variable "after Canseco" is equal to one for every year after the last year that the player played with Canseco. Canseco played with the following teams in the following years: Oakland Athletics (1985–1992), Texas Rangers (1992–1994), Boston Red Sox (1995–1996), Oakland Athletics (1997), Toronto Blue Jays (1998), Tampa Bay Devil Rays (1999–2000), and Chicago White Sox (2001). In 2000, Canseco played 61 games for Tampa Bay and 37 for the New York Yankees, therefore, he is coded as being only with Tampa Bay that year.

[12] The results are not sensitive to using the division-level batting average instead of the slugging percentage.

The unobserved ability of player i, μ_i, is controlled for by including fixed-effects for each player i.

The main parameters of interest are β_1 and β_2, which indicate whether Jose Canseco affected the performance of his current or former teammates respectively. We model the potential effect of Canseco on his peers as an intercept effect, since the main factor is likely to be whether the person takes steroids or not, rather than learning how to inject steroids over time. Also, the distinction between playing "with Canseco" and playing "after Canseco" is important since even if a player did learn about steroids from Canseco, we do not know when he learned about it during his time with Canseco, but we can be sure that he already acquired the knowledge after playing with Canseco. The inclusion of a fixed-effect for each player means that we are exploiting variation in performance levels within the career of each player, rather than exploiting variation in the types of players that may have played with Canseco over time. In this manner, the empirical strategy controls for the endogenous personnel decisions of team managers. Therefore, identification of the parameters of interest comes from seeing whether variation within a given player's performance over time deviates from the typical player's experience profile in a way that is correlated with being a current or former teammate of Jose Canseco.

The basic fixed-effect regressions for all non-pitchers are presented in Table 3. Column (1) shows that after controlling for all the other variables, playing on the same team with Canseco had no effect on the home run output of a given hitter (the estimate for β_1 is -0.16 with standard error 0.49). However, home run production picks up significantly after playing with Canseco (the estimate for β_2 is 0.97 with standard error 0.44). The same pattern exists for several other performance measures: strikeouts, RBIs, intentional walks, and "base-on-balls." Each of these performance measures increase in a statistically significant way after playing with Jose Canseco, but rarely are they statistically significant while playing with Canseco. It is worth noting that an increase in each of these measures is indicative of a higher performing "power hitter": more home runs, more strikeouts, and more attempts by the other team to "pitch around" a dangerous hitter (expressed by more intentional walks and base-on-balls). This leads us to test whether the effect of Canseco on his teammates may differ according to the position of the player. Table 3 presents the p-value on an F-test which tests for the equality of all coefficients for "power hitters" and "position players", as defined above. The results indicate that the coefficients are significantly different across the two groups for almost all of the outcome measures. As a result, we now present results for the two groups separately.

Table 4 performs the same analysis in Table 3 after restricting the sample to power hitters. The results are very similar to Table 3 in terms of significance, but the magnitudes of the coefficients are much bigger for power hitters. The effect of "after Canseco" increases from 0.97 to 1.97 for home runs, 3.14 to 5.74 for strikeouts, and 2.98 to 5.24 for RBIs.[13] As noted above, higher values for these measures are indicative of a higher performing "power hitter", which suggests that Canseco improved the performance of power hitters.

However, Table 4 again reveals no significant impact of playing with Canseco at the same time. The reason why playing with Canseco has a much smaller effect than playing "after Canseco" may be due to the idea, mentioned above, that players who learn about steroids from Canseco do not take steroids during the whole time they are playing "with Canseco," but do use them during the entire time that they are former teammates with him. Alternatively, it may take some time for Canseco's positive effect to be realized, or this pattern may be due to the fact that players who play with him spend more of their time as former teammates of Canseco than being current teammates of him. For example, power hitters who played at least one season with Canseco in our sample spent 15 percent of their seasons on a team with Canseco and 39 percent of their seasons being former teammates with him. Also, the smaller effect of playing with Canseco may be due to the idea that Canseco took away scarce team resources such as playing time, attention from coaches and trainers, etc. If this were true, then similar peer effects should be found for other baseball stars. As we show later, we do not find similar effects for other stars, which casts doubt on the hypothesis that star players "crowd out" the performance of

[13] The results are very similar if we control for managerial quality with 193 dummy variables for each manager instead of the manager's lifetime winning percentage. The coefficient for homeruns in Table 4 becomes 1.94 with a standard error of 0.61 (the coefficient in Table 4 is 1.97 with a standard error of 0.59). In addition, similar findings are obtained if we restrict the sample to years in which the player had at least 200 times at-bat – the coefficient becomes 1.67 with a standard error of 0.72. However, since the number of at-bats is an outcome which we will show later to be endogenous to playing with Canseco, we prefer to keep the sample restricted to years with at least 50 at-bats.

other players. If, however, we do not differentiate between current and former players by using one variable which indicates whether the player either plays currently or in the past with Canseco, the coefficient for home runs is 1.40, and is still highly significant with a standard error of 0.52.

The coefficients in Table 4 are significant not only in the statistic sense, but also in terms of their magnitudes. The estimated effect of playing "after Canseco" on home runs is 1.97, which is 20% of the mean home run production of power hitters (9.83) displayed in Table 1. After playing with Jose Canseco, a typical power hitter is also estimated to increase his RBIs by 12 percent (a coefficient of 5.24 compared to the mean RBIs of 42.38). Apparently, the benefits of playing with Canseco were quite large.

Table 5 presents additional results for power hitters using alternative measures of performance. The first three columns show that Canseco had no discernible effect on steals, fielding percentage, and fielding errors. Neither of these outcomes is considered particularly important for power hitting, nor are they typically thought of as being affected by physical strength. So, the lack of any effect for these outcomes strengthens the interpretation of the results in Table 4 that Canseco had a significantly positive effect on the hitting power of his former teammates by affecting their physical strength.

