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Dynamic Effort, Sustainability, Myopia, and 110% Effort

Stephen Shmanske[†]

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Abstract

By definition, giving 100% effort all of the time is sustainable, but begs the question of how to define 100% effort. As a corollary, once a benchmark for defining 100% effort is chosen, it may be possible, even optimal, to give a greater amount of effort for a short period of time, while recognizing that this level of effort is not sustainable. This dynamic effort provision problem is analyzed in the context of effort and performance by National Basketball Association (NBA) players over the course of a season. Within this context, several benchmarks for sustainable effort are considered, but these are rejected by the data. Meanwhile, the data are consistent with the proposition that NBA players put forth optimal effort, even if such effort is not always sustainable.

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[†] Department of Economics, California State University, East Bay, Hayward, CA 94542, stephen.shmanske@csueastbay.edu

Introduction

The usual starting point for the analysis of effort provision considers the incentives inherent in nonlinear payout schemes known as the tournament compensation model. Pioneered by Lazear and Rosen (1981), tournament models have analyzed effort, as proxied *ceteris paribus* by performance, in a variety of settings, including the final rounds of a golf tournament [Ehrenberg and Bognanno (1990a, 1990b)]. Effort provision also responds to other incentives and disincentives such as an incentive to shirk during one's final contract when future salary will no longer be determined by present effort and performance [Krautmann and Solow (2009)]. These models are essentially static in nature in that current effort depends on current incentives, which may be changing, but not on lagged effort nor on the expected future demand for effort. But if giving more (or less) effort in one period influences the amount of effort that one is able to supply in the next period, then the provision of effort is a dynamic phenomenon.

Consider National Basketball Association (NBA) players who must supply effort over an 82-game regular season. The notion of sustainability is brought in because players have scarce energy with which to supply effort. Indeed, energy expended in one game, if not recouped in the rest period between games, will impact the player's ability to supply effort in the next game. In this context there is a maximum, constant, amount of effort that could be supplied in each game. By definition, this level of effort is sustainable, but it is almost certainly not optimal. For example, it would be optimal to give greater effort at the end of a close game while fully realizing that such an effort level is not sustainable. Unsustainably supplying super effort is probably what is meant by colloquial reference to athletes giving 110%. The notion of unsustainably supplying 110% effort for a short duration requires a benchmark level of 100%

sustainable effort for comparison sake, and this becomes problematic because the notion of sustainability is vague enough to encompass a variety of ideas.

Sustainability is a loosely defined buzzword albeit one with a positive connotation. If an action or a policy is not sustainable, then it is not possible to continue it over a time horizon that is usually not explicitly stated. Environmentalists and other advocates for or against a certain policy will use its sustainability or lack thereof as a rhetorical device in their arguments. Such rhetoric may be effective; superficially, it seems obvious that sustainability is good and unsustainability is bad.

Economists, however, rarely use sustainability as a benchmark in evaluating actions, opting instead for optimality. Economists think in terms of benefits and costs, in total and on the margin, and if the benefits outweigh the costs, the action is desirable regardless of its sustainability. If such a desirable action is unsustainable it means only that at some future point the costs of the action will start to outweigh the benefits, at which point the action is no longer optimal and ceases to be undertaken. Note also that a fully sustainable action may be desirable to pursue for a period of time and then may cease to be desirable and cease to be continued if other costs or benefits change. Thus, sustainability is neither necessary nor sufficient for any action to be economically pursued. Likewise, unsustainability is neither necessary nor sufficient for any action to be eschewed. About the only thing that can be said about an unsustainable action is that it cannot continue forever and, therefore, must change at some future point. In this view it is surprising that, as a buzzword, sustainability carries any cache in the first place.

This paper extends the received static analysis of effort provision by adding dynamic feedback components from one period's effort to the next, and sheds light on the relationship between optimal actions and sustainable actions by examining the game-by-game effort expended by NBA players over the course of a season. In a nutshell, this paper considers several candidates for a benchmark level of sustainable effort and compares them to the dynamically optimal effort expended, by examining the statistically testable implications that come out of the comparisons.

A verbal discussion of theoretical relationships between optimal effort and sustainable effort is presented in the next section. The following section develops these ideas more formally with the goal of obtaining a regression model that can confront these theories. The data used to test the hypotheses are described in the fourth section. The results follow and a short summary concludes the paper.

Sustainable versus Optimal Effort

Consider a model in which a flow of effort can come from a stock of stored energy. The stock of energy is depleted, perhaps fully, perhaps only partially, as effort is expended during an NBA game. Then, following the game, the stock of energy is replenished during the rest period between games. Thus, the available stock of energy for game t, K_t, is defined recursively as a positive function of the amount of energy available for game t-1, K_{t-1}, a negative function of the amount of energy used up in supplying effort in game t-1, E_{t-1}, and a positive function of the amount of rest between games t-1 and t, denoted, R_t, and thought of as the amount of rest leading up to game t. Thus, $dK_t/dK_{t-1} > 0$, $dK_t/dE_{t-1} < 0$, and $dK_t/dR_t > 0$.

