Technological Peer Effects Between Workers: Evidence from Professional Baseball

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Abstract

This paper examines peer effects between workers in the same firm. We depart from the existing literature by showing that peer effects can be based on income maximization considerations stemming from the underlying technological production function, rather than relying on psychological considerations between workers such as peer pressure, social norms, and shame. In addition, we demonstrate that a higher level of effort from one worker may increase or decrease the effort of fellow workers. In particular, we show that positive externalities should exist between complementary workers or workers who are competing with each other, while workers who are substitutes may free ride off the effort each other, and thus generate negative peer effects. The theory is tested using panel data on the performance of baseball players from 1970 to 2003. The empirical analysis shows that a player's batting average significantly increases with the batting performance of his peers, but decreases with the quality of the team's pitching. Furthermore, a pitcher's performance increases with the pitching quality of his peers, but is unaffected by the batting output of the team. These results are inconsistent with behavioral explanations which predict that shirking by any kind of worker will increase shirking by all fellow workers. The results are consistent with positive peer effects between complementary players and negative peer effects between substitutable players. These findings are robust to controlling for individual fixed-effects, and to using changes in the composition of one's peers in order to produce exogenous variation in the performance of one's peers.

Keywords: Peer Effects, Team Production, Externalities

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1 Introduction

This paper examines how peer effects between workers in the same firm shape the individual incentives and subsequent performance of workers. Studying the nature of peer effects between workers is crucial to the understanding of how organizations and workplaces are operating, and therefore, can help identify the organizational changes necessary to optimally utilize peer effects in order to boost effort and performance. In contrast to the current literature, we focus on explaining why peer effects between workers may be a rational response which depends on the team production technology, rather than relying on psychological considerations as the underlying reason for the peer effect. In addition, we break from the existing literature by allowing for peer effects to work in two directions. For example, the current literature focuses on the idea that a high level of effort or performance by a given worker generates positive externalities that induce other workers to increase their effort level, or that lower effort by one worker causes other workers to follow suit. We refer to both of these phenomena as a "positive" peer effect in the sense that a change in effort by one worker causes others to change their effort in the same direction. However, it is possible that peer effects are "negative" in the sense of generating other workers to change their effort or performance in the opposite direction. Therefore, this paper contributes to the existing literature by showing that the peer effect can work in both directions, even within the same firm at the same time.

In particular, we show that positive externalities should exist between complementary workers or workers who are competing with each other for the same position. However, workers who are substitutes may free ride off the effort of each other, and thus generate negative peer effects between co-workers. Therefore, the source of the peer effect in our model is very different from the existing literature. Peer effects in our framework are not a product of psychological pressure between workers, such as peer pressure, norms, or shame. Our results indicate that the economic fundamentals underlying the production technology within the firm are possible explanations for the size and direction of the peer effect. That is, a positive peer effect in our framework is simply a result of workers rationally responding to their peers' behavior when tasks are complementary, whereas rational behavior leads to negative peer effects when tasks are substitutable.

The theory is tested using panel data on the performance of baseball players on every team from 1970 to 2003. The game of baseball provides a clear case where pitchers and non-pitchers can safely be defined as substitutes for each other in team performance – since preventing runs and scoring runs are perfect substitutes in the team's goal of scoring more runs than the opposing team. In addition, players who are not pitchers are often complements with each other since it usually takes more than one player to get a hit in order to score a run for the team. The empirical analysis shows that a player's batting average significantly increases with the batting performance of his peers, but decreases with the quality of the team's pitching. Furthermore, a pitcher's performance increases with the pitching quality of his peers, but is unaffected by the batting output of the team. These results do not support a behavioral explanation for peer effects between players, since a typical behavioral response should cause workers to change their effort in the same direction regardless of the other player's role or function. Thus, psychological considerations are unlikely to explain our findings that players respond differentially to peers according to their role and function on the team. Overall, the results are more consistent with a peer effect based on rational considerations of income maximization, which produce positive peer effects between complementary players and players who are competing for the same position, and negative peer effects between substitutable players.

Our empirical findings are robust to controlling for individual fixed-effects, age, year effects, tenure, team, home ballpark characteristics, and managerial quality. The inclusion of individual fixed-effects means that the results cannot be explained assortative matching between complementary or substitutable players at the team level, since the analysis is exploiting variation over time within a given player's performance. In addition, the results are robust to using a first-differences specification, as well as restricting the sample to only those workers who change teams (changing all of their peers), or using a sample of only those workers who remain with the same team, manager, and home ballpark in consecutive years. Furthermore, in order to control for unobserved yearly shocks which may affect the performance of the whole team, we instrument the yearly performance of one's peers with the lifetime performance of one's peers. Yearly variation in this instrument stems only from changes in the composition of one's peers, since each player's lifetime performance is constant for each year. Results using this instrument are very similar to the OLS estimates. Finally, we show that the results are similar using data from the 1879 to 1970 seasons.

By providing empirical support for the dependence of peer effects on the degree of substitutability and complementarity between workers, the paper makes a theoretical and empirical contribution to the literature on peer effects and working in teams. There is a growing literature that stresses the importance of one's peers and environment in determining the outcomes of individuals. Most of this literature is concerned with examining how peers and environmental factors affect youth behavior regarding their educational achievements, health, criminal involvement, work status, and other economic variables.[1] This paper differs by looking at peer effects between adults, and by looking at the context of behavior in the workplace. The literature on the interaction of worker effort within a firm is not extensive. Winter (2004) shows theoretically the optimality of offering differential incentive contracts in order to elicit worker effort which generates externalities on other workers. Kandel and Lazear (1992) examine the theory of team production within the firm and focus on how teams produce social pressure to solve the free-riding problem, but they do not consider how peer effects could go in both directions according to the underlying technology. The most related paper to ours is by Ichino and Maggi (2000) who examine shirking behavior within the firm, and see how changes in the place of work explain changes in shirking behavior for the same worker. Some of our empirical specifications employ a similar identification strategy in the sense that we exploit differences in the composition of one's peers to explain changes in the performance of the individual. However, our paper differs by examining the theoretical and empirical differences in the peer effects across workers depending on whether they are substitutes or complements with each other. In this manner, the paper makes a contribution to the literature by providing both theoretical and empirical evidence for both positive and negative peer effects among workers in a real work environment.

