The Competitive Effects of PEDs
MLB in the Post-testing Era

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Abstract

For a profit maximizing sports league, performance enhancing drug (PED) testing is a way in which to avoid some of the costs of player PED use while maintaining competitive balance. Profit maximizing teams have a countervailing incentive to want to employ PED-using players that arises from competition. Using a modified version of the competitive talent market model and estimates of MLB team financials from *Forbes*, I show that PED testing increased the competitive balance of MLB by altering the risk-return trade-off faced by teams for employing PED-using players. For a typical MLB team, I estimate that testing reduced franchise value by an average of 3 million in 2005 dollars over the last ten years. This result reflects significant impacts on teams' non-gate revenues, player costs, and future profit growth from PED suspensions. Using variation over time in MLB's testing policy, I also estimate the number of minor and major league suspensions per season (~20 minor and ~4 major league) characteristic of a policy which balances the costs and benefits of player PED use at the league and team levels. At times over the last ten years MLB has come close to achieving such a policy, falling short most often because of an overabundance of minor league suspensions.

1. Introduction

The demand for professional sports is thought to be rooted in the "uncertainty of outcome" principle first expressed in Rottenberg (1956). It states that the more competitive the outcome of a game, the more fans are willing to pay to see it. Player use of PEDs may lower demand by altering sports fans' perceptions of competitiveness. This is a potential cost to the competing teams that goes unpaid when the offending players are unknown and cannot be punished in accordance with the economic losses they create. However, PEDs may also inadvertently raise demand if their undetected use and increased player performance lead to extraordinary athletic achievements by way of the "superstar effect" of Rosen (1981).[2]

For a profit maximizing sports league, PED testing is a way in which to avoid some of the costs associated with fans' perceptions of competitiveness by discouraging player PED use. In contrast, profit maximizing teams have a countervailing incentive to want to employ PED-using players that arises from competition. This is because team profits are thought to be a function of team wins, while league profits are not for the simple fact that for every winner there must be a loser at the

[1] The opinions expressed herein are those of the author and do not represent the views of the Federal Reserve Bank of Chicago or the Federal Reserve System.
[2] Hausman and Leonard (1997) document the impact of the superstar effect in the NBA.

league level. Instead, league profits are commonly thought of as being determined by the competitive balance of the league, which is, in turn, a function of the distribution of "talent" across its teams. As a result, the impact of PED testing on individual teams may differ from the effect on the league as a whole, because the incentives at the team and league level often do not align.

In this paper, I show that PED testing increased the competitive balance of MLB by altering the risk-return trade-off faced by teams for employing PED-using players. Using a modified version of the competitive talent market model and estimates of MLB team financials from *Forbes*, I estimate the impact of MLB's PED testing program on both the league and its teams. By incorporating several channels through which the testing program may have affected franchise values, I present evidence that for a typical MLB team testing resulted in an average reduction in franchise value of 3 million in 2005 dollars over the 2005-2014 seasons. This result reflects significant impacts on teams' non-gate revenues, player costs, and expected future profit growth.

Finally, using variation over time in MLB's PED testing policy, I also estimate the number of minor and major league suspensions per season (~20 minor and ~4 major league) characteristic of an optimal PED testing policy which balances the costs and benefits of player PED use at the league level while incentivizing the participation of teams in the testing program. After discussing how recent season's test results compare to this benchmark, I conclude with a discussion of potential challenges the league may face going forward as well as improvements it could make in the next collective bargaining agreement in conjunction with the players' union in order to counteract the recent rise in both major and minor league suspensions.

2. MLB's PED Testing Policy

PED testing in MLB began in June 2001 for minor league players who are not represented by the Major League Baseball Players Association (MLBPA) and, hence, not subject to collective bargaining rules.[3] Testing at the major league level soon followed suit as part of MLB's August 2002 collective bargaining agreement (CBA), which provided for survey testing during the 2003 and 2004 seasons. This agreement contained a threshold level of 5% for total use that would subsequently trigger a clause instituting a formal testing system with penalties to begin the following season.

The threshold level was found to be exceeded in November 2003, as MLB announced that between 5% and 7% of 1,438 samples tested positive for PEDs. Formal testing began with the 2004 season, with punishments ranging from assignment to a treatment program for a first offense to a 1-year suspension without pay for a fifth positive test result. However, the Joint Drug Prevention and Treatment Program currently governing all MLB players did not become effective until January 2005. Under this more stringent system, players are subject to suspensions without pay for a first offense and the public release of positive test results.[4]

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[3] Steroid use, possession, or sale had been previously banned in MLB after Commissioner Fay Vincent issued a memo in 1991 to that effect, although testing was limited to "reasonable cause" cases requiring cooperation of the MLBPA and advance notice given to the player.
[4] See Grossman et al. (2012) for additional background on performance enhancing drug testing in MLB.

This agreement was the result of nearly 15 years of collective bargaining between the MLBPA, team owners, and more than one MLB commissioner, and has subsequently been amended over time to increase the length of suspensions, types of PEDs, number of tests, etc.[5] Many of the initial changes to the testing program were highly controversial. This was especially true in the case of making positive test results public, which did not begin for either league until spring training prior to the 2005 season. However, more recent changes have been the result of amicable, at least by historical standards, collective bargaining between MLB and the MLBPA.

Table 1 summarizes MLB's PED testing program. The suspension schedules in this table demonstrate that over time the major league program has gradually taken the same shape and form as the preceding minor league program. First-time offenses went from 15-game suspensions under the initial minor league program and simple placement into a treatment program under the initial major league system in 2004 to uniform 80-game suspensions under the latest revision to the Joint Drug Prevention and Treatment Program, which was implemented during the 2014 season. Maximum penalties went from lifetime bans in minor league baseball and one season in major league baseball to lifetime bans in both leagues over the same time frame.

In addition, there has been considerable change in the types of drugs classified as performance enhancing substances under the testing program. MLB's testing programs were established so that the schedule of banned drugs has generally followed Schedule III of the Code of Federal Regulations' Schedules of Controlled Substances. As Congress has added to this list through acts such as the Anabolic Steroid Control Act of 2004, this number has greatly expanded. MLB has also added drugs such as Ephedra and other amphetamines, as well as human growth hormone (HGH), testosterone, and known masking agents, to its list of banned substances.

Testing procedures have also changed over time. The league standardized the collection and analysis of its players' samples early on, moving them to the World Anti-Doping Agency in 2004 and putting in place a semi-independent governing body to oversee its drug testing program. Subsequent rulings by this body in arbitration with the league and the MLBPA have also resulted in further improvements.[6] All professional players are now randomly tested multiple times a year, with tests during the season and offseason, and can be tested with cause at any other time as determined by the Joint Drug Prevention and Treatment Program's guidelines and its subsequent amendments.[7] The Commissioner's office also retains the right to suspend players based on outside

[5] As an aside, at least one MLB team unsuccessfully attempted to conduct its own testing. It was banned from doing so only by an arbitration ruling, which stipulated that such a policy must be negotiated as part of a collective bargaining agreement.

[6] A famous example here is the arbitration ruling that reversed the first PED suspension of Ryan Braun of the Milwaukee Brewers. In his case, the collection of his urine samples was found to violate the timeliness and storage protocol of the program, which led MLB to tighten the oversight and gathering of samples.

[7] The average number of tests per year cited in table 1 is based on my reading of the total number and types of tests each player is subject to taking under the current testing program. Individual players may end up taking more or fewer tests depending on their testing history and the random selection process.

sources of evidence of possession or use. However, this right has been invoked infrequently and usually only in cases where substantial evidence existed.[8]

Table 2 provides a breakdown of the testing results based on a database that I have maintained since 2005 containing information on major and minor league PED suspensions.[9] From the 2005 through the 2014 seasons, roughly 400 players were suspended under the testing program, with minor league players accounting for about 85% of positive tests. Nearly 30% of the positive tests since testing began occurred during 2005. The number of suspensions then stabilized at around 20-40 per season before spiking into the 40-60 range as additional banned substances and tests were added during the 2012 and 2013 seasons. Subsequent seasons have seen some improvement, but suspensions remain elevated from their low of 22 in 2008.

Repeat offenders under the testing program are uncommon (almost 95% of suspensions are for first-time offenses), suggesting either that one positive test is enough to deter further use or players are better able to hide their future use after an initial positive test. Splits by American League (AL) versus National League (NL) indicate that more suspensions can be attributed to NL teams, so that perhaps differences in league rules such as the use of a designated hitter (DH) in the AL may play a role in player PED use. However, within leagues, suspensions are fairly evenly distributed across divisions. Finally, the distribution of test results by position (pitcher versus hitter) suggests a slightly lower likelihood of a positive test for pitchers.

Figure 1 plots the total number of PED suspensions for each team along with its average percentage of total suspensions per season.[10] Every team has had players test positive, and a number of teams have had an inordinate number of players test positive compared to the hypothesis that users are uniformly distributed across teams. This likely implies that there existed a strong incentive from competition for teams to want to employ these players. No single team, however, accounts for more than 8% of total suspensions on average; and, overall, there exists considerable diversity across teams in the use of PED-using players. For instance, big-market teams such as the New York Yankees (NYY) and Los Angeles Dodgers (LAD) have very similar test results to small-market teams like the Houston Astros (HOU) and Kansas City Royals (KC).