Columns (4) and (5) in Table 5 show that power hitters significantly increase their playing time (number of times at-bat and number of games played in a season) after playing with Canseco.[14] Contrary to the outcomes in the first three columns, playing time should increase for a power hitter if his hitting prowess has improved.[15] The effect of Canseco on playing time could be a reason why we see several power hitting performance measures increase in Table 4 after playing with Canseco. For example, a power hitter will naturally tend to hit more home runs and RBIs if they have more chances at bat. The final column of Table 5 re-runs the regression for home runs but controls for the number of at-bats. In comparison to the results in Table 4 which did not control for the number of at-bats,

[14] Since playing time is clearly an endogenous outcome which seems to be affected by Canseco, our preferred specification does not include playing time as a control variable.

[15] Also, Canseco claimed that steroids help players recover from injuries faster, which could also increase playing time. In his personal case, he claimed that steroids extended his career by enabling him to play with serious back problems.

the results are much smaller but still statistically significant. That is, a player's home run production increases after playing with Canseco even if we condition on the number of chances at bat.

We now turn our attention to see if Canseco had a similar effect on other types of players (not power hitters). The upper panel of Table 6 runs similar regressions for a sample of skilled position players (not pitchers or power hitters) and pitchers. The results indicate that skilled position players did not increase their home run production after playing with Canseco, but they did significantly increase their batting average.[16] Canseco had no discernible effect on fielding percentage and steals. These results suggest that Canseco had no effect on measures which clearly should not be affected by steroids (fielding percentage and perhaps steals), but did have an effect on an outcome which is very important for these types of players (batting average). The last two columns of Table 6 indicate that Canseco had no effect on the main performance measure for pitchers, the ERA. However, Canseco did increase a pitcher's playing time, indicated by a significant coefficient of 8.96 on innings pitched, which represents a nine percent increase relative to the mean number of innings played by pitchers in our sample. This pattern of results is again consistent with the idea that Canseco had an effect by influencing the physical strength of his teammates – which is more likely to affect a pitcher's endurance relative to his ERA.

4 The Peer Effect of Similar Players

Having established that Canseco had a positive effect on power hitters and players in other roles (pitchers and position players), we now examine whether other baseball stars of the same era generated similar effects on their teammates. To allow for the possibility that other players may also generate a positive effect by transmitting knowledge about steroids, we estimate the peer effect of those that were named by Jose Canseco in his book. In addition, we estimate the peer effect for Ken Caminiti who acknowledged that he took steroids during the height of his career. For the sake of a simple comparison, we also present results for three famous players who have never been mentioned as being involved

[16] Although not reported, very similar results are obtained for "on-base percentage". For position players, the coefficient is 0.009 (s.e. 0.004) for batting average and 0.008 (s.e. 0.004) for on-base percentage.

in steroid use: Ken Griffey Jr., Ryne Sandberg, and Cecil Fielder. As shown in Table 2, all of the players are similar in the sense of having outstanding careers. Later, we will systematically choose 26 players who had similar careers as Jose Canseco, and compare the results for Canseco to those obtained for all 26 players.

Table 7 presents the results for power hitters using the same regression specification used to estimate the peer effect of Jose Canseco, but using one of the ten other players instead of Jose Canseco as the independent variable. One striking pattern that emerges is that many of the coefficients are negative, in contrast to the results for Canseco which are positive on most outcomes. The second striking pattern is that very few coefficients are significant, again in contrast to Canseco where most of the coefficients are significant. In fact, not one coefficient among the seventy presented for the other players (10 players across 7 outcomes) is positive and significant, in contrast to four out of seven for Canseco. Therefore, it is clear that the results for Jose Canseco are very unusual in comparison to players who had similar careers and even players who are suspected to have used steroids (Caminiti and Giambi admitted to steroid use, and Palmeiro tested positive in 2005). Furthermore, this analysis shows that the statistically significant results for Canseco are not simply a product of a large sample size, since the same sample was used to analyze the peer effect of the other ten players.

The bottom panel of Table 6 presents a similar analysis for non-power hitters and pitchers. In contrast to the upper panel of Table 6 which showed a positive effect of Canseco on batting average and innings pitched, only one of the ten other baseball stars (Palmeiro) had a positive effect on these measures of performance. However, in contrast to Canseco, Palmeiro had a seemingly negative effect on the performance of power hitters in Table 7. The other players exhibit no significant positive effect for any measure of performance, so once again, Jose Canseco seems to be unusual in terms of his effect on peers.

To check the robustness of the results, we now systematically choose a sample of power-hitting players who were comparable to Jose Canseco. Canseco made his professional debut in 1985, so we restrict our sample to players that started their career between 1981 and 1989. Next, we take only those players who are either on the top 100 list of career home runs or those that were home run hitting champions for any given year between 1985 and 2001 (for either league). Players on the all-time list obviously had great careers, while those that were hitting champions in a given year had at least one spectacular season. Jose Canseco matches both of those criteria, as do several other players on the final list. Table 8 shows the final list of 27 players and indicates which criteria they matched to be included in the sample. The sample includes 7 players that we already examined (Canseco, Griffey Jr., Fielder, Sandberg, McGwire, Palmeiro, and Gonzalez) and 20 new players. The estimated peer effect of each one of these players is presented in Table 9, which shows the estimated effect of each player on five different performance measures for power hitters (home runs, strikeouts, intentional walks, RBIs, and slugging percentage) and two performance measures for position players (batting average and slugging percentage).

Table 9 shows once again how strikingly different Jose Canseco is from the rest of this elite group of players. The estimated effect for Canseco is positive and significant for four of the seven outcomes. For the other 26 players, only 7 percent of the coefficients are positive and significant at the 10 percent level. Furthermore, the coefficients that are positive and significant are scattered among many players, which means that the other outcomes for these players are either not significant or negative. With the possible exception of Williams, there is no other player that has a systematically large and significant positive effect across several outcomes. A few players do reveal a systematic pattern, but the pattern indicates a negative effect on other players. This seems to be the case for Griffey, Bonds, Sosa, Belle, Gaetti, and Palmeiro. These players are considered among the best within the 27 players listed in Table 9, so once again, the completely opposite pattern for Canseco accentuates how truly unique he was.