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

2 Technological Peer Effects

In this section, we show how peer effects can emerge from the technological properties of the team production function without any behavioral effect such as peer pressure, norms, or shame. The model will show that if two agents are dealing with tasks which are complementary in the team production function, then we should see a "positive" peer effect in the sense that a high performance by one agent will increase the effort of the other agent. In contrast, if the two agents' tasks are substitutes in production, then we should see a "negative" peer effect whereby a high performance on the part of one agent will trigger the other agent to reduce effort. Hence, the nature of the peer effect will be a function of the technology of team production. We will model the externalities between players using the concept of strategic substitution and complementarity (see Milgrom and Shannon (1994) and Topkis (1998)).

Consider an environment of n players working in a team $N = \{1, ..., n\}$. Each player decides on an effort level e, where $0 \leqq e < \infty$. An effort level e by player i generates a performance $p_i(e)$ by player i. The cost of exerting e units of effort is $c(e)$ and is assumed to be common for all players. A player's wage function is defined on the profiles of performances for all the players on the team (see Alchian and Demsetz (1972), Holmstrom (1982) and Itoh (1991)). Let $w_i(\ p_1, ..., p_n)$ denote player $i's$ wage for the vector of performances $p_1, ..., p_n$. A pair of players i and j are said to be competitors (within the same team) if $i's$ wage is decreasing with $j's$ performance (i.e. $\frac{\partial w_i}{\partial p_j} < 0$ and $\frac{\partial w_j}{\partial p_i} < 0$). The two players are said to be collaborators if one agent's wage is increasing with the other agent's performance (i.e. $\frac{\partial w_i}{\partial p_j} > 0$ and $\frac{\partial w_j}{\partial p_i} > 0$). For a pair of collaborating players i and j, we say that i and j have complementary tasks if their marginal products are increasing with the other player's performance, so that $\frac{\partial^2 w_j}{\partial p_i \partial p_j} = \frac{\partial^2 w_j}{\partial p_j \partial p_i} > 0$. The tasks of agents i and j are substitutable if their marginal product is decreasing with the other agent's performance, so that $\frac{\partial^2 w_i}{\partial p_i \partial p_j} < 0$ and $\frac{\partial^2 w_j}{\partial p_j \partial p_i} < 0$.[2]

We further assume the following assumptions on the primitives of the model:

[2] Our conditions on the cross derivative are equivalent to the property of supermodularity and submodularity of the wage function as a function of the vector of performances (see Topkis (1998)).

1. The performance function is increasing and concave in a player's effort level: $p_i'(e) > 0$ and $p_i''(e) < 0$.

2. Fixing the performances of all players other than i to be p_{-i}, player $i's$ wage of $w_i(p_i, p_{-i})$ is an increasing and concave function of player $i's$ performance p_i.

3. The cost function of effort is increasing and convex: $c'(e) > 0$ and $c''(e) > 0$.

This simple framework yields Proposition 1 which asserts that positive peer effects are expected to arise among players who are collaborating on complementary tasks and negative peer effects will arise when agents are collaborating on tasks with substitution[3].

Proposition 1 *Let i and j be collaborating players with complementary (substitutable) tasks. Fix the level of performance of all players other than i and j to be p_{-ij}, and consider two performance levels for player j, $p_j < \overline{p}_j$. Let e be $i's$ best response to (p_{-ij}, p_j) and $\overline{e}$ be $i's$ best response to $(p_{-ij}, \overline{p}_j)$. The best responses under these two scenarios yields $e < \overline{e}$ ($\overline{e} < e$).*

Proof: Without loss of generality let $i = 1$ and $j = 2$. Fixing $p_3, ..., p_n$ we now consider w_i as a function of p_1 and p_2 only. For a performance level p_2 by player 2, player $1's$ maximization problem is given by:

$$\max_{e} \quad w_1(p_1(e), p_2) - c(e) \tag{1}$$

which yields the first order condition:

$$\frac{\partial w_1}{\partial p_1}(\cdot, p_2)\frac{\partial p_1}{\partial e} = c'(e) \tag{2}$$

Consider now a higher performance level by player 2, $\overline{p_2}$. The complementarity condition implies that $\frac{\partial w_1}{\partial p_1}(\cdot, p_2)$ is increasing in the performance of player 2 so the value of this derivative increases with $\overline{p_2}$. Furthermore, $\frac{\partial p_1}{\partial e}$ is constant in p_2. If we hold the effort level of player i fixed at e, increases in $\overline{p_2}$ increase the left hand side of equation (2), which violates the first order condition. If we allow player 1 to increase his effort level, e, then

[3] The case of complementarity corresponds to the notion of supermodular game (see Topkis 1998).

$p_1(e)$ increases and $\frac{\partial w_1}{\partial p_1}(\cdot, p_2)$ declines because of the concavity of w_i in its first argument. Furthermore, $\frac{\partial p_1}{\partial e}$ declines as well because of the concavity of p_1 in effort. Hence, the left hand side of equation (2) declines by increasing e. On the other hand $c'(e)$ increases when e increases because of the convexity of c. Hence, the first order condition in equation (2) is solved for a higher level of e when player 2's performance is higher, yielding the result in Proposition 1. The case of substitution between the tasks of players 1 and 2 is proved in a similar manner. Q.E.D.

We point out that if players i and j are competing with each other, then player $i's$ best response to an increasing performance by player j may either be an increase of effort or a decline of effort. The ambiguity here results from the fact that the property of competition imposes no condition on the second-order cross-derivatives. Intuitively, if player $j's$ performance increases, player i may decide to increase his effort in order to match the performance of his competitors or he may find it optimal to reduce effort because beating his competitor is now a "lost case" and not worth the cost of such a large effort.

In the model specified above, the wage function was defined directly on the vector of performances by each team member. The technology of team production is therefore made implicit in the model. However, a special case of the model allows for the technology to be given explicitly. Consider a team in which agents' individual performances are aggregated into a team performance $f(p_1, p_2, ..., p_n)$. Assume each agent's wage $w_j(p_j, f)$ is some linear function of the team's aggregate performance.[4] We now define complementarity and substitution in terms of the technology alone. Specifically, we say that the tasks i and j are complementary if $\frac{\partial^2 f}{\partial p_i \partial p_j} > 0$ and they are substitutable if $\frac{\partial^2 f}{\partial p_i \partial p_j} < 0$. Because wages are linear functions of team production, f , complementarity implies $\frac{\partial^2 w_i}{\partial p_i \partial p_j} > 0$ and substitution implies $\frac{\partial^2 w_i}{\partial p_i \partial p_j} > 0$. Hence, according to Proposition 1, complementarity between workers will produce positive peer effects and substitution between workers will yield negative peer effects. It is easy to verify that the same results apply when $w_j(\cdot, f)$ is a convex function of f.