3. The Costs of Detection and Prevention

MLB's titling of its drug testing policy as the Joint Drug Prevention and Treatment Program is reflective of the trade-off it faces in aligning league, team, and player incentives and its stated goals

[8] Most of the early suspensions for HGH occurred in this fashion prior to the use of blood testing. However, the most famous example is the suspension of Alex Rodriguez of the New York Yankees based on second-hand testimony and accounts of PED use.
[9] This information was assembled from press releases at mlb.com, milb.com, and other sources as noted in the table. Excluded under the domestic player category are positive tests for minor league players in the Dominican and Venezuelan Summer Leagues as well as the Mexican League.
[10] Some discretion must be used in assigning positive tests to teams when players switch teams or are released. Whenever possible, I have accrued a positive test to the team the player was with when the positive test was announced.

with regard to player PED use. It is unclear whether the league, in conjunction with the players' union, has struck an optimal balance in this regard. Below, I summarize the problem of designing a PED testing policy that efficiently achieves these twin aims and discuss several necessary conditions that must characterize such a policy. A more complete mathematical derivation can be found in Appendix A.

3.1. An Optimal PED Testing Policy

It remains to be seen just how effective MLB's measures have been in actually deterring player PED use. By raising the cost of being caught using these drugs, the league has simultaneously raised the benefit to a player from trying to hide his drug use. This effect is the very nature of the adverse selection problem that arises from incomplete information as to the validity of a player's performance, and is the very reason the league needs to understand the relationship between its policy and the responses of its players and teams.

An optimal PED testing policy minimizes both the costs of *detecting* and *preventing* PED use subject to the participation of players and teams in the testing program, as well as achieves the league's objective of maximizing league profits (or franchise values) by maintaining competitive balance in terms of the distribution of talent across its teams. Such a policy, therefore, depends crucially on the nature of the profit functions of both MLB and its teams with respect to player PED use.

When modeling this decision, I assume that PED testing, T, operates as a revelation mechanism of the distribution of player talent, $Q(T)$, for the league and its teams, which is an implicit function of the testing parameters in terms of fines, suspensions, etc. Building off of Becker et al. (2006), I then posit that the league must choose a level of testing, T^*, that maximizes league profits, which takes as arguments a revenue function, $R[Q(T)]$, defined in terms of the distribution of talent across teams, and an enforcement cost function, $C[N(T)]$, that depends implicitly on the supply function, $N(T)$, giving the number of players who use PEDs as a function of the testing parameters.

In addition, the testing policy must invoke the voluntary participation of all major league teams so that $N(T)$ is the greater of zero or the value that solves $\pi(N(T)) = 0$, where $\pi(N(T))$ is the aggregate profit of all teams in MLB attributable to player PED use. This team participation constraint ensures that on average MLB teams are indifferent to the testing system and represents an example of enforcer compensation in the spirit of Becker and Stigler (1974). Without this constraint, teams may engage in deviating behavior that undermines league objectives. With it, the league is able to incentivize its teams in order to better align its interests with those of its teams.

The problem of the league is then to choose the level of T that makes the marginal PED-using player consistent with its objectives of maximizing league profits and incentivizing team participation in the testing program indifferent to PED use:

$$\max_T R[Q(T)] - C[N(T)] \; s.t. \, N(T) = N^*(T) \equiv \arg\max\{N(T) \geq 0, \pi\big(N(T)\big) = 0\}.$$

An optimal PED testing policy, therefore, maximizes league value by both altering the competitive balance of the league in order to maximize league revenues and minimizing the direct and indirect costs of testing for MLB teams consistent with their participation in the testing program, i.e.,

$$\frac{\partial R}{\partial Q}\frac{\partial Q}{\partial T} - \frac{\partial C}{\partial N^*}\frac{\partial N^*}{\partial T} = 0.$$

Insofar as league revenues are increasing in competitive balance, i.e., $\frac{\partial R}{\partial Q} > 0$, and competitive balance is increasing in the testing parameters, i.e., $\frac{\partial Q}{\partial T} > 0$, league marginal revenue from PED testing will be positive and $T^* > 0$.[11] The direct costs of testing for MLB teams then appear through the term, $\frac{\partial C}{\partial N^*}$, and indirect costs appear as $\frac{\partial N^*}{\partial T}$. The former include reductions in team profits from the demand effects of players caught using these drugs, while the latter include the adverse selection costs of identifying users from the entire population of players who can spend resources to avoid detection.

There are two possible solutions to this problem. The first equilibrium is where T^* is chosen to satisfy an additional incentive compatibility constraint for players that makes them indifferent to PED use. In this case, $N^* = 0$, i.e. in effect a complete prohibition of PED use results. However, when T^* does not satisfy player incentive compatibility, this may no longer be the case as teams may benefit from having a positive number of players spend resources to avoid detection. In this equilibrium, not all PED users are identified and teams are compensated just enough to ensure their participation in the testing program.

3.2. Is the Current Policy Optimal?

Evaluating the current policy with respect to an optimal one requires an understanding of whether or not player incentive compatibility has been achieved, as this information is crucial in the determination of the long-run equilibrium likely to emerge. In line with the analysis of Becker et al. (2006), the more inelastic the demand for PEDs, the more costly the testing system becomes over time. This is because the more inelastic demand is, the more players are willing to take actions to circumvent the prohibition. Thus, an optimal policy depends progressively on player incentive compatibility and the ability of players to mask their PED use, because the increasing costs of enforcing it quickly outweigh the benefits from reducing consumption.

The changes in MLB's testing program between the 2005 and 2006 seasons, which tripled suspensions but reduced positive tests by only 60%, indicates a highly inelastic demand for performance enhancing drugs.[12] Therefore, the second equilibrium is much more likely to be the long-run equilibrium. In this case, teams and players are compensated in such a way as to avoid the spiraling costs associated with a complete prohibition. In fact, the evolution of the current policy highly resembles the second equilibrium described earlier. MLB has chosen to address its PED problem by determining the direct and indirect costs of testing on the expected net returns for teams by means of increased suspensions without pay for the player and making test results public

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[11] This need not be the case, though, if, for instance, $\frac{\partial Q}{\partial T} < 0$. In this case, the league may want to actually *not* test, i.e. $T^* = 0$. This is, perhaps, one way to view the "Steroid Era" in MLB. Given sufficiently rampant PED use among players, ensuring that no team was at a competitive disadvantage by turning a blind eye to player PED use would be optimal in this framework.

[12] This does not even take into account that the frequency of testing also increased by allowing for offseason testing, which would imply an even more inelastic demand.

knowledge. The teams are not further punished for employing a player caught using PEDs. This type of behavior is entirely consistent with some slackness being permitted in player incentive compatibility, which allows for some PED use to be hidden in order to compensate teams and ensure their participation in the testing program.

The analysis above also establishes several necessary conditions for the current policy to be considered optimal. First, MLB profits must not have decreased in response to the introduction of the PED testing program. Figure 2 plots the combined franchise value of all 30 MLB teams based on annual estimates compiled by *Forbes*, for 1991-2014.[13] Franchise values can be thought of as an expected stream of future discounted team profits (e.g., Vrooman (1997)), such that the combined franchise value of all MLB teams is an approximate measure of league profits. The rapid growth in MLB franchise values post-testing, seen in this figure, is suggestive that this condition is met.[14]

The team participation constraint provides another necessary condition for an optimal policy. Under this constraint, MLB teams should be indifferent on average to the testing system. As noted earlier, a positive impact on the league as a whole does not necessarily imply that the testing program was a positive development for all of the league's teams. MLB's testing program likely altered the competitive balance of the league. Whether or not a team benefited from this change depends on its competitors' and its own reliance on PED-using players and how strongly its fanbase cares about the PED consumption of its players relative to winning games.

To answer this question, one then needs to understand how the testing program impacted team profits from player PED use. This is the task of the next section. However, in order to preview what is to come, a key result that will be shown there is that the distribution of team wins per player cost (or wins per dollar of player salaries) is proportional to the distribution of teams' shares of player talent. Therefore, it is possible to see even at this stage whether or not the competitive balance of MLB was indeed impacted by the PED testing program.

Figure 3 plots kernel densities of the log transformation of team wins per player cost pre- and post-testing (panel A) along with a quantile-quantile plot comparing the distributions (panel B).[15] It is quite evident from this figure that the distribution of team talent shares exhibits much less variance post-testing than pre-testing[16], suggesting that the competitive balance of MLB has increased since the period from 1998-2004 often referred to as the "Steroid Era". The ultimate impact of this change on team and league profits is the focus of the next section where team and league profits are modeled as a function of minor and major league player PED suspensions.

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[13] *Forbes* estimates the value of each MLB team prior to the beginning of each season based on revenues, costs, etc. through the prior season. The publication's methodology can be found at www.forbes.com/mlb-valuations/.
[14] A Wald test for a structural break post-2005 in a regression of franchise value on a linear time trend rejects the null of no trend-break at the 99% confidence level.
[15] The log transformation both induces normality of the distributions and allows for the isolation of the constant of proportionality, which is then removed by differencing the data with team and season-specific means, i.e. team and season fixed effects.
[16] This visual observation is confirmed by a range of parametric and semiparametric statistical tests for the equality of variance of two distributions.

4. A Competitive Talent Market Model

As the basis for understanding how MLB's PED testing policy impacted the competitive balance of the league and the profits of its teams, I augment the competitive talent market model of Ferguson et al. (2000) to include PED testing.[17] I consider both revenue and cost channels through which testing may affect team profits and franchise values. Throughout, I assume that teams must price the risk of losing player services in a given season to testing before player test results are revealed.

