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

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ABSTRACT

Using a modified version of the competitive talent market model and estimates of MLB team financials from *Forbes*, we 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. This result reflects significant impacts on teams' non-gate revenues, player costs, and franchise values from PED suspensions. Using variation over time in MLB's testing policy, we 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, but in recent seasons has fallen well short of this goal.

The opinions expressed herein are those of the authors and do not represent the views of the Federal Reserve Bank of Chicago or the Federal Reserve System.

Keywords

Major League Baseball; performance enhancing drugs; competitive talent market model

1. INTRODUCTION

In this paper, we incorporate drug testing into the competitive talent market model of Ferguson et. al (2000) in order to analyze the impact of player performance enhancing drug (PED) use on Major League Baseball (MLB) and its teams. We show that the introduction of PED testing increased the competitive balance of MLB, and estimate the number of PED suspensions per season characteristic of an optimal testing policy which balances the costs and benefits of player PED use at the league and team levels. At times MLB has come close to achieving such a policy, but in recent seasons has fallen well short of this goal.

Economists view the demand for professional sports as being rooted in the "uncertainty of outcome" principle first expressed in Rottenberg (1956). It states that the more competitive the outcome of a game is likely to be, the more fans are willing to pay to see it. Player use of PEDs lowers demand by altering fans' perceptions of competitiveness. This is a cost to the league and its teams that goes unpaid when the offending players are unknown. For a profit maximizing sports league, PED testing is a way in which to mitigate this cost by discouraging 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 league level. Instead, league profits are commonly thought of as being determined by the competitive balance of the league (see, for instance, Vrooman (1995) and Fort and Quirk (1995)), which is, in turn, a function of the distribution of talent across its teams. As a result, the impact of player PED use 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.

PED testing operates as a revelation mechanism of the distribution of *true* player talent for the league and its teams. An optimal PED testing policy from the perspective of MLB must therefore minimize both the costs of *detecting* and *preventing* player PED use subject to the participation of its teams in the testing program in order to achieve the league's objectives. Building off of the work of Becker et al. (2006) on the supply and demand for illegal drugs, such a policy entails a level of testing, T^*, maximizing league profits, or value, taking as arguments a revenue function, $R[Q(T)]$, defined in terms of the distribution of talent across teams, $Q(T)$, and an enforcement cost function, $C[N(T)]$, depending on the number of PED-using players as a function of the testing parameters, $N(T)$.

$$\max_{T}\big[R[Q(T)] - C[N(T)]\big] \; s.t.$$
$$N(T) = N^*(T) \equiv \arg\max\{N(T) \geq 0, \pi\big(N(T)\big) = 0\}. \quad (1)$$

The voluntary participation of all teams in the testing program is invoked by requiring 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 MLB teams attributable to player PED use. This team participation constraint represents an example of enforcer compensation in the spirit of Becker and Stigler (1974), ensuring that, on average, MLB teams are indifferent to testing and do not engage in behavior that undermines league objectives.

The problem of the league can, thus, be summarized as the choice of testing parameters in terms of fines, suspensions, etc. that makes the marginal PED-using player consistent with its objectives indifferent to PED use:

$$\frac{\partial R}{\partial Q}\frac{\partial Q}{\partial T} - \frac{\partial C}{\partial N^*}\frac{\partial N^*}{\partial T} = 0. \quad (2)$$

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 $T^* > 0$.[1] For a unique solution to exist with $N^*(T^*) > 0$, it must be that $R[Q(T)]$ is strictly increasing and concave in T and $C[N^*(T)]$ is strictly decreasing and convex in T.[2] This will be the case so long as there exists diminishing returns to the *detection* of PED users and increasing returns to the *prevention* of PED use. We maintain this assumption, drawing on the observations of Becker et al. (2006) on the costliness and effectiveness of illegal drug prohibitions.

2. PED TESTING IN MLB

Formal PED testing, with positive results made public and suspensions without pay assessed to all offenders, began in MLB during spring training prior to the 2005 season. Various changes have since been made to the Joint Drug Prevention and Treatment Program for both major and minor league players. A complete history of the program can be found in Appendix C.