It is important to note that our findings refute the idea that a common shock to all players in the same environment is responsible for the estimated peer effect of Jose Canseco. In general, the identification of a peer effect is difficult to disentangle from common shocks or unobserved characteristics shared by a group of people. However, there are several indications that this is not driving our results. First, Canseco played on ten different teams throughout his career, and the evidence is consistent with his claims to have injected steroids into the six named players during his tenure with at least three teams. Second, the positive effect of Canseco on his peers shows up after they no longer play with him, and therefore, play for various teams across the league. A common, sustained shock across various teams which affects only former teammates of Jose Canseco is highly unlikely. Third, although team managers may have surrounded Canseco with certain types of players, it remains a mystery why a team would do this only for Canseco and not the other 30 comparable power-hitters that we checked, and it is not likely that a manager would have the incentive or foresight to build a team around players that would significantly improve their performance after they no longer play with Jose Canseco. In addition, the analysis includes a fixed-effect for each player, which means that changes in the composition of players should not drive any of our results, since we are exploiting variation over time "within" the career of each player rather than variation across players. Finally, we found no evidence of similar peer effects for six power-hitters who played with Canseco and shared the same coaches and team characteristics. Taken as a whole, these findings present strong evidence that the effect is coming from Canseco and not the shared characteristics of the team or the endogenous decisions of team managers.

5 The Peer Effect in the Drug Testing Era (Post-2003)

In 2003, Major League Baseball introduced random drug testing to crack down on the rumored use of steroids by players. In 2004, penalties were introduced for those found using steroids, and the results from this testing program showed a sharp drop in steroid use from 2003 to 2004.[17] These findings suggest that the peer effect of Jose Canseco could be different in the post-2003 era. To investigate this possibility, we perform a similar analysis but include an interaction between the "after playing with Canseco" dummy with a dummy variable for the years after 2003 (2004-2009). (Canseco stopped playing in 2001, so we cannot include an interaction between "playing with Canseco" and a dummy variable

[17] Testing with penalties began in 2004 and became stiffer in 2005. See http://mlb.mlb.com/mlb/news/drug_policy.jsp?content=timeline. There is evidence that the drop in use began in 2004: In response to the results of the 2004 drug tests, Selig (commissioner of baseball from 1998) says "he's "startled" by the drop in positive test results from 5-to-7 percent in 2003 to between 1-to-2 percent in 2004."

for years after 2003.)

Table 10 presents our earlier results and compares them to the new specification which allows the peer effect of Canseco to change after 2003. The results across all outcomes for power hitters and position players show a striking pattern: the peer effect of Canseco disappears completely after 2003. The coefficient on "after playing with Canseco" becomes larger for every performance measure compared to our previous analysis, while the interaction coefficient is negative for every outcome. A series of F-tests performed on each outcome reveals that the "after Canseco" effect in the post-2003 era (the sum of the "after Canseco" coefficient and the coefficient on the interaction of "after Canseco" with the post-2003 dummy) is insignificantly different from zero for each outcome, while the effect in the pre-testing era is positive and significant for most of the outcomes (home runs, strikeouts, and RBIs for power hitters; and batting average for position players).

This pattern is consistent with the hypothesis that Canseco improved the performance of his peers prior to 2004 by passing on his knowledge of steroids, but this knowledge became obsolete during the crackdown on steroid use in the post-2003 seasons. Furthermore, these findings suggest that our earlier analysis was biased downwards, since we restricted the effect of Canseco to be constant in the pre- and post-steroid testing periods. Evidence for this bias is provided by the increase in size and significance of the "after Canseco" coefficient for every performance measure. Overall, the results in Table 10 present supporting evidence that Canseco did improve the performance of his peers through his steroid knowledge, and that steroid testing has proved to be an effective tool to contain the use and spread of unethical behavior by players to gain a competitive advantage.

6 Conclusion

Our analysis demonstrates that Jose Canseco had a significant effect on his former teammates. Specifically, we find that Canseco had a positive impact on outcomes such as home runs, strikeouts, RBIs, base-on-balls, and playing time. The pattern of results are all indicative of increased power hitting performance. In addition, we find a positive effect of

Canseco on the endurance of his fellow pitchers. For all measures of performance, however, the positive effect of Canseco disappears after 2003, the year that drug testing was implemented. In this manner, the results are consistent with Jose Canseco's claims that he helped his teammates increase their physical strength by introducing them to steroids, since physical strength is considered an important factor in hitting power and physical endurance.

We have no direct evidence, however, that Jose Canseco's teammates learned about steroids directly or indirectly from him. We do know that the evidence strongly supports his claims that he improved the physical strength of his teammates, but we have no proof that the mechanism responsible for this effect was steroids. It is possible that his teammates learned about strength conditioning or other work habits. However, this paper provides the first systematic study which shows that the evidence is consistent with Canseco's accusations. In particular, our findings support his claims that he started a contagion of steroid use in the late 1980's by teaching his peers and trainers about the benefits and technology of performance enhancing drugs. The Mitchell Report (2007) provides additional controversial evidence on the widespread use of steroids in baseball, but almost all of the evidence concerned current players or drug use in the last five to ten years. The Mitchell Report (2007) is silent on how the epidemic was ignited in the late 1980's and early 1990's, and does not offer any indication of whether steroids are effective or not. In fact, the report cites evidence (page 9) which indicates that the use of human growth hormone is not effective at all. Our findings are consistent with Canseco's claims that steroids and human growth hormone are highly effective, and that he was at the forefront of transmitting the technology of how to use them throughout professional baseball in the late 1980's and early 1990's. As a result, our study supports recent findings on the effectiveness of steroid use, while being the first to examine the transmission of steroid use among players.[18]

[18] Schmotzer, Kilgo, and Switchenko (2008, 2009) and Addona and Roth (2010) use the players mentioned in Mitchell report to find a positive impact of steroids on the performance of batters (runs created) and pitchers (pitch velocity), respectively. Schmotzer, Kilgo, and Switchenko (2009) find that steroid use increase hitting power by about 18 percent, which is very similar in magnitude to our findings. Addona and Roth (2010), in addition, find evidence that human growth hormone is used in recovery (a negative correlation with velocity). This is consistent with our findings about increased innings pitched. De Vany

Even though we do not provide direct evidence of steroid use, the evidence is not consistent with other explanations. This is best illustrated by our findings that no other player seems to have affected his teammates in the way that Jose Canseco did. After checking to see whether 30 other power-hitting stars affected their teammates, we find that none of them exhibited anything close to what we see with Jose Canseco. Across several outcomes that are indicative of being a good power hitter, Jose Canseco had a strong and significant impact. For the 30 other players, hardly any of the effects were significant, and most of the coefficients that were significant were in the opposite direction (decreasing the performance of their peers). Clearly, Jose Canseco had a very unusual effect in comparison to players who had similar careers and even players who are suspected of using steroids. That is, Canseco is not just generally different from everyone else, but he appears to be unique even among known steroid users (Caminiti, Giambi, and Palmeiro). Therefore, if the source of the effect that Canseco apparently had on his teammates' batting power was due to something other than steroids (work ethic, batting techniques, weight training regimen, etc.), why do we not see similar positive effects from other elite players on their peers as well? Moreover, why does the positive peer effect of Canseco disappear after drug testing was introduced in 2003?