4.1. Revenues

In each season, *i=1,…,N* MLB teams are taken to be revenue-maximizing with monopoly pricing power in their local markets so that they set the price of attending a regular season game, p_i, subject to their local demand functions, $A(w_i, x_i, p_i)$:

$$R_i^* = \max_{p_i} p_i A(w_i, x_i, p_i)\tau(b_i)\, \alpha(z_i, s_i)\,. \quad (1)$$

The demand for games depends not only on the cost of attendance, but also on a vector of exogenous local market characteristics, x_i, the number of PED suspensions, s_i, for each team in a given season, and the likelihood of winning a game as measured by a team's winning percentage, w_i. Other gate revenue streams, such as All-Star games hosted and post-season games, are captured in the multiplier $\tau(b_{it})$, reflecting the ratio of total to regular season gate revenue and depending on a set of indicator variables, b_i. Non-gate revenue is assumed to be unrelated to wins following Blass (1992) and is reflected in the multiplier $\alpha(z_i, s_i)$ capturing the ratio of total to gate revenue, depending on exogenous factors, z_i, in addition to s_i.

In this way, PED testing is assumed to have a differential impact on the gate and non-gate revenue of each team. One way in which to rationalize this decision is that whether or not a fan pays to attend a game is a fundamentally different choice from whether or not a fan pays for a player's jersey (or, equivalently, whether a corporation chooses to purchase season tickets versus becoming a corporate sponsor). In the latter cases, there is an element of the fan (or corporation) lending his (or its) reputation to the player or team and vice versa.

I further allow for differentiation between the gate and non-gate revenue effects of PED suspensions by breaking s_i into separate components for minor and major league players. Conceivably, a suspension of a minor league player should have a much smaller effect on an MLB team’s gate and non-gate revenues than the equivalent for a major league player.

4.2. Wins

Wins in the Ferguson et al. (2000) framework are produced by bundling player characteristics q at hedonic prices ρ in a competitive labor market according to a constant returns-to-scale production function $Q_i = f(q_i)$ to form a measure of team talent, or quality.[18] A team's winning percentage, i.e.,

[17] Variations of the competitive talent market model are also discussed in El-Hodri and Quirk (1971), Scully (1974), Vrooman (1995), and Fort and Quirk (1995).
[18] For my purposes, it is not necessary to specify any further restrictions on the production function. However, it is common in the empirical literature to assume that it takes a Cobb-Douglas form. Ferguson et al. (2000) provide an example based on Scully (1989).

wins divided by games played, depends on the vector of talent choices of all N teams in the league, Q, such that $w_i(Q)$ corresponds to the strategy used by team i to produce wins. Teams take their opponents strategies, Q_j, as given and can affect w_i only through the choice of their own strategy, Q_i, so that the model defines a Nash equilibrium across teams characterized by the set of best-response functions Q^*.

I assume that test results are unknown at the time team quality decisions are made. Therefore, a player's potential use of PEDs in a season is a characteristic in the vector q that is bundled by teams along with other player characteristics, such as offensive and defensive talent. The expected costs and benefits of player PED use to MLB teams are then associated with a price in the price vector ρ set in the competitive market for player services. Thus, PED testing operates as an ex-post revelation mechanism of a player's true skill *and* a team's willingness to risk employing PED users.

To capture this fact, I modify the Ferguson et al. (2000) framework, which equates a team's winning percentage to its share of overall league quality scaled by the number of unique contests between teams, so as to down-weight team quality in each season in proportion to each team's share of PED suspensions in that season $\left(\kappa_i = \frac{s_i}{\sum_{i=1}^{N} s_i}\right)$:

$$w_i = \frac{N}{2}\frac{(1-\kappa_i)Q_i}{\sum_{i=1}^{N}(1-\kappa_i)Q_i}. \tag{2}$$

Teams without PED suspensions in a given season receive the full benefit of their purchased player services in terms of winning percentage, and may also benefit by having a higher share of revealed league quality if other teams' players are suspended. Teams with PED suspensions are revealed to have lower team quality, negatively impacting their winning percentage; but if PED suspensions are spread roughly equally across teams, the impact on winning percentages will be minimal. Thus, I have introduced into the model an externality whereby an individual team's outcomes will depend on the league-wide distribution of PED suspensions in each season.

4.3. Player Costs

An equilibrium for MLB teams in the market for player services is then defined with respect to Q under the assumption that the league is able to drive a wedge, μ, between the marginal revenue product and marginal cost of player services. The original intention of Ferguson et al. (2000) for this parameter was to capture changes in the relative bargaining power of the league and the players' union. However, one can also view this parameter as capturing league rules, such as PED testing, which aim to alter the competitive balance of the league in order to maximize league revenues. As such, an increase/decrease in μ corresponds to an increase/decrease in league power and a decrease/increase in teams' player costs. For this reason, I pose the labor wedge as a function of both variables related to the collective bargaining process, y_i, and team PED suspensions.

Implicit in this calculation is a Nash equilibrium over games with respect to team quality, $\frac{\partial w_i}{\partial Q_i}$. Solving for this Nash equilibrium yields the following characterization of team cost functions[19]

[19] Ferguson et al. (2000) contains a mistake in the derivation of the cost function that was subsequently corrected in Brave et al. (2008).

$$C_i^* = (1 - \mu(y_i, s_i))\frac{\partial R_i^*}{\partial w_i} w_i (1 - \kappa_{it})(1 - \frac{2}{N} w_i), \tag{3}$$

where C_i^* is ex-post player costs with PED testing.[20] This cost function contains two wedges between the marginal cost and revenue product of each team: first, a "labor wedge", μ, which depends on the *total* number of PED suspensions in a given season for each team; and second, an additional "testing wedge" resulting from the competitive interactions between teams in the market for PED-using players that depends on a team's *share* of PED suspensions in a given season.

Equation 3 makes clear that the impact of PED testing on a team's player costs is multifaceted. The first-order effect results from the cost savings of a PED-using player's suspension without pay. Players, though, contribute to team wins. If the loss of a player significantly impacts team performance, then revenues are likely to be negatively impacted as well, lowering a player's potential marginal revenue product and a team's willingness to pay for his services. Going one step further, a team's performance on the field is also affected by its competitors' decisions about whether or not to employ PED users. A team may still be willing to roll the dice on a suspected PED-using player if it thinks that it may be able to gain a competitive advantage.

A fanbase that responds inelastically to suspensions makes it more likely that the competitive effects of testing will dominate a teams' decision-making. Conversely, the more sensitive revenue streams are to suspensions, the less valuable any competitive advantage becomes. Teams must weigh the costs and benefits of employing a suspected PED-using player and set their payrolls accordingly. Team profits may potentially be increasing with PED suspensions, as long as a team remains in the portion of the league-wide distribution of suspensions associated with competitive advantages to employing PED-using players.

The league must then take these competitive interactions into account when setting its policy in collective bargaining with the players' union in order to ensure the cooperation of its teams. Combining equations 2 and 3 and assuming a 162 game season, one arrives at the result mentioned earlier that a team's wins per player cost, $W_i = \frac{162 * w_i}{C_i^*}$, is proportional to its share of revealed player talent. Furthermore, taking logs of equation 4 isolates the team-specific constant of proportionality and motivates the above analysis of figure 3.

$$\frac{W_i}{C_i^*} = \frac{81N}{C_i^*}\frac{(1 - \kappa_i)Q_i}{\sum_{i=1}^{N}(1 - \kappa_i)Q_i} \tag{4}$$

4.4. Profits

League and team profits in this model are determined in very different ways. For teams, maximizing profits entails choosing a ticket price that maximizes regular season gate revenue and a level of team quality which minimizes player costs given a desired winning percentage. Conversely, the league can affect its profitability only through negotiation with the players' union over the size of the labor wedge, including the parameters of PED testing, and the implicit competitive balance

[20] The complete derivation of this equation can be found in Appendix B.

"tax" imposed on its teams by the testing wedge. Maximizing league profits then entails minimizing the negative impact of testing on team franchise values given a desired level of competitive balance.

Team profits in the model are given by

$$\pi_i^* = R_i^* - C_i^* \tag{5}$$

whereas league profits can be expressed in terms of the franchise value of an average MLB team,

$$FV_t = \sum_{l=0}^{\infty} \beta^l E[\pi_{t+l}] = \pi_t \frac{(1+g)}{\beta - g} = \pi_t g(v_i, s_i), \tag{6}$$

representing the discounted expected value of future profits. In order to write league profits in this form, one must assume that the function $g(v_i, s_i)$ represents a team-specific discount rate, β, and constant expected profit growth rate, g. Driving this function are a set of team-specific exogenous variables, v_i, and, separately, minor and major league PED suspensions. Allowing suspensions to impact team profits and franchise values in possibly different ways captures the different roles they play in determining league and team revenues.

5. Evaluating MLB's PED Testing Program

I estimate my model on a panel of 30 MLB teams using data from the 2005-2014 seasons. The model's six estimating equations for ticket prices, attendance, gate revenues, revenue multipliers, player costs, and franchise values are described in Appendix C. Estimation follows the iterative nonlinear feasible generalized least squares method detailed in Zellner (1962). This procedure, often referred to as nonlinear seemingly unrelated regression (NLSUR), produces the equivalent of maximum likelihood estimates of the model's parameters. Standard errors are calculated using a cluster-robust estimator of the joint error variance matrix by clustering on season identifiers.