[4]There may be two reasons to expect that an individual's wage is affected by the aggregate team performance. First, higher team performance may generate higher profits, and thus, increase the value of the maginal product of labor. Secondly, a higher team performance can serve as a signal for aspects of a player's ability that are not reflected in performance measures which are easy to observe or quantify.

Proposition 1 demonstrates a framework in which an agent's choice of effort is rationally affected by the performance of his or her peers. It is important to note that in this framework, peer effects are the result of purely technological considerations, as they depend only on the way individual performances are aggregated into team performance. Psychological factors such as peer pressure and shame play no role in creating the peer effect. Our purpose here is not to claim that peer effects are never a product of behavioral considerations. Rather, we would like to demonstrate that peer effects *can* be fully rational and arise from the properties of the technology without relying on behavioral responses. Indeed, the remainder of the paper presents evidence from professional baseball players that peer effects between workers are significant, and appear to be based on a rational response to the technology.

3 The Data and Background

The data was obtained from the "Baseball Archive" which is copyrighted by Sean Lahman, and is a freely available on the internet for research purposes. The data contains extensive personal and yearly performance information on players, coaches, and teams from 1871 through the 2003 season. The main analysis focuses on the more "modern" period from 1970 to 2003 because Major League Baseball underwent a major expansion and restructuring into divisions just prior to that period. However, data from 1871 to 1969 are used to check the robustness of the main results.

The game of baseball presents an ideal case where the performance of each player is easily measured in a uniform way, and in complete isolation from the performance of his teammates. This contrasts with other sports, such as basketball, where total performance is hard to quantify and where the actions of one player, which do not always show up in statistics, can complement or come at the expense of the performance of his teammates. In addition, baseball players are easily divided into two distinct types: pitchers and batters. The function of pitchers is to prevent the other team from scoring runs, while the function of a batter is primarily to help score runs for the team. In this sense, the two types of players are perfect substitutes for one another in team production – since the goal is to score more runs than the other team. However, there is complementarity among the batters since it typically takes a series of hits within the same inning to score a run for the team. That is, a typical "hit" is meaningless for the team by itself (unless it is a home run), and therefore, the marginal productivity of getting a hit increases with the batting performance of the players who batted right before you. Therefore, batters can be considered complements with each other in team performance while batters and pitchers can be considered substitutes for each other.

In addition, pitchers are typically divided into two types: "starters" and "relief" pitchers. Starting pitchers typically start the game and continue until they get tired or into trouble, and then relief pitchers are called in to finish the game. A relief pitcher can ruin a good performance by the starter with a bad performance, or he could "save" the game with a good performance. Since multiple starting pitchers are never used in the same game, starting pitchers can be considered substitutes and competitors with each other, while being complements with relief pitchers.

Table 1 presents summary statistics for the main sample of players from the 1970 to 2003 seasons. The sample includes all batters who batted at least 50 times in a season and pitchers who pitched in at least 10 games. The main performance measure for batters is the "batting average" (BA), which is defined as the number of hits divided by the number of opportunities to bat ("at-bats") in a season. According to Table 1, batters obtain a hit in 26 percent of their chances. Another conventional measure of batting performance is the "on-base-percentage", which takes into consideration other ways a batter can get on base (walks, hit by pitch, etc.).[5] The standard indicator of a pitcher's performance is called the ERA (Earned Run Average). This measure takes the number of bases that a pitcher allows the opposing team to obtain, and scales it by the number of innings played, so that it represents the average number of runs which would have been scored off the pitcher in a full game.[6] As such, a higher ERA reflects poorer performance. The average ERA is

[5] The exact definitions of the batting measures are as follows: batting average equals the number of hits divided by the number of at-bats. On-base-percentage is defined as (hits+walks+number of times hit by pitch) divided by (at-bats+walks+sacrifice flies+number of times hit by pitch). Slugging percentage is equal to (singles + 2*doubles + 3*triples + 4*home-runs)/(at-bats).

[6] The ERA is calculated by: (number of earned runs/innings pitched)*9.

4.83 for starting pitchers and 4.70 for relief pitchers.[7] Another indicator of a pitcher's performance is the "opponent's batting average" which is defined as the number of hits allowed divided by the number of batters faced. Although there are only small differences in the average performance measures between starting and relief pitchers, the differences in their roles is highlighted by the average number of games pitched (44 for relief pitchers versus 30 for starters) and the average number of games started (19 for starters versus 0 for relief pitchers).

Table 2 presents the transition matrix between the various positions. There are no transitions between pitchers and the other positions, which justifies treating them as completely distinct types players who are not competing with each other for the same position. In addition, there are very few starting pitchers who become relief pitchers in consecutive years, and vice versa. This lack of mobility between different roles is also displayed by batters when they are divided up into three main categories: (1) "skilled positions" (second base, third base, and short-stop) which emphasize fielding skills at the expense of hitting prowess, (2) "power positions" (first base, outfielders, and designated hitters) which primarily emphasize power hitting, and (3) "catchers" which have distinct fielding skills and are typically power hitters. The diagonal elements of the transition matrix in Table 2 for batters are always above 92 percent, which indicates that there is very little mobility or substitution between these roles for batters. Therefore, players across these categories are considered complements in the production of team runs. The next section examines whether there is any empirical evidence for peer effects between players on the same team, and whether the nature of the peer effect depends on the role of each player.

4 The Basic Regression Analysis

This section examines how the performance of individual players varies with the performance of his fellow workers. The basic regression equation is the following:

[7] A pitcher was defined as a starting pitcher if he started at least one game in the season.

$$performance_{ikt} = \beta_0 + \beta_1(teammates'\ pitching\ ERA)_{kt} + \beta_2(teammates'\ batting\ ave)_{kt} + \mu_i + \beta_3(other\ controls)_{kt} + \varepsilon_{ikt}$$

where the performance of player i on team k in year t depends on his teammates' pitching performance in year t, his teammates' batting performance in year t (not including the batting performance of pitchers),the fixed ability of player i represented by μ_i, other observable control variables, and the unobserved random component, ε_{ikt}. It is important to note that the pitching and batting variables for the teammates of player i do not include the performance of player i, and therefore, these variables vary at the individual level. The other control variables include: the batting average in team k's division (excluding his own team) in year t which controls for the quality of the pitching and batting in the team's division in the same year, the team manager's lifetime winning percentage which is an indicator for the quality of the team's coaching, the ballpark hitting and pitching factors which control for whether the team's ballpark is easy or difficult for batters in year t, tenure of the player in professional baseball (number seasons played in the league), year effects, and dummy variables for each division. The unobserved ability of player i, μ_i, is controlled for by using a fixed-effects specification (dummy variables for each player) or by using a first-differences specification between consecutive years. In this manner, the regression controls for the average performance of player i and his other control variables, so that the peer effects are identified by seeing whether player i's performance is higher or lower than his average in seasons where the other batters and pitchers are performing well or poorly. In this manner, the regression is identifying peer effects by explaining deviations from player i's average performance.