All of this evidence points to the powerful effect one worker can have on many other co-workers. This particular case demonstrates how a "peer effect" could be generated by one worker increasing the productivity of other workers, rather than working through behavioral channels such as peer pressure, shame, guilt, etc. Furthermore, this is a case where the mechanism is likely to involve unethical means. As the literature on crime suggests, unethical behavior by one person can cause others to follow suit.[19] In the context of the workplace, once one worker starts doing it, he may obtain a competitive advantage which can only be neutralized by other workers doing the same. This phenomenon could explain the widespread use of performance-enhancing drugs in other sports like cycling and track

(2010) shows that the home run increase in recent years is consistent with a Pareto distribution (leading to geniuses), and therefore, is not necessarily due to steroid use. Dinardo and Winfree (2010) show that De Vany's findings does not rule out that steroid use could also be behind the increase.

[19]See Glaeser et al. (1996). Bayer, Hjalmarsson, and Pozen (2009) show that criminals may acquire criminal human capital from each other while serving in jail.

and field. Outside the world of sports, similar forces may be at work in terms of accounting practices, unprofessional behavior by lawyers, overly aggressive subprime lending, political corruption, public disclosures, cheating by students, accuracy in journalism, reporting in academic research, etc.

By demonstrating that unethical practices can spread through a contagion effect, our analysis leads to several potential policy implications. The most obvious policy implication is to increase the punishment on individuals practicing unethical behavior and/or transferring their knowledge of such practices to other workers. In addition, policies could be designed specifically to stop the spread of unethical behavior among workers. In particular, the firm (or trade organization) could reward individuals for reporting unethical practices of other workers. For example, under IRC Section 7623, the IRS authorizes the payment to those reporting tax evasion of up to 30% of the tax recovered (see Hesch, 2009). This kind of policy could be effective through two channels: it would reduce incentives to engage in questionable activity, and if the worker does engage in such behavior, the worker would be more likely to keep the information to himself rather than share it with others. That is, this policy could be effective even if there are few instances of actual reporting. Another possible way of containing a contagion is the use of group punishment for the actions of individual workers. If a firm is punished for the unethical practices of a workers, then the firm is more likely to increase its monitoring of workers and will be more likely to punish, rather than reward, questionable practices which may give the firm a competitive advantage. Group punishment is also likely to produce peer pressure among workers to avoid unsavory tactics.

Overall, this paper highlights the idea that in the absence of a rigid and persistent enforcement mechanism and proper policies, there could be a contagion of unethical behavior. This can be caused by a general degeneration of social norms, spread of knowledge or skill, or from market forces creating a "rat race" where workers are willing to do just about anything to remain competitive.

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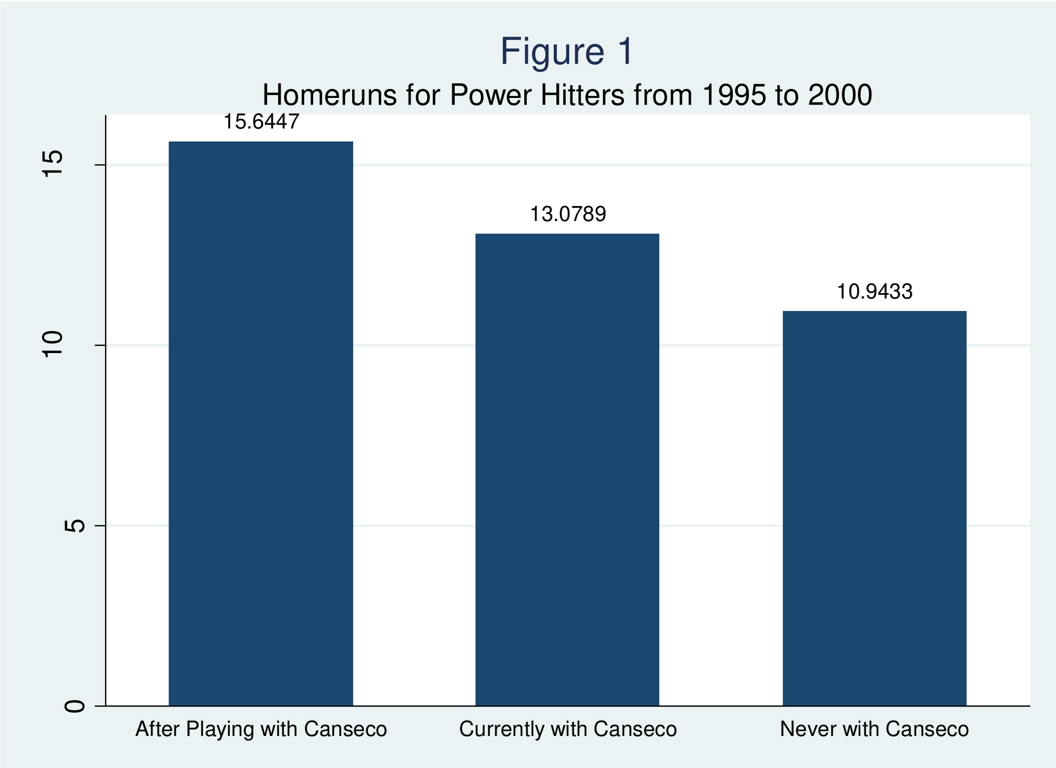
Figure 1
Homeruns for Power Hitters from 1995 to 2000
15.6447
13.0789
10.9433
0
5
10
15
After Playing with Canseco
Currently with Canseco
Never with Canseco