5.1. Data

The primary data sources for this purpose were the online databases maintained by Rodney Fort and Sean Lahman, available at https://sites.google.com/site/rodswebpages/codes and http://www.seanlahman.com/baseball-archive/statistics, respectively. Additional data were taken from Haver Analytics or compiled by the author from MLB websites and BaseballReference.com as necessary. Appendix C lists the variables used in the model unrelated to PED suspensions.

To construct κ_{it}, I use both minor and major league PED suspensions, even though minor league players do not contribute directly to the performance of the major league team. The reasons for this are two-fold. The winning percentage function ultimately captures teams' competitive strategies. Both minor and major league players should figure into these decisions. For instance, the quality of a team's minor league players often plays an instrumental role in their ability to shape their major league roster by trading for other teams' major league players. Similarly, some teams rely heavily on developing "homegrown" talent through their minor league system to either fill gaps in their major league roster or deal with injuries, thereby producing a direct connection between the quality of its minor and major league players in a given season.

5.2. Semi-Elasticities

Table 3 reports semi-elasticities with respect to PED suspensions.[21] The estimated impact of MLB's PED testing program on team revenues can be seen in the top rows of the table. One PED suspension corresponds to a roughly 1% increase in gate revenue, with the impact nearly twice as large for a major versus minor league suspension and not statistically significant from zero in either case. In contrast, one major league PED suspension translates to a roughly 2.0% decrease in the revenue multiplier, nearly four times as large as that for a minor league suspension. Both effects, however, are statistically significant, suggesting that both types of suspensions negatively impacted MLB teams' non-gate revenues during this period.

The impact on total revenues (not shown in the table) from a PED suspension is the sum of the gate revenue and revenue multiplier semi-elasticities. A major league suspension results in a much larger decline in total revenue than a minor league suspension, which instead produces a very small, and statistically insignificant, positive impact on total revenue. The opposite is true, however, for expected future profit growth, where a minor league suspension equates to a statistically significant 1.0% decrease and a major league suspension produces a small positive, but statistically insignificant, effect. This result is intuitive in that minor league players contribute less to an MLB team's current revenues and costs than they do to its expected future revenues and costs.

The impact on player costs from PED testing can also be seen in table 3. A PED suspension results in a statistically significant 2.1% increase in player costs via the labor wedge, which is consistent with an increase in the bargaining power of the MLBPA. Insofar as the MLBPA acts as an additional "enforcer" of its testing program, this result is consistent with incentivizing its participation in the testing program. It may also explain why resistance from the players' union has subsided significantly since 2002. Counteracting this effect, however, were the competitive effects of testing. A PED suspension on average decreased team player costs through the testing wedge by a statistically significant 3.1%, such that the net impact of both wedges on player costs was slightly negative. In this sense, the model confirms the result in figure 3 that PED testing altered the competitive balance of the league by reducing player costs for a given winning percentage.

The bottom rows of table 3 demonstrate that on average a major league suspension during this period resulted in a larger negative impact on current profits than a minor league suspension, which is associated with a small increase in profits. Minor league suspensions had a larger negative impact on franchise values through their negative impact on expected future profit growth. The semi-elasticities for profits and franchise values to both minor and major league suspensions, however, are not statistically significant. Therefore, it cannot be ruled out in a statistical sense that MLB's PED testing policy during this period had a net neutral effect on it teams. In this sense, it could be considered as meeting the criteria for an optimal policy described earlier.

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[21] Table A1 reports all estimated elasticities (or semi-elasticities). Table A2 maps all of the model parameters to the cells in table A1. Both tables can be found in Appendix D. To get a sense of how different these estimates are from Ferguson et al. (2000), I also computed price and income elasticities for attendance (not reported in the table). While Ferguson et al. (2000) estimate their model on a much different era of MLB with a different dataset; my estimates are in fact very similar to theirs. Demand is estimated to be nearly unit price elastic and slightly income inelastic.

5.3. Counterfactuals

To examine the economic significance of the effects described in table 3, I next construct counterfactual estimates of team franchise values, profits, total revenues, and player costs assuming no PED suspensions for every team. The difference between the estimates of these variables given a team's observed number of suspensions and its counterfactuals is then a measure of how much more/less costly it would have been for a team to produce the same winning percentage with no PED-using players. If MLB's testing policy truly had a net neutral effect on it teams, then these differences should be small on average during this period.

Table 4 presents a team-by-team breakdown of the average effects of PED testing during this period. Some teams were impacted by PED testing more so than others. For an average MLB team, I estimate that PED testing resulted in a reduction in franchise value of 3.1 million in 2005 dollars during 2005-2014. In contrast, PED testing resulted in an increase in profits of 0.86 million in 2005 dollars for an average MLB team. Underlying this are cost savings of 0.64 million in 2005 dollars and an increase in revenue of 0.22 million in 2005 dollars for an average MLB team. The difference between the impact on franchise values and profits, therefore, reflects a fairly sizeable effect of PED testing on team's expected future profit growth during this period.

Figure 4 shows how total team profits (panel A) and franchise values (panel B) due to PED testing have evolved over time as MLB has altered the parameters of its testing program. By far the most costly change to the testing program from the league's perspective was the initial public release of test results in 2005. The league-wide loss of franchise value in this season was almost $300 million. To put this figure in perspective, the average MLB franchise value in 2005 was of a roughly similar magnitude. In contrast, the 2007-2011 seasons were associated with much smaller annual losses of about 25 million on average in 2005 dollars. Since the 2011 season, the league has struggled to maintain this momentum, with annual losses averaging around 125 million in 2005 dollars.

Interestingly, one potential reason for this can be seen in the impact of PED testing on team profits shown in panel A. Only the 2005 and 2012 seasons are associated with negative team profits due to PED testing. MLB significantly increased the cost of a positive test to the player following the 2005 season and also altered the CBA during the 2012 season to further strengthen the testing program. In both instances, team profits due to PED testing increased considerably in the following seasons. Such behavior is consistent with the league trying to avoid violating the team participation constraint on a period-by-period basis. However, in doing so, it appears to have created a short-run incentive for teams to exploit at the expense of longer-run losses, i.e. a time inconsistency problem. This is particularly true for minor leagues players who were caught using PEDs.

The number of minor and major league suspensions in each season can be seen in panels C and D in figure 4. The horizontal lines in these panels represent the number of suspensions during the 2009 season. The 2009 season stands out as the only one during this period where franchise value from PED testing was slightly positive. In this sense, it can be considered as an example of an optimal policy. By comparing the results in recent seasons against this benchmark, it is possible to get a sense of the total number of suspensions (24) and the relative mix (20 minor and 4 major league suspensions) that MLB should currently be aiming to achieve. For instance, while major league suspensions in 2014 were only slightly above their 2009 level, minor league suspensions remained elevated. Though not seen in the figure, this trend appears to have held for the 2015 season as well.

Figure 4 makes clear that both teams and players have adapted to the testing system over time. In the equilibrium that appears to have resulted in MLB PED testing, the league must rely on its teams to help it limit future player drug use. If the total number of suspensions required to compensate teams is high, then it becomes increasingly difficult to limit PED use. On the other hand, if the number is too low, then the league may face the prospect of trying to enforce a complete prohibition of PED use, which is likely to be extremely costly to the league, its teams, and its players. According to my estimates, the binding nature of this constraint seems to apply for major league suspensions; while there seems to be more room for reducing the number of minor league suspensions in order to limit the effects of testing on both team profits and franchise values.

6. Conclusion

From MLB's perspective, there are both positives and negatives to take away from my estimates of the impact of PED testing on its teams. The current PED testing program appears to have been pretty close to an optimal policy on average over the last ten years. Furthermore, the total number of PED suspensions required to compensate teams for their efforts to limit player PED use is actually rather low at a little less than 1 per team per season. This suggests that continued support for the testing program will be forthcoming from the league's teams. However, my results also suggest that MLB will likely continue to face difficulties in calibrating its testing program to its players' demand for PEDs. This is because, with teams only standing to gain on average from 4 or fewer major league suspensions, the optimal PED testing policy is not that much different than a complete prohibition of PED use at the major league level. Looking ahead to the next collective bargaining agreement, MLB may have to rely more heavily on the self-policing activity of the MLBPA in order to further discourage major league player use of PEDs.

My analysis also raises the obvious question of how to combat the recent rise in minor league player PED use in the next CBA. Here, it may be wise for MLB to consider taxing teams for minor league suspensions in order to increase the current cost to the team of employing a minor league PED user. This could be implemented in the form of a revenue sharing rule which stipulated that in any season where minor league suspensions exceeded 20 in total, teams with minor league suspensions in that season would be forced to pay into a revenue sharing pool a total value equal to the estimated profits from minor league PED use in that season in proportion to their number of suspensions. This revenue sharing pool could then be redistributed to teams without a minor league suspension in that season as an extra incentive to discourage minor league PED use. Alternatively, compensation could take the form of an equivalent monetary value in draft picks or amateur international signing allotments.