The basic fixed-effect regressions for pitchers and batters are presented in Table 3. Column (1) shows that after controlling for all the other variables, a given batter has better than average years when the other batters on the team are doing well. In contrast, column (2) shows that a batter's performance decreases when the pitchers on his team are pitching well. (It is important to keep in mind that a lower ERA indicates higher pitching performance.) The specification in column (3) includes the performance measures of both the batters and pitchers as explanatory variables, and the results are essentially unchanged.

Thus, the results are robust to estimating the peer effect of pitchers and batters separately (columns (1) and (2)) or when they are estimated together in column (3). Therefore, the results are not a product of a high correlation between the two variables, and the effect of each one is unaffected by controlling for the other.

Columns (4)-(6) present the basic results for pitchers, where the regression explains the performance of a given pitcher with the batting and pitching performance of the other members of the team. The estimates indicate that a pitcher performs better when his fellow pitchers are doing better, but there is no significant effect of the team's batting performance on a pitcher's performance – a finding which repeats itself throughout the paper. Again, the effect of the player's fellow pitchers on his own performance is robust to the inclusion or exclusion of the team's batting performance. Regarding the other control variables, they all have the expected signs and are generally significant for the batting and pitching regressions, although it is worth noting that the results are robust to excluding them.

One explanation for the pitching results which immediately comes to mind is that a coach is more likely to let a pitcher stay in the game longer, or use him in more games, if the other pitchers on the team are weaker. That is, the coach will let the pitcher struggle longer in the game when there are weaker replacements on the bench, thus inducing a positive correlation between a pitcher's ERA and those of his fellow pitchers. We can try to control for this by including the number of innings and games played by the pitcher into the regression. After adding these variables into the specification, the coefficient on his teammate's ERA goes from 0.523 (t-statistic of 6.51) to 0.625 (t-statistic 8.01). Therefore, the evidence for peer effects across pitchers appears stronger even after controlling for how long the pitcher is left in the game. However, including these variables is problematic since a player's performance and playing time are clearly determined simultaneously. For this reason, we choose not to include these variables in the core specification, but it is worth noting that the results are robust to including the amount of playing time into the regressions for both pitchers and batters.

Although many of the coefficients of interest are significant statistically, the implied magnitudes are not very large. If we take a two standard deviation change in the batting average of a player's teammates (0.024 from Table 1), the predicted change in a player's batting average based on the results in the third column of Table 3 is 0.005, which is only 13 percent of the standard deviation in a players batting average (0.039 in Table 1). The predicted change in a batter's batting average due to a two standard deviation change in the team's pitching ERA would be 0.0032 (the coefficient 0.282 in Table 3 multiplied by 100, multiplied by two times 0.579, the standard deviation of Team ERA in Table 1). The predicted change in a pitcher's ERA due to a two standard deviation change in his teammates' ERA is 0.588 (the coefficient 0.523 in Table 3 multiplied by two times 0.562, the standard deviation of a starting pitcher's teammates' ERA in Table 1). This predicted increase represents a little more than 23 percent of the standard deviation of a starting pitcher's ERA. Although these predicted changes are not very large, computing these predictions from such little variation in the team performance measures will naturally yield small changes in the predicted performance of an individual player. In addition, adding 5 points (the predicted change of 0.005 for a batter from the other batters on the team) or increasing a pitcher's ERA by 0.562 would probably not be considered entirely trivial to a fan or a player.

Table 4 performs a similar analysis to Table 3 but controls for unobserved heterogeneity by using a first-difference specification between consecutive years rather than using fixed-effects. The results are very similar qualitatively in the sense that a batter is shown to be affected by the batting and pitching performance of his teammates, while a pitcher is affected only by his fellow pitchers. The magnitudes of the coefficients are a little different from the estimates in Table 3, with some smaller and some bigger in magnitude, but inferences regarding significance are very similar. Overall, the results in Tables 3 and 4 show that batters have better than average years when they are playing with better batters and weaker pitchers, while pitchers play better than average when teamed with better pitchers.

Since all of the regressions control for player-specific fixed-effects, the results cannot be explained by patterns of assortative matching between complementary or substitutable players (see Kendall (2003)) which may induce a similar pattern of correlations across batters and pitchers at the team level. For example, if batters are complementary with each other, then it makes sense that team managers will make an effort to match good batters with each other on the team. In addition, budget considerations may induce managers to decide whether the team specializes in good hitting or good pitching, thus producing a negative correlation between batting performance and pitching prowess at the team level. However, our analysis abstracts from correlations at the team level by exploiting variation over time in a player's own performance. Therefore, explanations based on assortative matching between players or budget-based considerations cannot explain why an individual player's own performance varies across years according to the performances of his peers.

Overall, the results are consistent with the theory that players should be positively affected by the performance of their fellow workers when they are complements in production like batters are in the production of runs, but negatively affected by the performance of their fellow workers when they are substitutes in production, like batters and pitchers in the game of baseball. Although the finding that a pitcher is positively affected by other pitchers is consistent with the theory, the theory cannot explain why a pitcher does not seem to react in either direction to the team's batting performance. However, the fact that there is a differential reaction to both types of players from both types of players is strong evidence against a behavioral explanation for the results. A typical behavioral response would be for any worker to work harder when his peers are working harder, regardless of whether they are complements or substitutes in team production. This prediction is clearly rejected in the analysis. So, the differential responses according to the role of each type of player can be viewed as strong evidence for the idea that peer effects may be a rational response which depends on the team production technology.