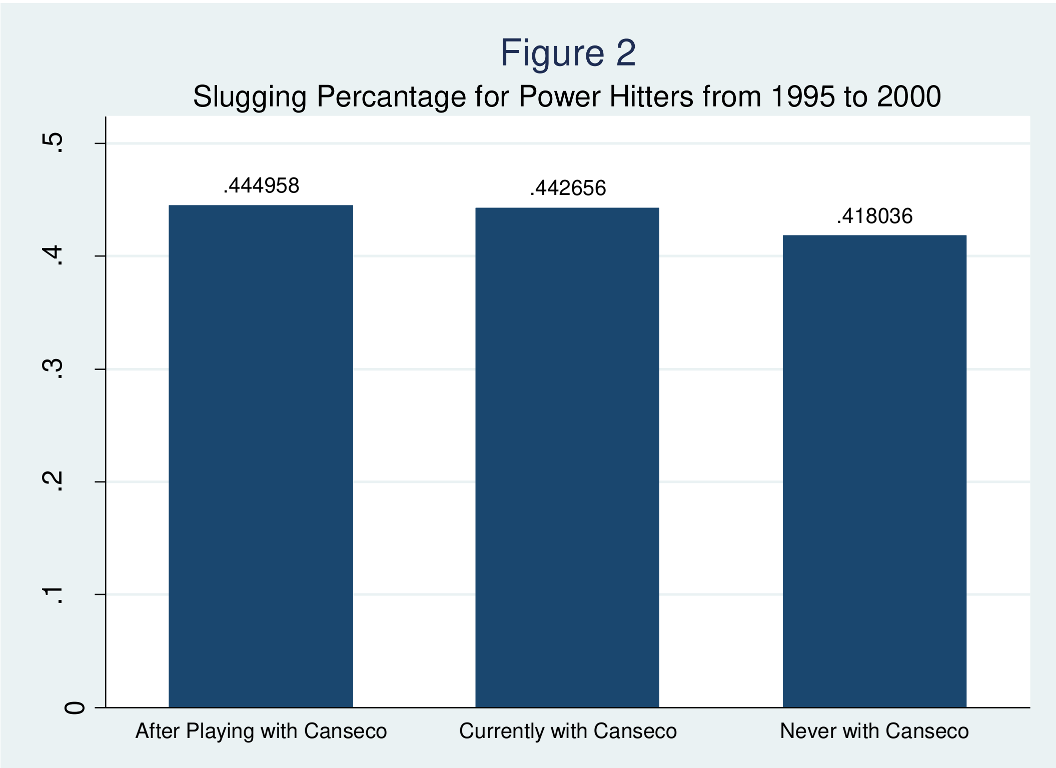
Figure 2
Slugging Percantage for Power Hitters from 1995 to 2000
.444958
.442656
.418036
0
.1
.2
.3
.4
.5
After Playing with Canseco
Currently with Canseco
Never with Canseco

Table 1: Summary Statistics

	Power Hitters		Position Players	
	Mean	Standard Deviation	Mean	Standard Deviation
Home Runs	9.83	9.87	6.87	8.11
Strikeouts	53.51	34.27	49.79	31.43
RBIs	42.38	31.26	37.40	26.94
Slugging Percent	0.401	0.087	0.364	0.079
Batting Average (BA)	0.258	0.040	0.253	0.038
Intentional Walks	3.28	4.42	2.32	3.17
Base On Balls	32.52	25.02	30.76	22.69
Steals	6.26	10.61	7.03	9.99
Fielding Percent	0.983	0.020	0.968	0.019
Errors	6.17	5.31	10.86	7.17
At-Bats	312.51	176.36	335.33	181.69
Games	99.07	41.01	103.56	41.26
Ever with Canseco	0.108	0.310	0.112	0.315
Currently with Canseco	0.016	0.127	0.018	0.132
Division Slugging Pct.	0.417	0.025	0.418	0.025
Manager Winning Pct.	0.500	0.042	0.500	0.042
Ballpark Hitting Factor	100.20	4.59	100.14	4.64
Observations	11,397		5,820	

	Pitchers	
	Mean	Standard Deviation
Earned Run Average	4.26	1.48
Innings Pitched	100.75	68.95
Ever with Canseco	0.115	0.319
Currently with Canseco	0.018	0.135
Observations	14,214	

Table 2: Mean Performance Measures for Nine Baseball Stars

	Home Runs	Batting Average	Slugging Pct.	RBIs	Strike-outs	Intent-ional Walks	Base on Balls
Jose Canseco	28.25	0.268	0.515	85.06	117.50	3.81	55.62
Rafael Palmeiro	28.45	0.286	0.511	91.75	67.40	8.55	67.65
Jason Giambi	27.27	0.274	0.509	88.67	92.53	5.87	84.13
Mark McGwire	36.44	0.262	0.584	88.38	99.75	9.38	82.31
Juan Gonzalez	27.13	0.285	0.531	87.75	79.56	4.63	28.56
Ivan Rodriguez	16.05	0.297	0.469	66.53	72.63	3.32	25.63
Ken Caminiti	15.93	0.267	0.439	65.53	77.53	7.40	48.47
Dave Martinez	5.36	0.264	0.370	36.00	57.43	3.07	36.50
Ken Griffey Jr.	30.00	0.280	0.533	87.10	83.90	11.71	62.05
Ryne Sandberg	18.80	0.283	0.448	70.73	83.93	3.93	50.73
Cecil Fielder	24.54	0.251	0.472	77.54	101.23	5.85	53.31
All Power Hitters	9.83	0.258	0.401	42.38	53.51	3.28	32.52

Table 3: The Effect of Canseco on Hitting Statistics for All Non-Pitchers

	Home Runs	Strikeouts	RBIs	Slugging Percentage	Batting Average	Intentional Walks	Base on Balls
Playing with Canseco	-0.156 (0.487)	-3.464* (1.846)	-1.112 (1.631)	0.002 (0.005)	0.003 (0.003)	-0.154 (0.252)	-1.193 (1.280)
After Playing with Canseco	0.966** (0.444)	3.143* (1.686)	2.979** (1.490)	0.006 (0.005)	0.004* (0.002)	0.376 (0.230)	1.657 (1.169)
Individual Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies for Each League	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-value on F-statistic	0.001	0.001	0.033	0.658	0.106	0.053	0.000
Observations = 17217 Players = 2732							

Standard errors are in parentheses. * indicates significance at the 10% level, and ** indicates significance at the 5% level. Each column represents a separate regression, with the dependent variable indicated at the top of the table. The sample includes data from the 1970 to 2009 seasons. Jose Canseco has been deleted from the sample. Year dummies are included for every year in each league. The "additional controls" include the player's number of years in the league (tenure), tenure squared, slugging percentage for each division in each year (not including the player's own team), manager's lifetime winning percentage, and ballpark hitting factor. The p-value is for the f-statistic which tests the hypothesis that all the coefficients (except for the league-year dummies) are identical for power hitters and position players.