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Table 1: The Evolution of the Performance Enhancing Drug Testing Policy of Professional Baseball

2001-2004

	MILB	MLB
Public Results	No	No
# of Random Tests per Year	2-3	2
Offseason Testing	Yes	No
Major Banned PED Types	Steroids, HGH (2002)	Steroids
Drug Testing Program	MILB Drug Prevention and Treatment	MLB CBA 2002
Government Legislation	Anabolic Steroid Control Act 2004	Anabolic Steroid Control Act 2004
Year Formal Testing Started	2001	2004
First Offense	15 games (Treatment Program pre-2004)	Treatment Program
Second Offense	30 games	15 day
Third Offense	60 games	25 day
Fourth Offense	1 season	50 day
Fifth Offense	Lifetime ban	1 season

2005

	MILB	MLB
Public Results	Yes	Yes
# of Random Tests per Year	3	2
Offseason Testing	Yes	No
Major Banned PED Types	Steroids, HGH	Steroids, HGH
Drug Testing Program	MILB Drug Prevention and Treatment	MLB CBA 2002
First Offense	15 games	10 days
Second Offense	30 games	30 days
Third Offense	60 games	60 days
Fourth Offense	1 season	1 season
Fifth Offense	Lifetime ban	Lifetime ban

2006

	MILB	MLB
Public Results	Yes	Yes
# of Random Tests per Year	3	3
Offseason Testing	Yes	Yes
Major Banned PED Types	Steroids, HGH, Amphetamines**	Steroids, HGH, Amphetamines**
Drug Testing Program	MLB Joint Drug Prevention and Treatment	MLB Joint Drug Prevention and Treatment
First Offense	50 games	50 games
Second Offense	100 games	100 games
Third Offense	Lifetime ban	Lifetime ban

** Amphetamines have their own penalty structure of additional testing for the first offense, 25 games for the second, and 80 for the third.

2007-2011

	MILB	MLB
Public Results	Yes	Yes
# of Random Tests per Year	3 on average	3 on average
Offseason Testing	Yes, expanded	Yes, expanded
Major Banned PED Types	Steroids, HGH, Amphetamines	Steroids, HGH, Amphetamines
Drug Testing Program	MLB Joint Drug Prevention and Treatment Addendum	MLB Joint Drug Prevention and Treatment Addendum
First Offense	50 games	50 games
Second Offense	100 games	100 games
Third Offense	Lifetime ban	Lifetime ban

2012-2013

	MILB	MLB
Public Results	Yes	Yes
# of Random Tests per Year	4-5 on average**	4-5 on average**
Offseason Testing	Yes, expanded	Yes, expanded
Major Banned PED Types	Steroids, HGH, Amphetamines***	Steroids, HGH, Amphetamines**
Drug Testing Program	MLB Joint Drug Prevention and Treatment Addendum	MLB Joint Drug Prevention and Treatment Addendum
First Offense	50 games	50 games
Second Offense	100 games	100 games
Third Offense	Lifetime ban	Lifetime ban

** An additional 1400 random urine tests are added and collection rules are modified.
*** HGH blood testing is added during spring training/offseason (2012) and the regular season (2013). Testosterone levels are tracked (2013).

2014

	MILB	MLB
Public Results	Yes	Yes
# of Random Tests per Year	5-6 on average**	5-6 on average**
Offseason Testing	Yes, expanded	Yes, expanded
Major Banned PED Types	Steroids, HGH, Amphetamines, DHEA***	Steroids, HGH, Amphetamines, DHEA***
Drug Testing Program	MLB Joint Drug Prevention and Treatment Addendum	MLB Joint Drug Prevention and Treatment Addendum
First Offense	80 games	80 games
Second Offense	162 games	162 games
Third Offense	Lifetime ban	Lifetime ban

** 800 urine and 400 blood random tests are added. Violaters are subject to 6 additional urine and 3 blood tests per season for rest of career.
*** Carbon Isotope Ratio Mass Spectrometry tests are randomly performed at least once for every player on an HGH blood test sample.

Table 2: Performance Enhancing Drug Suspensions of Domestic Players* Covering the 2005-2014 Seasons

Season	Freq.	Percent
2005	98	27
2006	36	10
2007	27	7
2008	22	6
2009	24	7
2010	28	8
2011	31	8
2012	58	16
2013	43	12
2014	34	9

League	Freq.	Percent
AL	173	45
East	52	33
Central	50	32
West	55	35
NL	215	55
East	71	36
Central	63	32
West	62	32

# of Offenses	Freq.	Percent
1	378	94
2	22	5
3	1	0

Position	Freq.	Percent
Pitcher	183	47
Fielder/DH	208	53

Level	Freq.	Percent
MILB	345	86
MLB	56	14

* Excludes players suspended in the Dominican and Venezuelan Summer Leagues and the Mexican League.

Sources: MLB.com and MILB.com press releases, Baseball America, USA Today, TheBizofBball.com, SteroidList.com, and TheSteroidAge.com