5 Alternative Explanations and Robustness Checks

5.1 Different Performance Measures

We now examine whether the results in Tables 3 and 4 are robust to using different measures of a player's performance. As a basis for comparison, the first column in the upper panels of Tables 5 and 6 replicate the batting regression results already seen in Tables 3 and 4 for the fixed-effects and first-differences specifications respectively. The first column in the bottom panels of Tables 5 and 6 use the "on-base-percentage" of a player instead of a player's batting average as the dependent variable. This measure differs from the batting average by considering the ability of a player to get on base by a "walk" or getting hit by a pitch rather than only by hitting. Tables 5 and 6 show that the results using "on-base-percentage" as the dependent variable are virtually identical to those using a player's batting average as the performance measure. Although not shown, the results are also similar if we use a player's home-run output as the dependent variable. Tables 7 and 8 present results for pitchers using a different measure of a pitcher's performance: the opposing team's batting average while he was pitching. As a basis for comparison, the first columns in Tables 7 and 8 replicate the results for pitchers seen in Table 4 using a pitcher's ERA as his performance measure. The first column in the bottom panel uses the opposing team's batting average as the dependent variable, and the results are very similar to those obtained using the ERA as a pitcher's performance measure. Therefore, the results for pitchers and batters appear to be robust to using alternative, conventional measures of a player's performance.

5.2 Switching Teams

One can think of players switching teams as potentially an ideal "natural experiment" which produces variation in one's peers, and thus allows for identification of the peer effect on individual performance. Ichino and Maggi (2000) use this strategy to test for whether changing locations affects the shirking behavior of workers. The second column in Table 6 replicates the first-differences analysis, but uses only the sample years where the player changed teams across consecutive years. The results are virtually identical to those using the full sample in column (1). The results are also very similar using the restricted sample of pitchers who changed teams in column (2) of Table 8. Therefore, the results show that players bat better when they move to teams with better batters and worse pitchers, while pitchers play better if they move to a place with better pitchers.

5.3 Not Switching Teams

One explanation for the previous set of results is that there might be an unobserved reason why certain teams have good batting but bad pitching, and when a player moves to that team his performance changes accordingly. For example, it could be that the player is affected by the coaching change, or that certain ballparks favor batters over pitchers, or the team could play in a new division where teams are very strong in pitching or batting, or the team's city may be in a part of the country where the weather favors pitching or batting. The basic regressions in Tables 3 and 4, as well as the previous regressions using only the sample of team-changers, control for many of these scenarios by including measures of managerial quality, indices for whether the ballpark favors batting or pitching, the batting average of the division in the same year, and division dummy variables. However, these measures may be imperfect. So, to completely control for this scenario, we restrict the fixed-effect analysis only to the seasons in which the player played for the same team, manager, and ballpark (the combination of which the player stayed with the longest). For batters, the fixed-effect analysis is presented in column (2) of Table 5, while the first-difference analysis using a sample of players who do not change teams in consecutive years is shown in column (3) of Table 6. For pitchers, the respective regressions are in column (2) of Table 7 and column (3) in Table 8. Overall, the results are very similar to those using the whole sample and the sample of players who changed teams. However, the magnitudes of the coefficients tend to be weaker for the players who stay on the same team over consecutive years versus those that change teams. This tendency is most likely due to the fact that most of the variation in one's peers comes from players changing teams, and thus, all of their peers from one season to the next. The fact there is enough variation in one's peers even within the same team in consecutive seasons to explain variation in an individual's performance supports the interpretation that the main results are not due to endogenous moving.

5.4 Complements or Competition between Players?

The positive effect of fellow batters on the individual performance of a batter, or fellow pitchers on the pitching performance of an individual pitcher, could theoretically be due to the complementarity between players or the competition between players for increased playing time. The "complements" story says that the marginal product of one player's output increases with the output of his peers. This is true for batters since it often takes a series of hits in order to score a run for the team, and it is also true for pitchers since some of them start games and others are called upon to finish the same game. However, the "competition" story says that workers will need to work harder to preserve their jobs and get promoted if their fellow workers are also working harder. We now attempt to isolate these two stories by dividing batters and pitchers into types of positions which are clearly not substitutable (i.e. no competition between players of each type).

As discussed above, Table 2 divides pitchers into "starters" and "non-starters" while the positions of batters can be categorized as either a "skilled position", a "power position", or a "catcher." Table 2 demonstrates that there is very little mobility between these types of positions, so it is reasonable to assume that there is very little competition between players across these types of positions. Therefore, the analysis is now performed using the average performance of player i's teammates, but using only those teammates which play a different position than player i. For batters, the fixed-effect results are presented in column (3) of Table 5 while the first-difference results are in column (4) of Table 6. The results are virtually identical to those using the average performance of all the player's fellow teammates, including those that play the same position. For pitchers, the regressions are run separately for starting pitchers and non-starting pitchers, where the explanatory variables are the performance measure of the other group. The fixed-effect results for pitchers are in columns (3) and (4) of Table 7 while the first-difference results are in columns (4) and (5) of Table 8. Interestingly, the pitching performance of non-starters has a bigger effect on starting pitchers than vice versa. However, for starters and non-starters, the coefficients are significant and generally larger in magnitude than the coefficients in previous specifications which lumped all pitchers together. This general pattern points to larger "cross" effects across types of pitchers than within types of pitchers. This pattern bolsters the technology-based interpretation of the results since each pitcher is clearly more complementary with a pitcher of the other type than pitchers within the same type.

Overall, the analysis for batters and pitchers indicates that the performance of players which are not in competition with player i for the same position has a strong effect on the performance of player i. This is strong evidence in favor of the complementarity story, because it appears that only players which are complements with each other have strong positive externalities (batters on fellow batters or pitchers on other pitchers), while players who are clearly substitutes have strong negative effects on each other (pitchers on their fellow batters) or no effect at all (batters on their fellow pitchers). That is, there seems to be consistent pattern of results in favor of the importance of the degree of complementarity and substitutability between players in determining the direction and strength of the peer effect.

5.5 IV Results

The results so far are robust to looking at the whole sample, a restricted sample of players changing teams, a restricted sample of players staying with the same team, and to using the average performance of teammates playing positions different from player i. In addition, our use of fixed-effects controls for the overall, unobserved ability of each player. However, as Manski (1993) points out, there could be an unobserved factor responsible for the high or low performance of all players on the team in a given year, and therefore, this produces a correlation between the performances of players without there actually being a peer effect. If this explanation were true, it does not seem to be able to explain our results which show that the sign of the peer effect depends on the degree of substitutability and complementarity between players – since it is unlikely that an unobserved factor is inducing all batters to do better in the same year that the team's pitchers are having bad years.