Table 4: The Effect of Canseco on Hitting Statistics for Power Hitters

	Home Runs	Strikeouts	RBIs	Slugging Percentage	Batting Average	Intentional Walks	Base on Balls
Playing with Canseco	0.643 (0.638)	-1.194 (2.316)	0.605 (2.100)	0.003 (0.006)	0.002 (0.003)	-0.036 (0.333)	0.546 (1.616)
After Playing with Canseco	1.974** (0.588)	5.738** (2.137)	5.236** (1.937)	0.007 (0.006)	0.001 (0.003)	0.482 (0.308)	3.027** (1.491)
Individual Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies for Each League	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations = 11397 Players = 1816							

Standard errors are in parentheses. * indicates significance at the 10% level, and ** indicates significance at the 5% level. Each column represents a separate regression, with the dependent variable indicated at the top of the table. The sample includes data from the 1970 to 2009 seasons. The sample is composed of "power position" players which include players who spent a majority of their career in the following positions: catcher, first base, designated hitter, and the outfield. Jose Canseco has been deleted from the sample. Year dummies are included for every year in each league. The “additional controls” include the player’s number of years in the league (tenure), tenure squared, slugging percentage for each division in each year (not including the player’s own team), manager’s lifetime winning percentage, and ballpark hitting factor.

Table 5: The Effect of Canseco on other Performance Statistics for Power Players

	Steals	Fielding Percentage	Errors	At-Bats	Games Played	Home Runs
Playing with Canseco	-0.0385 (0.666)	-0.002 (0.002)	0.0870 (0.440)	-1.684 (12.40)	-0.833 (3.090)	0.701 (0.469)
After Playing with Canseco	0.244 (0.614)	0.002 (0.002)	-0.276 (0.406)	30.25** (11.44)	5.564* (2.851)	0.919** (0.433)
At-bats						0.035** (0.000)
Individual Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies for Each League	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes

Observations = 11397
Players = 1816

Standard errors are in parentheses. * indicates significance at the 10% level, and ** indicates significance at the 5% level. Each column represents a separate regression, with the dependent variable indicated at the top of the table. The sample includes data from the 1970 to 2009 seasons. The sample is composed of "power position" players which include players who spent a majority of their career in the following positions: catcher, first base, designated hitter, and the outfield. Jose Canseco has been deleted from the sample. Year dummies are included for every year in each league. The “additional controls” include the player’s number of years in the league (tenure), tenure squared, slugging percentage for each division in each year (not including the player’s own team), manager’s lifetime winning percentage, and ballpark hitting factor.

Table 6: The Effect of Canseco on the Performance Statistics for other Players

	Performance Measures for Skilled Positions					Performance of Pitchers	
	Home Runs	Batting Average	Slugging Percent	Fielding Percentage	Steals	ERA	Innings
Playing with Canseco	-1.708**	0.006	0.000	-0.001	0.902	-0.096	-0.798
	(0.714)	(0.004)	(0.008)	(0.002)	(0.912)	(0.114)	(3.924)
After Playing with Canseco	-0.764	0.009**	0.006	-0.002	-0.393	-0.131	8.961**
	(0.641)	(0.004)	(0.007)	(0.002)	(0.819)	(0.103)	(3.547)
After Playing With:							
Palmeiro	0.798	0.014***	0.025***	0.001	1.657**	-0.178*	8.944**
	(0.661)	(0.004)	(0.007)	(0.002)	(0.844)	(0.108)	(3.729)
Giambi	0.658	-0.001	0.000	-0.001	-0.478	0.187	-0.418
	(1.037)	(0.007)	(0.012)	(0.003)	(1.325)	(0.137)	(4.748)
McGwire	-0.0826	-0.001	0.004	0.001	-2.399**	-0.129	-11.05**
	(0.804)	(0.005)	(0.009)	(0.002)	(1.026)	(0.134)	(4.637)
Gonzalez	0.475	0.003	0.008	0.003	1.102	-0.0776	4.055
	(0.670)	(0.004)	(0.008)	(0.002)	(0.856)	(0.112)	(3.855)
Rodriguez	1.072	0.006	0.0103	0.003	0.714	-0.144	-0.432
	(0.758)	(0.005)	(0.008)	(0.002)	(0.967)	(0.128)	(4.435)
Martinez	-0.669	-0.003	-0.001	-0.001	-1.241	0.0802	-0.525
	(0.639)	(0.004)	(0.007)	(0.002)	(0.816)	(0.104)	(3.594)
Caminiti	0.544	-0.004	-0.002	0.003	-0.762	0.0690	2.602
	(0.820)	(0.005)	(0.009)	(0.003)	(1.052)	(0.126)	(4.348)
Griffey Jr.	-0.389	-0.001	-0.002	0.004	0.394	-0.0201	-2.547
	(0.772)	(0.005)	(0.009)	(0.002)	(0.986)	(0.124)	(4.301)
Sandberg	-0.675	0.010	0.023**	0.002	1.250	0.0244	-5.659
	(0.996)	(0.006)	(0.011)	(0.003)	(1.273)	(0.129)	(4.463)
Fielder	0.437	0.001	0.013	0.006**	0.295	-0.178*	8.944**
	(0.894)	(0.006)	(0.010)	(0.003)	(1.141)	(0.108)	(3.729)

Standard errors are in parentheses. Each column in the upper panel of the table represents a separate regression, with the dependent variable indicated at the top of the table. * indicates significance at the 10% level, and ** indicates significance at the 5% level. Skilled position players include players who played a majority of seasons in the following positions: second base, third base, and shortstop. The sample is from the 1970 to 2009 seasons. The sample size for position players is 5,820 which includes panel data on 916 players. The sample of pitchers includes 14,214 observations and 2,695 players. The control variables for each regression are those described in Table 3. In the lower panel of the table, each coefficient comes from a separate regression which is specified similarly to the ones in the top panel but use the indicated player instead of Jose Canseco as the treatment variable. ERA stands for "earned run average."