Figure 1: PED Testing Results by MLB Team

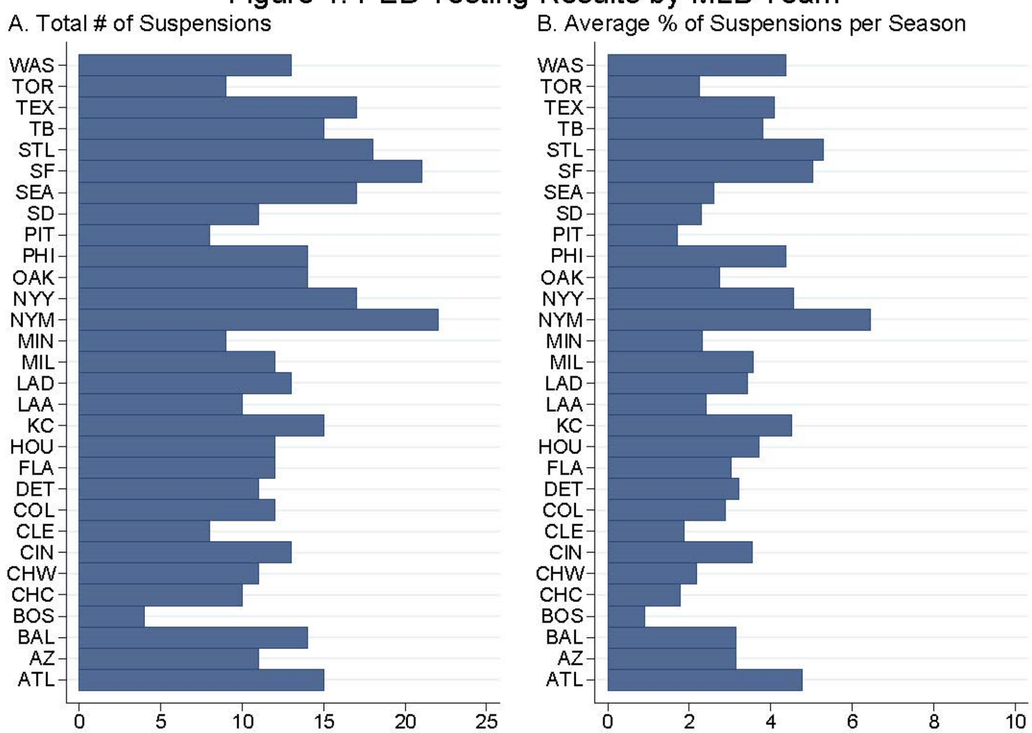


Figure 2: Total Franchise Value of All MLB Teams

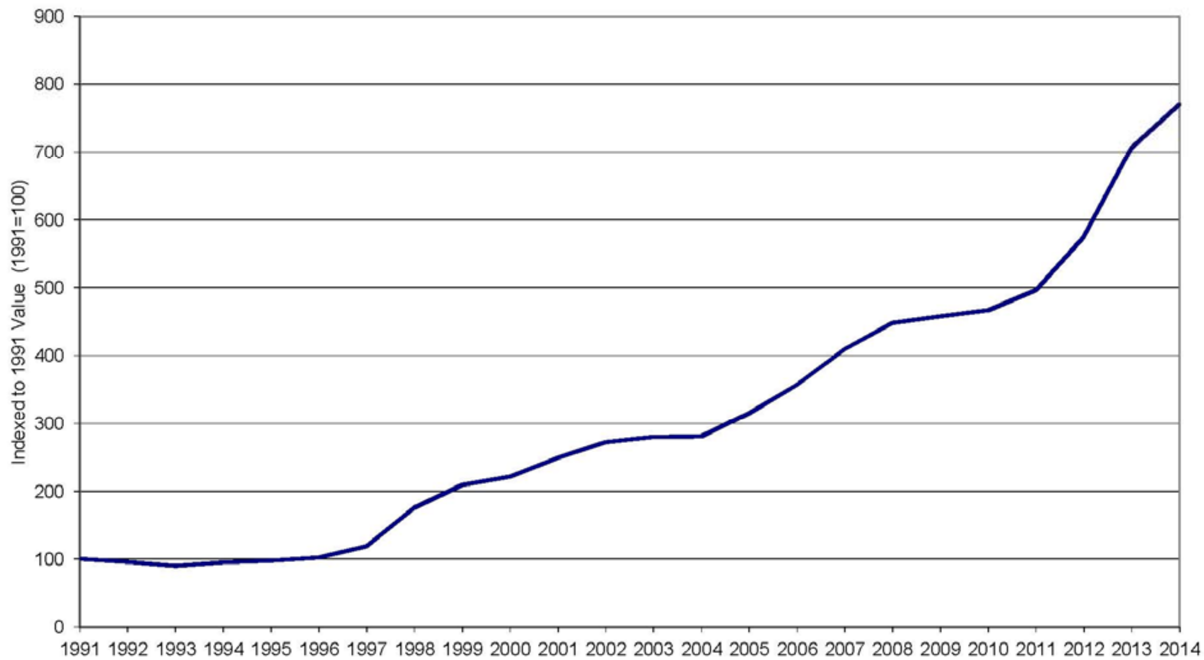


Figure 3: PED Testing and MLB Team Unit Labor Costs

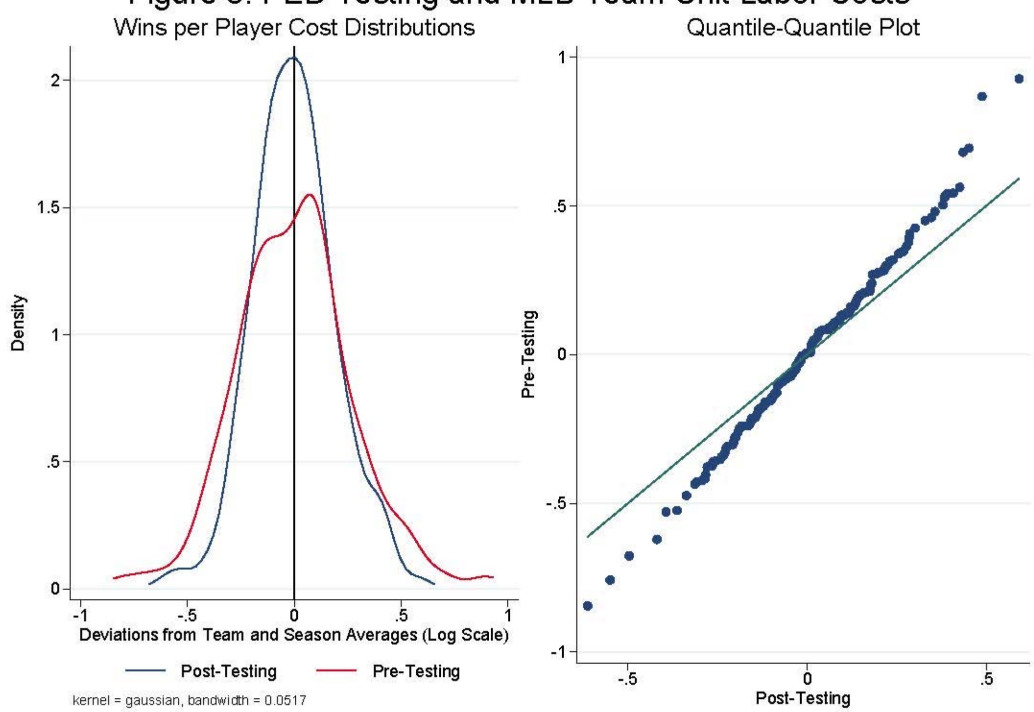


Table 3: Estimated PED Suspension Semi-Elasticities

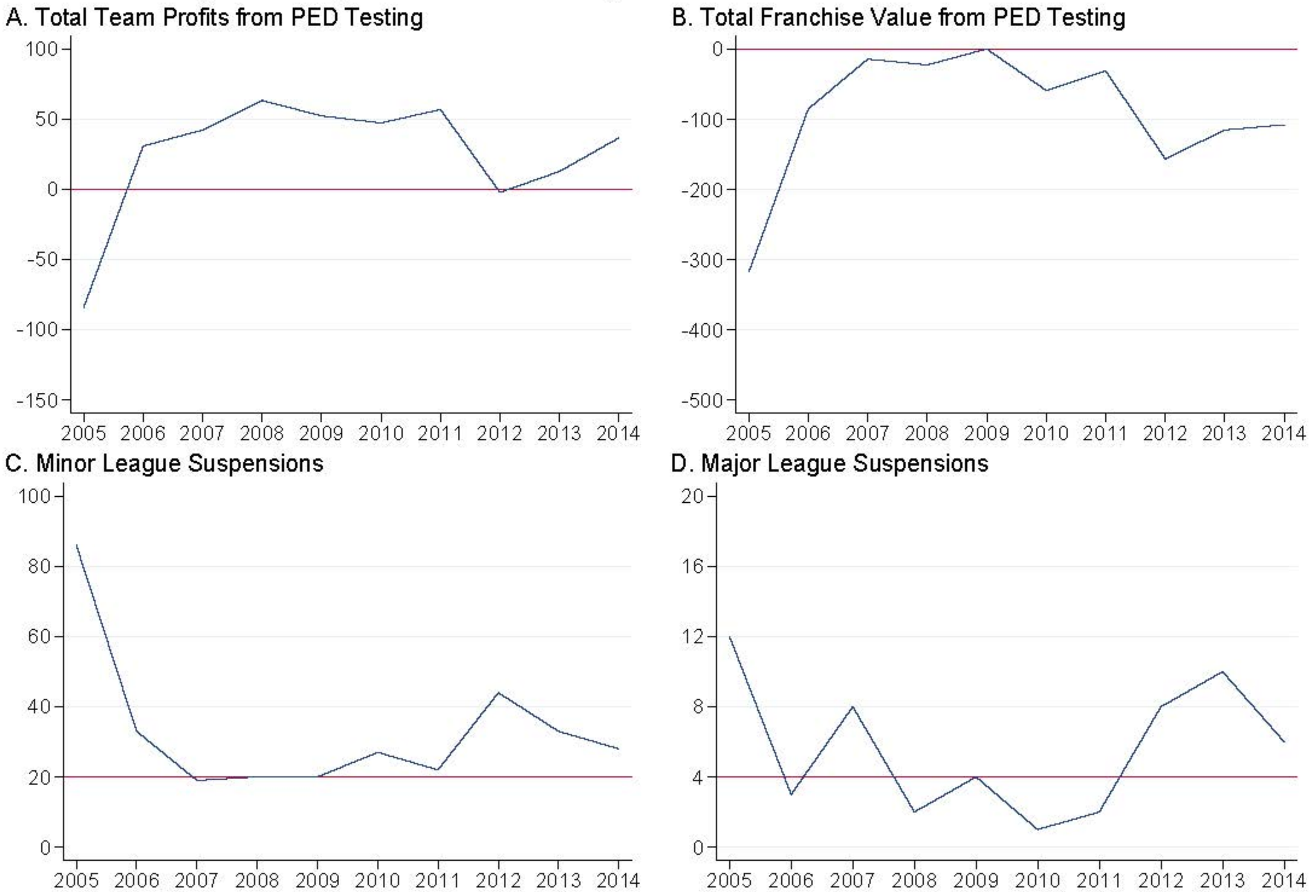
	MILB Suspensions	MLB Suspensions
Gate Revenue	0.007	0.012
	(0.011)	(0.024)
Revenue Multiplier	-0.005*	-0.018**
	(0.003)	(0.009)
Payroll: Labor Wedge	0.021***	0.021***
	(0.006)	(0.006)
Payroll: Testing Wedge	-0.031***	-0.031***
	(0.004)	(0.004)
Profit Growth	-0.009**	0.005
	(0.004)	(0.014)
Profit	-0.002	-0.011
	(0.032)	(0.039)
Franchise Value	-0.009	-0.003
	(0.016)	(0.042)

Cluster robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Average Effects of PED Testing (Mils. 2005$)

Team	Franchise Values	Profits	Revenues	Payroll Costs
Atlanta Braves (ATL)	-4.27	2.05	0.59	-1.46
Arizona Diamondbacks (AZ)	-2.43	0.89	0.27	-0.62
Baltimore Orioles (BAL)	-1.69	0.11	-0.21	-0.32
Boston Red Sox (BOS)	-1.15	0.14	0.03	-0.11
Chicago Cubs (CHC)	-3.79	-0.13	0.41	0.54
Chicago White Sox (CHW)	-4.44	0.06	0.5	0.44
Cincinnati Reds (CIN)	-2.48	0.81	0.22	-0.59
Cleveland Indians (CLE)	-2.14	0.25	0.15	-0.1
Colorado Rockies (COL)	-1.04	0.39	-0.12	-0.51
Detroit Tigers (DET)	-1.14	1.12	-0.02	-1.13
Houston Astros (HOU)	-3	0.6	0.39	-0.21
Kansas City Royals (KC)	-2.4	1.47	0.39	-1.09
Los Angeles Angels (LAA)	-0.98	1.09	0.14	-0.95
Los Angeles Dodgers (LAD)	-4.36	0.67	0.51	-0.16
Miami Marlins (MIA)	-6.25	1.27	0.42	-0.86
Milwaukee Brewers (MIL)	-2.16	1.3	0.16	-1.14
Minnesota Twins (MIN)	-1.89	0.5	0.19	-0.31
New York Mets (NYM)	-6.11	2.59	0.38	-2.21
New York Yankees (NYY)	-4.1	1.99	-0.31	-2.3
Oakland Athletics (OAK)	-4.07	0	0.41	0.41
Philadelphia Phillies (PHI)	-2.02	2.03	-0.01	-2.05
Pittsburgh Pirates (PIT)	-1.64	0.22	0.22	0
San Diego Padres (SD)	-0.73	-0.11	-0.31	-0.2
Seattle Mariners (SEA)	-3.98	-0.73	0.06	0.79
San Francisco Giants (SF)	-6.18	1.1	0.28	-0.82
St. Louis Cardinals (STL)	-7.29	2.6	0.9	-1.69
Tampa Bay Rays (TB)	-2.59	0.64	0.2	-0.43
Texas Rangers (TEX)	-3.29	0.63	0.16	-0.47
Toronto Blue Jays (TOR)	-1.63	0.85	0.33	-0.52
Washington Nationals (WAS)	-2.05	1.37	0.34	-1.03
MLB Average	-3.06	0.86	0.22	-0.64

Figure 4: Impact of PED Testing on Team Profits and Franchise Values



Values for profits and franchise values shown in Mils. 2005$.