However, to further examine this possibility, we repeat the analysis using the lifetime performance of player i's peers instead of their current performance in year t. Variation in the lifetime performance of one's peers stems only from changes in the composition of one's peers, since the lifetime performance of any given player does not change from year to year. In this sense, it is a similar identification strategy as the one employed by Ichino and Maggi (2000) and used above when we restricted the sample to players who move teams. However, the use of the lifetime performance of one's peers allows us to exploit changes in the composition of one's peers within the same team as well as across teams when players move.

The results for batters are presented in column (4) of Table 5 and column (5) of Table 6. The fixed-effect results using the lifetime batting average of one's peers in Table 5 are virtually identical to column (1) which uses the batting average of one's teammates in the current year. The first-difference results in Table 6 are little weaker in significance, but the magnitude is not much lower than the coefficient estimates in other specifications. For pitchers, the fixed-effect results are in column (5) of Table 7 while the first-difference results appear in column (6) of Table 8. The pitching results using the lifetime achievements of one's peers are very similar to those using their current achievements. Furthermore, the last column of Tables 5, 6, 7, and 8 repeat the analysis for batters and pitchers, but uses the lifetime achievements as an instrumental variable for the current performance of one's peers in a 2SLS regression. Again, the results are very similar to using the lifetime achievements directly as a regressor and to using the current performance of one's peers.

Finally, in order to net out the effect of player i's effect on the lifetime performance of his peers, column (5) in Table 5 repeats the analysis for batters but restricts the sample to only those years when player i is playing on a new team, and then explains his current performance with the lifetime achievements of his peers up to the year prior to him joining the team. Column (6) of Table 7 runs a similar regression for pitchers. Using this specification, the results for batters in Table 5 are unchanged from previous regressions, but the results for pitchers in Table 7 are not significant. This last result is probably due to the fact that prior lifetime results are more likely to be noisy for pitchers than batters (the coefficient of variation for a pitcher's ERA is 12 times larger than the coefficient of variation of a batter's batting average: 1.94 for pitchers versus 0.152 for batters in Table 1). The overall results in this section point once again to idea that batters are positively affected by other batters but negatively affected by their fellow pitchers, while pitchers seem to be positively affected by other pitchers, but not by their fellow batters.

5.6 Results from the 1879-1970 Seasons

Table 9 reproduces the core analysis for batters and pitchers using data from the 1879 to 1970 seasons in the American and National Leagues. In particular, Table 9 presents the fixed-effects and first-difference results for batters and pitchers for the main specification using the current performance of one's peers, as well as the specifications using the performance of one's peers who play in other "non-competing" positions and the lifetime performance of one's peers. Overall, the results are remarkably similar to those using data from the modern period of professional baseball, considering that there have been many changes over this time period in the structure of professional baseball, the popularity and growth of the sport, salaries, relations between players and management, etc. The only noticeable differences are the insignificant results for the first-difference specifications using the lifetime achievement variables. However, all of the other results are similar to the previous results, and using the lifetime achievement of one's peers yields significant results using the fixed-effects specification. Overall, the analysis using data from the period between 1879 and 1970 generally provides strong support for the main conclusions of the paper.

6 Conclusion

This paper analyzes how a player's performance is dependent on the performance of his peers. Using data on professional baseball players, the results show that a batter's performance increases with those of his fellow batters, but decreases with the quality of his team's pitching. The results also indicate that a pitcher's performance increases with the pitching performance of the other pitchers on the team, but is unaffected by the batting performance of the team.

The differential reaction to both types of players from both types of players suggests that the results are not likely to be explained by behavioral explanations such as peer pressure, guilt, and social norms. These types of explanations would predict that any type of workers will work harder when his peers are working harder, regardless of the function of his job in relation to the function of his peers. Therefore, the differential responses according to the role of each type of player can be viewed as evidence in favor of the idea that peer effects may be a rational response which depends on the team production technology. This interpretation is strengthened by the many robustness checks with different samples and specifications, as well as instrumenting the performance of one's peers with their lifetime performance. All of the variation in this instrument comes from changes in the composition of one's peers, and therefore, is unaffected by a one period shock which may affect the performance of all players on the team.

Although the empirical analysis is performed using data on baseball players, the results are likely to apply to all work environments where there is an element of team production. Whenever there are workers working on a joint project, there are bound to be complementarities and substitutability between different kinds of workers, and therefore, the framework analyzed in this paper is likely to be relevant. It is important to note that a key assumption driving the theoretical results is that an individual's wage is a function of the aggregate team performance. If this assumption did not hold, there would be no "technological" basis for a worker to alter his performance according to the output of his fellow workers, since his wage would be purely a function of his own individual performance. However, there are two main reasons to expect that an individual's wage is affected by the performance of the whole team, even in cases where there are effective ways to evaluate individual performances (see also Alchian and Demsetz (1972)). First, a higher team performance may generate higher profits, and thus, increase the value of the marginal product of labor. Secondly, a higher team performance can serve as a signal for aspects of a player's ability that are hard to observe or quantify, and thus, not reflected in typical performance measures. For example, individuals on a winning team project may be considered industrious workers who are able to work well together with fellow workers. Therefore, the "technological" motive for peer effects highlighted in this paper are likely to be relevant for many work environments where cooperation among workers on joint projects are important.

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Table 1: Summary Statistics for Batters and Pitchers, 1970-2003

	Batters	
	Means	Std.
Batting Average	0.256	0.039
On Base Percentage	0.323	0.047
Slugging Percentage	0.384	0.086
Teammates' Pitching ERA	4.009	0.579
Teammates' Batting Ave.	0.265	0.012
Tenure	6.09	4.353
Age	29.009	4.132
Division Batting Average	0.266	0.007
Ballpark Hitting Factor	100.22	4.817
Manager's Lifetime Winning Percent	0.501	0.042
Sample Size	13767	

	Pitchers			
	Starters		Relief	
	Mean	Std.	Mean	Std.
ERA	4.826	2.487	4.695	3.415
Opponents' Batting Ave.	0.285	0.097	0.279	0.108
Teammates' ERA	3.981	0.562	4.084	0.580
Teammates' Batting Ave.	0.260	0.012	0.261	0.012
Games Pitched Per Season	30.15	11.091	43.628	20.283
Games Started	19.279	11.741	0	0
Age	28.455	4.247	29.771	4.131
Tenure	5.402	4.338	5.545	4.249
Division Batting Average	0.265	0.007	0.267	0.007
Ballpark Pitching Factor	100.341	4.919	100.237	5.101
Manager's Lifetime Winning Percent	0.501	0.042	0.501	0.042
Sample Size	6691		3990	