Table 7: The Effect of other Great Power Hitters on other Power Position Players

	Home Runs	Strikeouts	RBIs	Slugging Percentage	Batting Average	Intentional Walks	At-Bats
After Playing with:							
Canseco	1.974**	5.738**	5.236**	0.007	0.001	0.482	30.25**
	(0.588)	(2.137)	(1.937)	(0.006)	(0.003)	(0.308)	(11.44)
Palmeiro	-1.962**	-6.565**	-7.173**	-0.015**	-0.008**	-0.726*	-45.27**
	(0.709)	(2.582)	(2.338)	(0.007)	(0.004)	(0.371)	(13.82)
Giambi	-0.831	-2.609	-1.959	-0.001	-0.004	-0.205	-15.20
	(0.809)	(2.943)	(2.666)	(0.008)	(0.004)	(0.423)	(15.76)
McGwire	-0.277	1.004	-1.602	0.007	-0.002	0.326	3.288
	(0.782)	(2.853)	(2.586)	(0.008)	(0.004)	(0.410)	(15.29)
Gonzalez	-0.834	-3.682	-3.819*	-0.001	-0.002	-0.0783	-19.16
	(0.622)	(2.262)	(2.047)	(0.006)	(0.003)	(0.326)	(12.11)
Rodriguez	-0.129	-0.493	-2.207	0.011	0.004	-0.166	-14.95
	(0.689)	(2.501)	(2.267)	(0.007)	(0.004)	(0.360)	(13.39)
Martinez	-0.536	-6.193**	-3.685*	-0.003	-0.001	0.0356	-23.23**
	(0.582)	(2.113)	(1.916)	(0.006)	(0.003)	(0.304)	(11.31)
Caminiti	-1.321*	-2.045	-5.293**	-0.012*	-0.006*	-1.134**	-18.29
	(0.705)	(2.563)	(2.322)	(0.007)	(0.004)	(0.368)	(13.72)
Griffey Jr.	-2.889**	-10.83**	-7.929**	-0.008	-0.001	-1.075**	-56.87**
	(0.732)	(2.668)	(2.415)	(0.007)	(0.004)	(0.383)	(14.27)
Sandberg	0.927	-1.892	1.301	-0.004	-0.005	0.169	-19.63
	(0.763)	(2.771)	(2.512)	(0.008)	(0.004)	(0.399)	(14.83)
Fielder	-1.365*	-4.375	-0.233	-0.006	-0.001	-0.490	-1.727
	(0.747)	(2.715)	(2.462)	(0.008)	(0.004)	(0.391)	(14.55)

Standard errors are in parentheses. * indicates significance at the 10% level, and ** indicates significance at the 5% level. Each coefficient came from a separate regression which is specified similarly to the ones in Table 4 but use the indicated player instead of Jose Canseco as the treatment variable. The displayed coefficient from each regression is for the variable "after playing with" the indicated player.

Table 8: The Best Home-Run Hitters of Canseco's Era

	Debut Year	Top 50 in Career Home Runs	Top 51-100 in Career Home Runs	Years Led League in Home Runs (1985-2001)
Jose Canseco	1985	X		AL88,AL91
Rafael Palmeiro	1986	X		
Mark McGwire	1986	X		AL87,AL96,NL98,NL99
Juan Gonzalez	1989	X		AL92,AL93
Ken Griffey Jr.	1989	X		AL94,AL97,AL98,AL99
Barry Bonds	1986	X		NL93,NL01
Sammy Sosa	1989	X		NL00
Fred McGriff	1986	X		AL89,NL92
Gary Sheffield	1988	X		
Cal Ripken Jr	1981	X		
Andres Galarraga	1985	X		NL96
Joe Carter	1983	X		
Cecil Fielder	1985		X	AL90, AL91
Larry Walker	1989		X	NL97
Albert Belle	1989		X	AL95
Matt Williams	1987		X	NL94
Gary Gaetti	1981		X	
Greg Vaughn	1989		X	
Ellis Burks	1987		X	
Chili Davis	1981		X	
Darryl Strawberry	1983		X	NL88
Ron Gant	1987		X	
Ryne Sandberg	1981			NL90
Jesse Barfield	1981			AL86
Kevin Mitchell	1984			NL89
Dante Bichette	1988			NL95
Howard Johnson	1982			NL91

The 27 players listed are the full sample of players that entered the league between 1981 and 1989 and are currently in the top 100 list of players for career home runs or led one of the two leagues in home runs for at least one year between 1985 and 2001.