Appendix

A. Deriving an Optimal PED Testing Policy

League profits are defined as the difference between a revenue function, $R[Q(T)]$, specified in terms of the competitive balance of the league, $Q(T)$ (i.e. distribution of player talent, Q), and an enforcement cost function, $C[N(T)]$. League profits are maximized by choice of PED testing parameters, T, subject to a participation constraint specified in terms of team profits, π, accruing from the hiring of PED-using players, N:

$$\max_{T}\big[R[Q(T)] - C[N(T)]\big] \;\; s.t.\, N(T) = N^{*}(T) \equiv \text{ arg max}\big\{N(T) \geq 0, \pi\big(N(T)\big) = 0\big\}.$$

In the first equilibrium, I assume that T^* must satisfy an additional player incentive compatibility constraint such that no player will find it in his best interest to use PEDs. In this case, the supply function nonnegativity constraint binds (i.e. $N^{*}(T^{*}) = 0$).

In the second equilibrium, $N^{*}(T^{*}) > 0$. League profits are then maximized by the T^* that solves

$$\frac{\partial R}{\partial Q}\frac{\partial Q}{\partial T} - \frac{\partial C}{\partial N^{*}}\frac{\partial N^{*}}{\partial T} = 0.$$

For a unique solution to exist in this case, it must be that $R[Q(T)]$ is strictly increasing and concave in T (as assumed in the text) and $C[N^{*}(T)]$ is strictly decreasing and convex in T. The latter will be the case, given an enforcement cost function that is strictly increasing and concave in the number of PED users (so that there exists diminishing returns to the *detection* of these players) and a supply function for PED users that is strictly decreasing and convex in the testing parameters (so that there exists increasing returns to the *prevention* of PED use).

B. Deriving Team Cost Functions with PED Testing

With the time subscript dropped for ease of exposition, marginal revenues in my competitive talent market model with PED testing are given by

$$\frac{\partial R_i^{*}}{\partial w_i} = \alpha(s_i, z_i)\tau(b_i)\frac{1}{2\gamma}[\theta\big(s_i, x_{ij}\big)\phi(w_i)]^2[\phi_1 w_i^{-1} - \phi_2(1 - w_i)^{-1}].$$

Differentiating the winning percentage function with respect to team quality after rearranging and substituting yields marginal products:

$$\begin{aligned}\frac{\partial w_i}{\partial Q_i} &= \frac{N}{2}\left[\frac{(1-\kappa_i)}{\sum_{i=1}^{N}(1-\kappa_i)Q_i} - \frac{(1-\kappa_i)^2 Q_i}{[\sum_{i=1}^{N}(1-\kappa_i)Q_i]^2}\right] \\ &= \frac{w_i}{Q_i} - \frac{2}{N}\frac{w_i^2}{Q_i} \\ &= \frac{w_i}{Q_i}\left(1 - \frac{2}{N}w_i\right).\end{aligned}$$

Multiplying these equations leads to marginal revenue products:

$$\frac{\partial R_i^*}{\partial w_i}\frac{\partial w_i}{\partial Q_i} = \alpha(s_i, z_i)\tau(b_i)\frac{1}{2\gamma}[\theta(s_i, x_i)\phi(w_i)]^2[\phi_1 w_i^{-1} - \phi_2(1 - w_i)^{-1}]\frac{w_i}{Q_i}\left(1 - \frac{2}{N}w_i\right).$$

Cost minimization on the part of teams given constant returns-to-scale production functions $Q_i = f(q_i)$ then yields the first order conditions

$$a(\rho_i) = \left(1 - \mu(s_i, y_i)\right)\frac{\partial R_i^*}{\partial w_i}\frac{\partial w_i}{\partial Q_i},$$

where $a(\rho_i)$ is the unit cost function equal to the Lagrange multiplier λ_i and marginal cost. Multiplying the first order conditions by $(1 - \kappa_i)Q_i$ and substituting in the expression for marginal revenue products, I obtain ex-post team player costs:

$$\begin{aligned}
C_i^* &= \left(1 - \mu(y_i, s_i)\right)\frac{\partial R_i^*}{\partial w_i} w_i(1 - \kappa_{it})\left(1 - \frac{2}{N}w_i\right)\\
&= \left(1 - \mu(y_i, s_i)\right)\alpha(s_i, z_i)\tau(b_i)\frac{1}{2\gamma}[\theta(s_i, x_i)\phi(w_i)]^2[\phi_1 w_i^{-1} - \phi_2(1 - w_i)^{-1}]w_i(1 - \kappa_{it})\left(1 - \frac{2}{N}w_i\right)\\
&= \left(1 - \mu(y_i, s_i)\right)\alpha(s_i, z_i)\tau(b_i)\frac{1}{2\gamma}[\theta(s_i, x_i)\phi(w_i)]^2[\phi_1(1 - w_i) - \phi_2 w_i]\frac{1 - \kappa_i}{1 - w_i}\left(1 - \frac{2}{N}w_i\right).
\end{aligned}$$

C. Estimating Equations and Variables

In order to estimate my model, I must first specify several functional forms. For this purpose, I follow Ferguson et al. (2000) and use the following attendance function:

$$\begin{aligned}
A_{it} &= \theta(s_{it}, x_{it})\phi(w_{it}) - \gamma p_{it},\\
\theta(s_{it}, x_{it}) &= \theta_0 s_{it}^{\theta_s}\prod x_{ijt}^{\theta_j},\\
\phi(w_{it}) &= w_{it}^{\phi_1}(1 - w_{it})^{\phi_2},
\end{aligned}$$

where x_{it} is a vector of local market demand factors.

A team's ratio of total revenue to gate revenue, $\alpha(s_{it}, z_{it})$, is specified as

$$\alpha(s_{it}, z_{it}) = \alpha_0 s_{it}^{\alpha_s}\prod z_{ikt}^{\alpha_k},$$

with z_{it} being a vector of local market non-gate revenue drivers.

I specify the league-determined cost term $\left(1 - \mu(y_i, s_i)\right)$ by

$$\mu(s_{it}, y_{it}) = \mu_0 s_{it}^{\mu_s}\prod y_{ilt}^{\mu_l},$$

which includes a vector, y_{it}, of exogenous factors affecting the labor wedge between teams' marginal costs and revenue products.

The constant discounted expected profit growth rate of team i in season t, $g(y_{it}, s_{it})$, is given by

$$g(v_{it}, s_{it}) = \chi_0 s_{it}^{\chi_s} \prod v_{imt}^{\chi_m},$$

where v_{it} is a vector of exogenous drivers of future profit growth.

Regular season gate revenue maximization and cost minimization imply that

$$\begin{aligned}
p_{it}^* &= \frac{1}{2\gamma}\theta(s_{it}, x_{it})\phi(w_{it}),\\
A_{it}^* &= \frac{1}{2}\theta(s_{it}, x_{it})\phi(w_{it}),\\
\alpha(s_{it}, z_{it}) &= \alpha_0 s_{it}^{\alpha_s} \prod z_{ikt}^{\alpha_k},\\
GR_{it}^* &= \tau(b_{it}) p_{it}^* A_{it}^*\\
C_{it}^* &= \mu(s_{it}, y_{it})\\
\times \quad & \alpha(s_{it}, z_{it})\tau(b_{it})\\
\times \quad & \frac{1}{2\gamma}[\theta(s_i, x_i)\phi(w_i)]^2[\phi_1 w_i^{-1} - \phi_2(1-w_i)^{-1}]\\
\times \quad & \frac{1-\kappa_i}{1-w_i}\left(1 - \frac{2}{N}w_i\right).\\
FV_{it} &= (\alpha(s_{it}, z_{it}) GR_i^* - C_i^*) g(v_{it}, s_{it}).
\end{aligned}$$

where τ is a multiplier that accounts for gate revenue received from All-Star and post-season games that depends on the indicator variables b_{it} . Taking logs yields the following six estimating equations and parameters, where I impose the restriction that the parameters ϕ_1 and ϕ_2 are both positive and sum to one in estimation such that $\phi(w_{it})$ exhibits constant returns-to-scale.