Table 2: Transition Matrix Between Positions, 1970-2002

Position in Period T		Position in Period T+1: Starting Pitcher	Relief Pitcher	2nd Base, 3rd Base, Short-stop	1st Base, Outfielder, Designated-hitter	Catcher
	Starting Pitcher	87.79	12.21	0.00	0.00	0.00
	Relief Pitcher	26.67	73.33	0.00	0.00	0.00
	2nd Base, 3rd Base, Short-stop,	0.00	0.00	92.95	6.77	0.27
	1st Base, Outfielder, Designated-Hitter	0.00	0.02	3.16	95.96	0.87
	Catcher	0.00	0.00	0.94	3.88	95.17

Table 3: Basic OLS "Fixed-Effects" Results for Batters and Pitchers, 1970-2003

	Batters			Pitchers		
	Batting Average			Pitching ERA		
	(1)	(2)	(3)	(4)	(5)	(6)
Teammates' Pitching ERA	0.318 (0.082)		0.282 (0.083)	0.521 (0.080)		0.523 (0.081)
Teammates' Batting Average		0.221 (0.031)	0.214 (0.031)		0.719 (3.133)	-0.915 (3.136)
Annual Division Batting Average	0.291 (0.065)	0.312 (0.062)	0.245 (0.065)	21.987 (6.179)	34.488 (5.945)	22.207 (6.224)
Manager's Lifetime Winning Pct.	0.052 (0.009)	0.025 (0.009)	0.034 (0.009)	-1.214 (0.834)	-2.556 (0.848)	-1.139 (0.874)
Ballpark Hitting Factor/1000	0.509 (0.078)	0.482 (0.077)	0.418 (0.079)			
Ballpark Pitching Factor				0.025 (0.007)	0.039 (0.007)	0.025 (0.007)
Division Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Tenure Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13767	13767	13767	10681	10681	10681

Standard errors are in parentheses. The coefficient and standard error for "Teammates' Pitching ERA" have been multiplied by 100 for the batting results, but not for the pitching regressions. Tenure and year dummies are included for every five year interval.

Table 4: Basic OLS "First-Differences" Results for Batters and Pitchers, 1970-2003

	Batters			Pitchers		
	Δ Batting Average			Δ Pitching ERA		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Teammates' Pitching ERA	0.424 (0.087)		0.388 (0.088)	0.352 (0.080)		0.348 (0.081)
Δ Teammates' Batting Average		0.178 (0.033)	0.166 (0.033)		2.982 (3.194)	1.554 (3.208)
Δ Annual Division Batting Average	0.297 (0.065)	0.356 (0.062)	0.252 (0.066)	23.699 (6.006)	32.048 (5.737)	23.226 (6.085)
Δ Manager's Lifetime Winning Pct.	0.034 (0.010)	0.011 (0.010)	0.020 (0.010)	-1.302 (0.167)	-2.175 (0.964)	-1.428 (0.978)
Δ Ballpark Hitting Factor/1000	0.291 (0.097)	0.301 (0.097)	0.221 (0.098)			
Δ Ballpark Pitching Factor				0.018 (0.009)	0.026 (0.009)	0.017 (0.009)
Δ Division Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Tenure Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10863	10863	10863	8026	8026	8026

Standard errors are in parentheses. The symbol "Δ" indicates the first difference between consecutive years in the variable for the same person. The coefficient and standard error for "Δ Teammates' Pitching ERA" have been multiplied by 100 for the batting results, but not for the pitching regressions. Tenure and year dummies are included for every five year interval

Table 5: Robustness Checks for Batters using Fixed-Effects, 1970-2003

	OLS					2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Batting Average						
Teammates' Pitching ERA/100	0.283 (0.083)	0.191 (0.141)	0.282 (0.083)	0.321 (0.083)	0.410 (0.197)	0.293 (0.083)
Teammates' Batting Average	0.214 (0.031)	0.142 (0.055)				0.150 (0.061)
Teammates' in Other Positions Batting Average			0.180 (0.026)			
Teammates' Lifetime BA				0.140 (0.057)		
Teammates' Lifetime BA Before Season					0.209 (0.093)	
On Base Percentage						
Teammates' Pitching ERA/100	0.384 (0.089)	0.229 (0.151)	0.384 (0.089)	0.422 (0.089)	0.595 (0.210)	0.388 (0.090)
Teammates' Batting Average	0.219 (0.034)	0.175 (0.058)				0.194 (0.066)
Teammates' in Other Positions Batting Average			0.175 (0.028)			
Teammates' Lifetime BA				0.180 (0.061)		
Teammates' Lifetime BA Before Season					0.225 (0.100)	
Sample Restriction	None	One ballpark, manager per player	None	None	First Season on New Team	None

Standard errors are in parentheses. The coefficients in each column of each of the two panels come from the same regression with the dependent variable defined by the panel. Each regression included the annual division batting average, manager's lifetime winning percentage, ballpark hitting factor, year dummies, tenure dummies, division dummies, and individual fixed-effects. The 2SLS regression uses "Teammates' Lifetime Batting Average" as the instrument for "Teammates Batting Average." The sample size in column (5) is 3968.

Table 6: Robustness Checks for Batters using First-Differences, 1970-2003

	OLS					2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
<u>Δ Batting Ave</u>						
Δ Teammates' Pitching ERA/100	0.388 (0.088)	0.650 (0.157)	0.207 (0.135)	0.340 (0.088)	0.424 (0.088)	0.401 (0.089)
Δ Teammates' Batting Average	0.166 (0.032)	0.174 (0.060)	0.104 (0.049)			
Δ Teammates' in Other Positions Batting Average				0.098 (0.027)		
Δ Teammates' Lifetime Batting Average					0.094 (0.072)	0.108 (0.083)
<u>Δ On Base Pct.</u>						
Δ Teammates' Pitching ERA/100	0.427 (0.092)	0.769 (0.167)	0.248 (0.142)	0.437 (0.093)	0.466 (0.093)	0.452 (0.094)
Δ Teammates' Batting Average	0.177 (0.034)	0.153 (0.064)	0.123 (0.053)			
Δ Teammates' in Other Positions Batting Average				0.114 (0.029)		
Δ Teammates' Lifetime Batting Average					0.054 (0.076)	0.062 (0.088)
Sample Restriction	None	Team Changers	Same ballpark, manager	None	None	None

Standard errors are in parentheses. The coefficients in each column of each of the two panels come from the same regression with the dependent variable defined by the panel. Each regression includes the Δ annual division batting average, Δ manager's lifetime winning percentage, Δ ballpark hitting factor, year dummies, tenure dummies, and the Δ division dummies. The 2SLS regression uses "Δ Teammates' Lifetime Batting Average" as the instrument for "Δ Teammates Batting Average."