Figure 1 summarizes positive PED test results for all MLB teams and their Minor League Baseball (MiLB) affiliates through the end of 2014 based on a database assembled from both MLB and MiLB press releases. Testing revealed statistically significant differences in player PED use across teams, suggesting that some teams valued more highly than others the talents of players at-risk of being caught using PEDs. The competitive interactions between teams in the market for player services is, therefore, likely to be a key feature in understanding how PED testing impacted MLB and its teams. The model we develop in the next section aims to capture this fact by relating the distribution of league-wide player PED use to team winning percentages, profits, and franchise values.

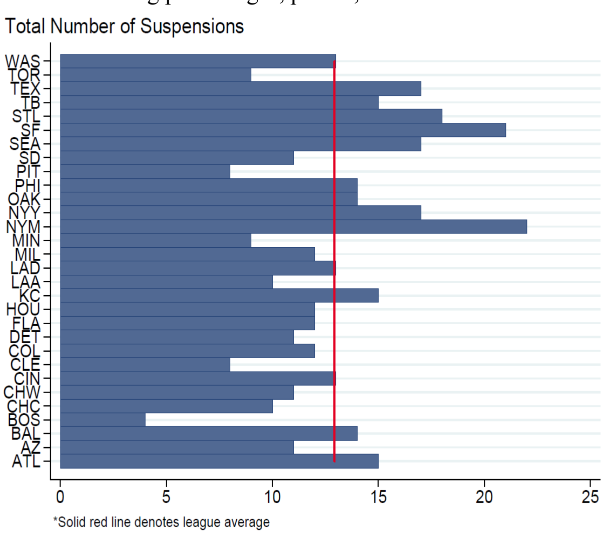

Figure 1: PED Testing Results by MLB Team

[1] 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**.** This is one way to view the "Steroid Era" in MLB, as turning a blind eye to the problem could potentially be optimal in this framework.

[2] An equilibrium with $N^*(T^*) = 0$ is also possible if T^* satisfies an additional incentive compatibility constraint for players that makes them indifferent to masking their PED use.

Our model also allows us to estimate the number of minor and major league PED suspensions (i.e. positive tests) characteristic of an optimal testing policy measured in terms of its impact on league and team values. A key component of this distinction between the impact of testing on the league and its teams relates to its effect on the distribution of player talent, i.e. the competitive balance of the league.

Figure 2 plots kernel densities for the pre- (1998-2004) and post-testing (2005-2014) distributions of MLB team wins per 2005 dollar spent on player salaries in deviations from team and season averages on a log scale. It can be shown in our model that the distribution of team wins per dollar after accounting for team- and season-specific factors (i.e. fixed effects) is a measure of competitive balance, i.e. the wider this distribution is the less competitive balance exists in MLB (see Appendix A).

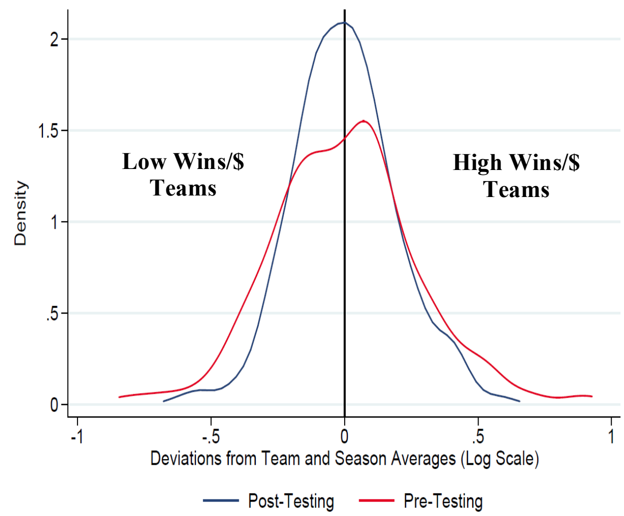

Figure 2: Wins per Player Cost (Mils. 2005$) Distributions

The post-testing distribution exhibits a statistically significant decline in variance relative to the pre-testing distribution, suggesting that PED testing improved competitive balance. This occurs as the number of both very Low and very High Wins/$ teams declined in the post-testing era, suggesting several possibilities for how PED testing impacted MLB teams: First, some highly efficient teams (High Wins/$) may have lost a source of competitive advantage relative to their peers, as testing raised the cost of hiring a PED user. Second, some highly inefficient teams (Low Wins/$) may have been forced to become more productive in their allocation of resources as overall PED use declined. Both possibilities are captured in our model through the introduction of wedges between the wages and marginal revenue products of PED and non-PED users.