Table 9: The Effect of the Best Home Run Hitters of Canseco's Era

	Power Hitters					Position Players	
	Home Runs	Strike-outs	Intent-ional Walks	RBIs	Slugging Percent	Batting Average	Slugging Percent
Canseco	1.974***	5.738***	0.482	5.236***	0.007	0.009**	0.006
	(0.588)	(2.137)	(0.308)	(1.937)	(0.006)	(0.004)	(0.007)
Palmeiro	-1.962***	-6.565**	-0.726*	-7.173***	-0.015**	0.013***	0.024***
	(0.709)	(2.582)	(0.371)	(2.338)	(0.007)	(0.004)	(0.007)
McGwire	-0.277	1.004	0.326	-1.602	0.007	-0.001	0.004
	(0.782)	(2.853)	(0.410)	(2.586)	(0.008)	(0.005)	(0.009)
Gonzalez	-0.834	-3.682	-0.078	-3.819*	-0.001	0.003	0.008
	(0.622)	(2.262)	(0.326)	(2.047)	(0.006)	(0.004)	(0.007)
Griffey Jr.	-2.889***	-10.832***	-1.075***	-7.929***	-0.008	-0.001	-0.002
	(0.732)	(2.668)	(0.383)	(2.415)	(0.007)	(0.005)	(0.009)
Bonds	-3.094***	-12.523***	-0.632**	-10.080***	-0.015**	-0.001	-0.013
	(0.650)	(2.370)	(0.317)	(2.146)	(0.007)	(0.005)	(0.009)
Sosa	-1.660***	-9.795***	-0.743**	-5.642***	-0.004	0.005	0.018**
	(0.643)	(2.344)	(0.336)	(2.124)	(0.007)	(0.004)	(0.007)
McGriff	-0.394	0.976	-0.356	-0.004	-0.002	-0.007	-0.015*
	(0.636)	(2.312)	(0.332)	(2.096)	(0.006)	(0.004)	(0.008)
Sheffield	-0.837	-5.920***	-0.623**	-0.599	0.004	0.004	0.011
	(0.587)	(2.136)	(0.307)	(1.934)	(0.006)	(0.004)	(0.007)
Ripken Jr.	-0.757	-3.493	-0.272	-2.556	-0.009	0.004	0.011
	(0.777)	(2.822)	(0.406)	(2.558)	(0.008)	(0.006)	(0.010)
Galarraga	-1.197**	-6.698***	0.348	-2.936	-0.001	-0.005	-0.015**
	(0.597)	(2.169)	(0.313)	(1.968)	(0.006)	(0.004)	(0.007)
Carter	0.690	1.792	0.337	4.966**	0.005	0.002	0.005
	(0.666)	(2.422)	(0.348)	(2.193)	(0.007)	(0.005)	(0.009)
Fielder	-1.365*	-4.375	-0.490	-0.233	-0.006	0.001	0.013
	(0.747)	(2.715)	(0.391)	(2.462)	(0.008)	(0.006)	(0.010)
Walker	-1.148	-5.738**	-0.733*	-2.812	-0.003	-0.001	-0.001
	(0.727)	(2.642)	(0.380)	(2.394)	(0.007)	(0.005)	(0.008)
Belle	-1.368*	-2.344	-0.898**	-5.623**	-0.013*	-0.012**	-0.011
	(0.704)	(2.559)	(0.368)	(2.319)	(0.007)	(0.006)	(0.010)
Williams	1.389**	-0.258	1.690***	1.247	0.020***	0.004	0.014
	(0.615)	(2.235)	(0.321)	(2.026)	(0.006)	(0.005)	(0.010)
Gaetti	-2.407***	-5.895**	-0.252	-9.425***	-0.016**	-0.007	-0.018**
	(0.632)	(2.296)	(0.330)	(2.080)	(0.006)	(0.005)	(0.008)
Vaughn	-0.502	-1.291	-0.597*	-0.807	-0.000	-0.002	0.001
	(0.663)	(2.411)	(0.347)	(2.185)	(0.007)	(0.005)	(0.009)
Burks	0.834	0.905	0.977***	1.606	0.010*	-0.004	-0.011
	(0.596)	(2.167)	(0.312)	(1.963)	(0.006)	(0.005)	(0.008)
Davis	0.974	5.021**	0.004	3.294	0.016**	0.001	0.008
	(0.629)	(2.284)	(0.328)	(2.070)	(0.006)	(0.004)	(0.008)
Strawberry	-1.200*	-3.515	0.369	-3.252	-0.007	-0.007	-0.016**
	(0.686)	(2.494)	(0.359)	(2.262)	(0.007)	(0.004)	(0.008)
Gant	-1.625**	-2.919	-0.325	-4.548**	-0.010	-0.010**	-0.017**
	(0.662)	(2.405)	(0.346)	(2.181)	(0.007)	(0.004)	(0.007)
Sandberg	0.927	-1.892	0.169	1.301	-0.004	0.010	0.023**
	(0.763)	(2.771)	(0.399)	(2.512)	(0.008)	(0.006)	(0.011)
Barfield	-1.137	-2.138	-0.014	-2.241	-0.015	0.009	-0.004
	(1.013)	(3.677)	(0.530)	(3.336)	(0.010)	(0.007)	(0.013)
Mitchell	0.238	1.768	0.070	-0.472	-0.001	-0.002	0.006
	(0.605)	(2.201)	(0.316)	(1.994)	(0.006)	(0.005)	(0.008)
Bichette	0.885	2.235	0.449	3.254	0.025***	-0.008*	-0.015*
	(0.662)	(2.408)	(0.346)	(2.180)	(0.007)	(0.005)	(0.008)
Johnson	0.291	-4.266*	-0.650*	-1.278	0.002	-0.001	0.002
	(0.668)	(2.425)	(0.349)	(2.199)	(0.007)	(0.004)	(0.008)

Standard errors are in parentheses. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. Each coefficient came from a separate regression which is specified similarly to the ones in Table 4 but use the indicated player instead of Jose Canseco as the independent variable. The displayed coefficient from each regression is for the variable "after playing with" the indicated player. The 27 players listed are the ones described in Table 8.

Table 10: The Effect of Canseco before and after 2003

	Power Hitters					Position Players	
	Home Runs	Strike-outs	Intent-ional Walks	RBIs	Slugging Percent	Batting Average	Slugging Percent
After Playing with Canseco	1.899*** (0.586)	5.712*** (2.127)	0.466 (0.307)	5.113*** (1.929)	0.005 (0.006)	0.009** (0.004)	0.005 (0.007)
After Playing with Canseco	2.467*** (0.613)	6.869*** (2.226)	0.487 (0.320)	6.413*** (2.018)	0.010 (0.006)	0.011*** (0.004)	0.012 (0.007)
Post-2003* After Playing With Canseco	-2.392*** (0.834)	-5.485* (3.031)	-0.0285 (0.436)	-5.705** (2.748)	-0.015* (0.008)	-0.008 (0.006)	-0.028** (0.011)
P-value on F-test for the sum of both coefficients	0.93	0.67	0.32	0.81	0.54	0.68	0.15

Standard errors are in parentheses. * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. The coefficient in the upper panel (for each column) comes from a separate regression than the two coefficients in the bottom panel. Each regression includes the same control variables described in Table 4. The reported p-value is for the F-test which tests for whether the sum of the two coefficients in the bottom panel equals zero.