$$\begin{aligned}
\ln p_{it} &= \ln \theta_0 - \ln \gamma - \ln 2 + \theta_1 s_{it}^{MILB} + \theta_2 s_{it}^{MLB} + \sum_{j=3}^{14} \theta_j \ln x_{ijt}\\
&\quad + \phi_1 \ln w_{it} + \phi_2 \ln(1 - w_{it})\\
\ln A_{it} &= \ln \theta_0 - \ln 2 + \theta_1 s_{it}^{MILB} + \theta_2 s_{it}^{MLB} + \sum_{j=3}^{14} \theta_j \ln x_{ijt}\\
&\quad + \phi_1 \ln w_{it} + \phi_2 \ln(1 - w_{it})\\
\ln GR_{it} &= \ln \tau_0 - \ln \gamma - 2\ln 2 + 2\ln \theta_0 + 2\theta_1 s_{it}^{MILB} + 2\theta_2 s_{it}^{MLB}\\
&\quad + \sum_{n=1}^{2} \tau_n \ln y_{int} + 2\sum_{j=3}^{14} \theta_j \ln x_{ijt} + 2\phi_1 \ln w_{it} + 2\phi_2 \ln(1 - w_{it})\\
\ln \alpha_{it} &= \ln \alpha_0 + \alpha_1 s_{it}^{MILB} + \alpha_2 s_{it}^{MLB} + \sum_{k=3}^{16} \alpha_k \ln z_{ikt}\\
\ln C_{it} &= \ln \mu_0 + \ln \alpha_0 + 2\ln \theta_0 - \ln \gamma - \ln 2 + \mu_1 s_{it}\\
&\quad + \alpha_1 s_{it}^{MILB} + \alpha_2 s_{it}^{MLB} + 2\theta_1 s_{it}^{MILB} + 2\theta_2 s_{it}^{MLB}\\
&\quad + \sum_{l=2}^{9} \mu_l \ln q_{ilt} + \sum_{k=3}^{16} \alpha_k \ln z_{ikt} + \sum_{n=1}^{2} \tau_n \ln v_{int} + 2\sum_{j=3}^{14} \theta_j \ln x_{ijt}
\end{aligned}$$

$$
\begin{aligned}
&+ 2\phi_1 \ln w_{it} + 2\phi_2 \ln(1 - w_{it}) + \ln[\phi_1(1 - w_{it}) - \phi_2 w_{it}] \\
&+ \ln(1 - \kappa_{it}) - \ln(1 - w_{it}) + \ln\left(1 - \frac{2}{N} w_{it}\right)
\end{aligned}
$$

$$
\begin{aligned}
\ln FV_{it} = {} & \ln \chi_0 + \chi_1 s_{it}^{MILB} + \chi_2 s_{it}^{MLB} + \sum_{m=3}^{5} \chi_m \ln v_{imt} \\
&+ \ln(\alpha(s_{it}, z_{it}) GR_i^* - C_i^*)
\end{aligned}
$$

Following Ferguson et al. (2000), included in x_{it} are the previous season's attendance, the per capita income of the home MSA (or city), and the number of other professional sports teams in the home city. To this list, I add the previous season's average ticket prices and the number of awards won by its players along with indicators for a team's division, whether a team opened a new stadium in the current season, and whether the team played in the post-season in the prior season. Several of these additional measures stem from the relevant literature summarized in Berri et al. (2006). For b_{it}, I include indicator variables for whether a team hosted an All-Star game and played in the post-season in the current season.

Included in z_{it} are indicators corresponding to a team's division and the seasons governed by each CBA, whether a team hosted an All-Star game and whether a team played in the post-season in the current season, as well as an indicator for whether a team signed a new regional television deal. Additionally, I include the number of awards won by its players in the previous season as well as lagged ratios of total revenue to gate revenue and a ``Fan Cost Index,'' which measures the total cost of attending a home game for a family of four, including expenses such as parking and concessions, to ticket prices in order to control for possible non-gate revenue dynamics left uncaptured by lagged ticket prices or attendance. In y_{it}, I also include indicators for CBAs and league divisions, as well as lagged player costs to control for the unmodeled dynamics of multi-year player contracts. The variables included in v_{it} are indicators for a new regional television deal, a new stadium, and a World Series championship as well as lagged franchise value.

Note that division indicators appear separately in x_{it}, y_{it}, and z_{it}. MLB's unbalanced game scheduling, under which teams within divisions play each other more frequently, violates the model assumption that teams play each other an equal number of times. In addition, interleague play which each season rotates the opponents a team faces from the opposing league (i.e. AL versus NL) based on a team's division introduces an additional level of complexity. Revenue-sharing rules are also often tied indirectly to a team's division. For instance, divisions in MLB are broken down geographically, such that larger market teams are concentrated in the East and West divisions of each league. Including division indicators in x_{it}, y_{it}, and z_{it} addresses these concerns in a reduced form fashion while preserving the basic structure of the Ferguson et al. (2000) model.

D. Estimated Model Parameters

Variables	(1) Gate Revenue$_t$	(2) Revenue Multiplier$_t$	(3) Payroll$_t$	(4) Profit Growth$_t$
Suspensions: MILB #	0.007	-0.005*	0.002	-0.009**
	(0.011)	(0.003)	(0.011)	(0.004)
Suspensions: MLB #	0.012	-0.018**	-0.006	0.005
	(0.024)	(0.009)	(0.023)	(0.014)
Suspensions: Total #			0.021***	
			(0.006)	
Real PCI$_t$	0.506***	-0.299***	0.208**	
	(0.103)	(0.043)	(0.107)	
Sports Market Size$_t$	-0.012	-0.030	-0.042*	
	(0.035)	(0.022)	(0.026)	
New Stadium$_t$ #	0.423***	-0.274***	0.149**	0.034
	(0.112)	(0.077)	(0.068)	(0.069)
Playoff Appearance #	0.098***	-0.125***	-0.027	
	(0.016)	(0.015)	(0.018)	
All-Star Host$_t$ #	0.060	-0.011	0.048	
	(0.054)	(0.029)	(0.047)	
Player Awards$_{t-1}$ #	0.001	-0.005	-0.004	
	(0.005)	(0.003)	(0.003)	
Winning Percentage$_t$	1.748***		1.748***	
	(0.008)		(0.008)	
Losing Percentage$_t$	0.252***		0.252***	
	(0.008)		(0.008)	
Ticket Price$_{t-1}$	0.598***		0.598***	
	(0.057)		(0.057)	
Attendance$_{t-1}$	0.853***		0.853***	
	(0.072)		(0.072)	
Revenue Multiplier$_{t-1}$		0.694***	0.694***	
		(0.062)	(0.062)	
Fan Cost to Ticket Price Ratio$_{t-1}$		0.232*	0.232*	
		(0.138)	(0.138)	
New TV Deal$_t$ #		0.057***	0.057***	0.070***
		(0.017)	(0.017)	(0.023)
NL East #	0.024	-0.009	-0.016	
	(0.042)	(0.032)	(0.040)	
NL Central #	0.141***	-0.078***	0.031	
	(0.039)	(0.028)	(0.026)	
NL West #	0.068*	-0.012	-0.013	
	(0.043)	(0.033)	(0.050)	
AL Central #	0.070	-0.050*	0.012	
	(0.048)	(0.030)	(0.038)	
AL West #	-0.040	0.030	-0.039	
	(0.063)	(0.045)	(0.049)	
CBA 2007 - 2011 #		-0.023	0.026**	
		(0.017)	(0.013)	
CBA 2012 - 2016 #		0.056***	0.033	
		(0.021)	(0.031)	
Payroll$_{t-1}$			0.281***	
			(0.028)	
Franchise Value$_{t-1}$				0.616***
				(0.037)
World Series Win$_{t-1}$				-0.121***
				(0.032)
Constant	4.352***	-0.594***	2.186***	-2.063***
	(0.446)	(0.124)	(0.430)	(0.220)

Cluster robust standard errors in parentheses. # denotes semi-elasticity.
*** p<0.01, ** p<0.05, * p<0.1

Variables	(1) Gate Revenue$_t$	(2) Revenue Multiplier$_t$	(3) Payroll$_t$	(4) Profit Growth$_t$
Suspensions: MILB	$2\theta_1$	α_1	$2\theta_1 + \alpha_1$	χ_1
Suspensions: MLB	$2\theta_2$	α_2	$2\theta_2 + \alpha_2$	χ_2
Suspensions: Total			μ_1	
Real PCI$_t$	$2\theta_3$	$2\alpha_3$	$2\theta_3 + 2\alpha_3$	
Sports Market Size$_t$	$2\theta_4$	$2\alpha_4$	$2\theta_4 + 2\alpha_4$	
New Stadium$_t$	$2\theta_5$	$2\theta_5$	$2\theta_5 + 2\alpha_5$	χ_3
Playoff Appearance	$\tau_1 + 2\theta_6$	α_6	$\tau_1 + 2\theta_6 + \alpha_6$	
All-Star Host$_t$	τ_2	α_7	$\tau_2 + \alpha_7$	
Player Awards$_{t-1}$	$2\theta_7$	α_8	$2\theta_7 + \alpha_8$	
Winning Percentage$_t$	$2\phi_1$		$2\phi_1$	
Losing Percentage$_t$	$2\phi_2$		$2\phi_2$	
Ticket Price$_{t-1}$	$2\theta_8$		$2\theta_8$	
Attendance$_{t-1}$	$2\theta_9$		$2\theta_9$	
Revenue Multiplier$_{t-1}$		α_9	α_9	
Fan Cost to Ticket Price Ratio$_{t-1}$		α_{10}	α_{10}	
New TV Deal$_t$		α_{11}	α_{11}	χ_4
NL East	$2\theta_{10}$	α_{12}	$2\theta_{10} + \alpha_{12} + \mu_2$	
NL Central	$2\theta_{11}$	α_{13}	$2\theta_{11} + \alpha_{13} + \mu_3$	
NL West	$2\theta_{12}$	α_{14}	$2\theta_{12} + \alpha_{14} + \mu_4$	
AL Central	$2\theta_{13}$	α_{15}	$2\theta_{13} + \alpha_{15} + \mu_5$	
AL West	$2\theta_{14}$	α_{16}	$2\theta_{14} + \alpha_{16} + \mu_6$	
CBA 2007 - 2011		α_{17}	$\alpha_{16} + \mu_7$	
CBA 2012 - 2016		α_{18}	$\alpha_{18} + \mu_8$	
Payroll$_{t-1}$			μ_9	
Franchise Value$_{t-1}$				χ_5
World Series Win$_{t-1}$				χ_6
Constant	$2\log\theta_0 - \log 4 - \log\gamma + \log\tau_0$	$\log\alpha_0$	$2\log\theta_0 - \log 2 - \log\gamma + \log\tau_0 + \log\alpha_0 + \log\mu_0$	χ_0