3. A COMPETITIVE TALENT MARKET

The framework we use to address the impact of PED testing on MLB and its teams is the competitive talent market model of Ferguson et. al (2000). We augment this model to include several channels by which PED testing may affect team gate and non-gate revenues, player costs, and franchise values. Functional forms and variables mirror those found in Ferguson et. al (2000) and the literature summarized in Berri et. al (2006), and are detailed in Appendix B. In what follows, the subscript i is used to reference an MLB team and t to reference an MLB season.

3.1 Revenue

We begin by characterizing team revenues, R_{it}^*. Teams are assumed to be gate revenue maximizing with monopoly power in their local markets to set ticket prices, p_{it}, subject to an attendance function, A; which in addition to prices depends on a team's winning percentage, w_{it}, a team's number of PED suspensions, s_{it}, and local market characteristics, x_{it}. Minor and major league suspensions are allowed to differentially affect team revenues. The function $\tau(b_{it})$ then accounts for other irregular gate revenue sources such as post-season and All-Star games hosted. Non-gate revenues are also impacted by PED suspensions through the revenue multiplier, α, which depends on PED suspensions in addition to z_{it}, a vector of team non-gate revenue drivers. However, non-gate revenue is assumed to be unrelated to winning percentage following Blass (1992).

$$R_{it}^* = \max_{p_{it}} p_{it} A(w_{it}, s_{it}, x_{it}, p_{it}) \tau(b_{it})\, \alpha(z_{it}, s_{it})\,. \tag{3}$$

3.2 Wins

A team's winning percentage is assumed to be proportionate to its share of league talent, the *latent* variable Q_{it}, down-weighted by its share of PED suspensions in a season, κ_{it}.[3] This introduces an externality into the model whereby all other team's PED suspensions affect a team's on-the-field performance. In addition, a team's off-the-field performance will also depend on the entire distribution of PED suspensions across teams and, thereby, affect its hiring choices.

$$w_{it} = \frac{N}{2} \frac{(1 - \kappa_{it}) Q_{it}}{\sum_{i=1}^{N} (1 - \kappa_{it}) Q_{it}}. \tag{4}$$

3.3 Player Costs

We pose a player's potential PED use as a characteristic in the Ferguson et. al (2000) framework that is hedonically priced prior to the realization of PED test results for a given season in the market for player services and bundled by teams prior to the season into team talent to win games. Cost minimization then implies the following relationship between a team's ex-post (i.e. after test results are revealed and the season ends) player costs, C_{it}^*, and its players' marginal revenue products.

$$C_{it}^* = (1 - \mu(y_{it}, s_{it})) \frac{\partial R_{it}^*}{\partial w_{it}} w_{it} (1 - \kappa_{it})(1 - \frac{2}{N} w_{it}), \tag{5}$$

The above equation contains two wedges: $(1 - \mu(y_{it}, s_{it}))$ and $(1 - \kappa_{it})$. We refer to the former as the "Labor Wedge" because it depends on league rules set in collective bargaining with the player's union, captured in y_{it}, which drive a wedge between a player's wage and marginal revenue product. PED testing is one of those negotiated rules. The latter wedge we refer to as the "Testing Wedge" as it captures the role played by the distribution of PED suspensions across teams in determining a team's ex-post player costs.

[3] A key feature of this hedonic pricing framework is that it does not require talent to be observed. See Appendix A for details.

3.4 Profit and Franchise Value

Team profits, π_{it}^*, are then easy to define, while we rely on an expected present discounted value framework to parameterize team franchise values, FV_{it}, in such a way that expected profit growth, g_{it}, depends on team-specific variables, v_{it}, and, separately, minor and major league PED suspensions. This is necessary because most PED suspensions are for MiLB players who only indirectly impact current profits.

$$\pi_{it}^* = R_{it}^* - C_{it}^* \tag{6}$$

$$FV_{it} = \sum_{l=0}^{\infty} \beta_{it}^{l} E[\pi_{i,t+l}] = \pi_{it} \frac{(1+g)}{\beta_{it} - g} = \pi_{it} g(v_{it}, s_{it}). \tag{7}$$

After assuming functional forms and taking logs, the resulting system of nonlinear seemingly unrelated regressions is estimated by maximum likelihood as described in Zellner (1962), clustering on seasons for a panel stretching from 2005-2014. Data on team financials are taken from estimates compiled by *Forbes*. All remaining data are from public sources such as the databases maintained by Rodney Fort and Sean Lahman.