Table 7: Robustness Checks for Pitchers using Fixed-Effects, 1970-2003

	OLS						2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pitcher's ERA							
Teammates' Pitching ERA	0.523 (0.081)	0.576 (0.114)					0.680 (0.206)
Teammates' ERA of Relief Pitchers			1.262 (0.083)				
Teammates' ERA of Starting Pitchers				0.643 (0.157)			
Teammates' Lifetime ERA					0.532 (0.161)		
Teammates' Lifetime ERA before season						0.261 (0.336)	
Teammates' Batting Average	-0.915 (3.136)	6.487 (4.599)	-3.499 (3.374)	-3.486 (6.601)	1.149 (3.134)	14.381 (8.457)	-1.403 (3.192)
Pitcher's Opponent's BA							
Teammates' Pitching ERA	0.014 (0.003)	0.016 (0.004)					0.025 (0.009)
Teammates' ERA of Relief Pitchers			0.034 (0.004)				
Teammates' ERA of Starting Pitchers				0.017 (0.006)			
Teammates' Lifetime ERA					0.020 (0.007)		
Teammates' Lifetime ERA before season						0.000 (0.014)	
Teammates' Batting Average	-0.204 (0.126)	0.091 (0.179)	-0.194 (0.150)	-0.508 (0.248)	-0.153 (0.126)	0.330 (0.338)	-0.237 (0.128)
Sample Restriction	None	One ballpark, manager per player	Starting Pitchers	Relief Pitchers	None	First Season on New Team	None

Standard errors are in parentheses. The coefficients in each column of each of the two panels come from the same regression with the dependent variable defined by the panel. Each regression includes the annual division batting average, manager's lifetime winning percentage, ballpark pitching factor, year dummies, tenure dummies, division dummies, and individual fixed-effects. The 2SLS regression uses "Teammates' Lifetime Pitching ERA" as the instrument for "Teammates Pitching ERA" The data for "opponents batting average" is missing for 1998-2002.

Table 8: Robustness Checks for Pitchers using First-Differences, 1970-2003

	OLS						2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ ERA							
Δ Teammates' Pitching ERA	0.348 (0.081)	0.498 (0.190)	0.204 (0.097)				0.551 (0.248)
Δ Teammates' ERA of Relief Pitchers				1.050 (0.086)			
Δ Teammates' ERA Starting Pitchers					0.593 (0.148)		
Δ Teammates' Lifetime Pitching ERA						0.410 (0.185)	
Δ Teammates' Batting Average	1.554 (3.208)	5.152 (7.301)	-0.831 (3.908)	3.821 (3.490)	-9.558 (6.254)	3.331 (3.197)	0.724 (3.350)
Δ Opponent's Batting Ave							
Δ Teammates' Pitching ERA	0.008 (0.003)	0.017 (0.009)	0.002 (0.004)				0.010 (0.012)
Δ Teammates' ERA of Relief Pitchers				0.026 (0.004)			
Δ Teammates' ERA Starting Pitchers					0.015 (0.006)		
Δ Teammates' Lifetime Pitching ERA						0.008 (0.009)	
Δ Teammates' Batting Average	-0.097 (0.137)	-0.143 (0.324)	-0.048 (0.164)	0.128 (0.159)	-0.702 (0.254)	-0.062 (0.136)	-0.106 (0.144)
Sample Restriction	None	Team changers	Same ballpark, manager	Starting Pitchers	Relief Pitchers	None	None

Standard errors are in parentheses. The coefficients in each column of each of the two panels come from the same regression with the dependent variable defined by the panel. Each regression includes the Δ annual division batting average, Δ manager's lifetime winning percentage, Δ ballpark hitting factor, year dummies, tenure dummies, and the Δ division dummies. The 2SLS regression uses "Δ Teammates' Lifetime Pitching ERA" as the instrument for "Δ Teammates Pitching ERA" The data for "opponents batting average" is missing for 1998-2002.

Table 9: Results for Pitchers and Batters, 1879-1970

	Fixed-Effect Results						
	Batters: Batting Ave			Pitchers: ERA			
Teammates' Pitching ERA	0.217 (0.068)	0.214 (0.068)	0.206 (0.068)	0.071 (0.035)			
Teammates' ERA of Relief Pitchers					1.402 (0.099)		
Teammates' ERA of Starting Pitchers						0.721 (0.453)	
Teammates' Lifetime ERA							0.541 (0.160)
Teammates' Batting Ave (BA)	0.263 (0.022)			1.213 (3.288)	1.479 (3.378)	-10.206 (14.717)	1.992 (3.300)
Teammates' in Other Positions BA		0.156 (0.018)					
Teammates' Lifetime BA			0.114 (0.032)				

	First-Differences						
	Batters: Δ Batting Ave			Pitchers: Δ ERA			
Δ Teammates' Pitching ERA	0.329 (0.074)	0.332 (0.074)	0.333 (0.075)	0.051 (0.037)			
Δ Teammates' ERA of Relief Pitchers					1.251 (0.102)		
Δ Teammates' ERA of Starting Pitchers						0.965 (0.542)	
Δ Teammates' Lifetime ERA							0.154 (0.207)
Δ Teammates' BA	0.182 (0.024)			1.677 (3.603)	3.482 (0.3.493)	8.081 (18.550)	2.174 (3.658)
Δ Teammates' in Other Positions BA		0.093 (0.020)					
Δ Teammates' Lifetime BA			-0.028 (0.041)				

Standard errors in parentheses. The fixed-effects sample sizes are 18092 for batters and 11202 for pitchers. The first-difference sample sizes are 13170 for batters and 7168 for pitchers. The ERA variables have been divided by 100 in the batting regressions. Additional control variables include those specified in previous tables for the earlier sample period. BA stands for "batting average."