4. RESULTS

Table 1 reports semi-elasticities and figure 3 plots corresponding average marginal effects on team revenues, player costs, profits, and franchise values for both MLB and MiLB PED suspensions as a function of league-wide PED suspensions in a season.

Table 1: 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

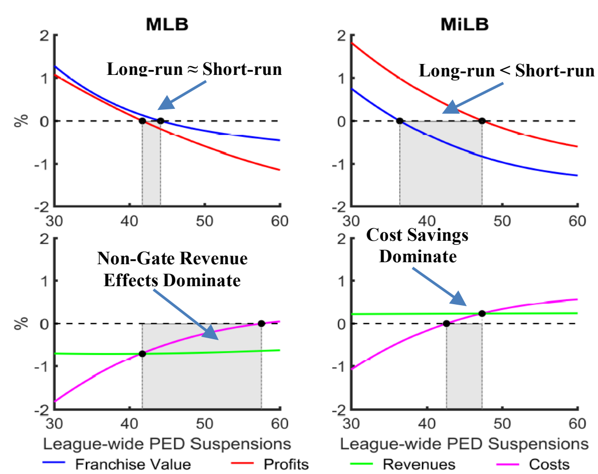

Figure 3: Average Marginal Effects of a PED Suspension

MLB suspensions are shown to have strong negative effects on revenues in figure 3. Table 1 demonstrates that this stems mostly from lower non-gate revenues, as one suspension reduces the revenue multiplier by 1.8% on average. In contrast, both figure 3 and table 1 make clear that MiLB suspensions negligibly impact revenues. Figure 3 and table 1 also show that there are potentially significant cost savings to be realized from having a player suspended (although less so for MiLB players) which come in the form of not having to pay the suspended player's salary during their suspension. Taken together this implies that there exists a fairly sizeable range of league-wide suspensions for which an MiLB suspension may actually benefit a team's bottom line, whereas this range is much smaller for an MLB suspension. Table 1 makes clear, though, that MiLB suspensions have much stronger, and statistically significant, impacts on franchise values through lower expected profit growth. This introduces a time inconsistency problem, shown in figure 3, where the long-run benefit to a team is much smaller than the short-run benefit for an MiLB suspension.

To put the magnitude of these effects in context, we devise a counterfactual scenario where we calculate what it would have cost each team to achieve the same winning percentage (and other exogenous covariates) during our sample period without any PED suspensions. For an average MLB team, the costs of testing were quite small at around 3 million 2005 dollars of franchise value (see Appendix D). Overall, this suggests a fair measure of success for MLB in achieving a policy which balances the costs of player PED use at the league and team levels. Furthermore, this near-optimal outcome appears to have been achieved by the league through raising payroll costs for some teams via the Labor Wedge by more than the reduction in salaries through the Testing Wedge and vice versa for other teams. The resulting distribution of player cost effects confirms our initial exploration in figure 2. Some teams indeed appear to have lost a source of competitive advantage relative to their peers as testing raised the cost of hiring a PED user, while others became more productive in their allocation of resources as overall PED use declined.

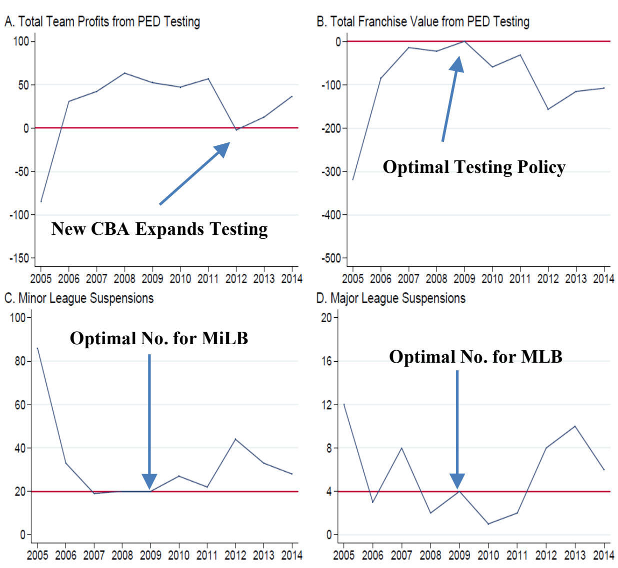

Figure 4: Impact of Testing on Profits and Franchise Values

Figure 4 plots the aggregate MLB team profit and franchise value gains/losses by season. The negative impacts of testing were highly concentrated in the initial 2005 season, where the total franchise value loss, at close to $300 million, was roughly equal to an average MLB franchise at that time. In contrast, from about 2007-2009 the testing program produced near-optimal outcomes. Using the 2009 season as a benchmark, our model suggests the league should aim for around 4 MLB suspensions and 20 MiLB suspensions per year. More recently, the negative impacts on franchise value have increased again, although the magnitudes of the losses are 30-50% of what they were in 2005. This deterioration generally has accompanied substantial changes made to the testing program which increased both the frequency of testing and the length of suspensions.

5. CONCLUSION

With collective bargaining taking place this year, it is likely that further changes to the testing program may be on the horizon. The recent rise of suspensions could make it difficult for MLB to meet our recommended target of 4 MLB and 20 MiLB suspensions going forward. While MLB PED usage has understandably been the focus of most discussion surrounding the testing program, our results suggest that targeting MiLB usage may also be effective for meeting the league's objectives. Furthermore, conventional strategies such as further increasing suspension length may not be ideal when used in isolation, as this would only serve to increase the potential cost savings to teams. Our analysis demonstrates that as a complementary policy the league could impose a revenue sharing penalty on teams with high numbers of PED users.

6. ACKNOWLEDGEMENTS

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APPENDIX

A. Deriving Team Cost Functions with PED Testing

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

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

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

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

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 given constant returns-to-scale production functions $Q_i = f(q_i)$ then yields the first order conditions

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

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, we obtain ex-post team player costs:

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

Combining this expression with equation 3 of the text and assuming a 162 game season, one arrives at the result mentioned earlier that a team's wins per player cost is proportional to its share of revealed player talent, where taking logs isolates the team-specific constant of proportionality and motivates the analysis of figure 2.

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

B. Estimating Equations and Variables

In order to estimate our model, we must first specify several functional forms. We follow Ferguson et al. (2000) and use the following attendance function

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

where x_{it} is a vector of local market demand factors: the previous season's attendance, the inflation adjusted per capita income of the home MSA (or city), the number of other professional sports teams in the home city, the previous season's average ticket price, and the number of awards won by its players, as well as indicators for the team's division, whether the team opened a new stadium in the current season, and whether the team played in the post-season in the prior season.

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. This includes indicators corresponding to a team's division, collective bargaining agreements, whether a team hosted an All-Star game, whether a team played in the post-season, and whether a team signed a new regional television deal. We also include the number of awards won by its players in the previous season and lagged ratios of both total revenue to gate revenue and a "Fan Cost Index" to ticket prices, where the Fan Cost Index measures the total cost of attendance for a family of four.

We specify the league-determined cost term $(1 - \mu(y_i, s_i))$ 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. This vector contains indicators for collective bargaining agreements and league divisions, as well as lagged player costs to control for the unmodeled dynamics of multi-year player contracts.

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} accounts for exogenous drivers of future profit growth with indicators for a new regional television deal, a new stadium, and a World Series championship in the prior season as well as lagged franchise value.

Regular season gate revenue maximization and cost minimization imply that

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

where τ is a multiplier that accounts for irregular gate revenue sources that depends on the indicator variables b_{it}, capturing All-Star and post-season games. Taking logs of the preceding six equations yields our estimating equations, where we 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.

C. A History of 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.[4] 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.

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.

Over time, the major league program's suspension schedule 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. The Commissioner's office also retains the right to suspend players based on outside sources of evidence of possession or use. However, this right has been invoked infrequently.[7]

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.[8]

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.

[4] 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.

[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] 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.

[8] This information was assembled from press releases at mlb.com and milb.com.. Positive tests for minor league players in the Dominican and Venezuelan Summer Leagues as well as the Mexican League were excluded from the analysis.

D. Additional Estimates

Table 2: Counterfactual Estimates (Mils. 2005$)

Team	Franchise Values	Profits	Revenues	Player 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