It is assumed that it is easier or less costly to supply effort the greater the amount of stored energy so that $dE_t/dK_t > 0$. By application of the chain rule to this partial effect and those in the preceding paragraph, the expected signs of the actual regression coefficients can be determined once the data, in particular the proxies for effort and rest, are described in the next section. For now, simply note that $dE_t/dR_t > 0$ and $dE_t/dE_{t-1} < 0$.

The preceding two influences on the supply of effort are backward looking, depending on previous effort levels and rest. There is also a forward looking, opportunity cost of supplying effort in game t. Indeed, effort expended in game t depletes the stock of energy available for the next game, especially if there is insufficient rest between games for a player's full recovery. Therefore, $dE_t/dR_{t+1} > 0$, may be an important factor in the supply of effort.

The demand for effort is simply described. First, assume that greater effort leads to greater performance, otherwise why try hard? Second, define greater performance as that which leads to an increase in the probability of winning the game, which is, after all, the ultimate goal. Finally, recognize that the marginal effect of performance on game outcome depends on the status of the game itself, especially the closeness of the score. For close games, the degree to which better performance can change the probability of winning is high, therefore, effort has greater value. For blowouts either way, better performance has little effect on changing the game's outcome, and the demand for effort is diminished.[1]

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[1]Empirical verification here will be tricky. In blowout losses, bad performance early in the game may have led to the blowout which decreases the demand for effort as the game winds down. In blowout wins, good performance early in the game contributes to the blowout which decreases the demand for effort as the game winds down. In close games, the demand for effort is high the whole game. In the data, effort is not observable, and performance is observable as

Economically speaking, optimal dynamic effort depends on the demand for and supply of effort as outlined above including the current game effects and the forward and backward-looking rest effects. Consider three versions of optimal effort. Dynamic effort should be appropriately correlated to measures that capture the static and dynamic effects on supply and demand as just explained. This will be called Model OD. If the dynamic effects are not important, then optimal static effort will depend on the current game effects but not on the forward or backward-looking rest effects. This will be called Model OS. Finally, if the dynamic effects are important, but the players and coaches ignore them, then the backward-looking rest variables will be important in a regression as current effort will be affected by previous effort provision, but the forward-looking opportunity cost of effort effect will be unimportant. This will be called model OM.

Whether these optimal (dynamic or static) effort levels are sustainable (that is, the player is giving 100% or less) or unsustainable (that is, the player is giving 110% effort) requires comparison to a benchmark, sustainable, effort level. Unfortunately, because of the vagueness of the concept, it is not clear what is meant by sustainability in this case. Therefore, consider the following three ways to characterize "sustainable" effort.

First, one could define 100% effort as a complete emptying of the tank of stored energy in each game.[2] The effort level achieved from game to game differs in this view. In doing so,

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an average over the whole game and not broken down as to early in game versus late in game.

[2] Sports fans without economic training will sometimes assert that the players are highly paid professionals who always give full effort and concentration to the task at hand, and if they

perhaps the idea of sustainability is being stretched too far.[3] Nevertheless, one could give 100% effort forever in this characterization. Also note that it is a definitional impossibility to give greater than 100% effort under this definition, but it is possible to shirk. This view has an interesting set of empirical implications. Since the store of energy is fully depleted at the end of each game, the amount of energy available for the next game depends only on the rest between games. Effort will be a function of backward looking rest, but not of forward looking rest, lagged effort, or the game situation. Call this Model A.

A second benchmark to which actual effort can be compared would require the same level of preparedness for each game, that is, $K_t = K^*$, which is a constant for all t. Meeting this benchmark exactly requires that the amount of effort expended in each game be the amount that can be replenished through the rest before the next game. Again, such a plan is sustainable by definition although it leads to a possibly different level of effort in each game. From this benchmark it is possible to give greater than 100% effort, but the consequence will be a lower state of preparedness for the next game. To get back on track, the effort in some future game must be lower than it otherwise could be (that is less than 100% effort) in order to build up the store of energy back to the level of K*. Empirically, if this type of sustainable effort is exactly provided, then effort is solely a function of forward looking rest and will not be correlated to

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do not, they are shirking.

[3] A forest could be completely clear-cut at differing pre-specified intervals forever. However, the yields per acre would not be identical through time and would depend upon the interval since the last harvest. This is not what is usually meant by sustainable forestry.

backward looking rest, lagged effort, or the current game situation. Call this Model B.

A third benchmark, perhaps, comes closest to the notion of sustainability as the ability to supply the same amount of effort in each game. In principle, one could calculate the closed form solution that maximizes a constant amount of effort that could be supplied in each game. A player starts with a stock of energy for game 1 and ends the season completely exhausting his energy at the end of the last game.[4] Compared to this benchmark, it is possible to give a greater amount of effort in a subset of games thereby necessitating a lesser amount of effort in other games to make up for it. By this benchmark, effort is a constant and is not related to lagged effort, backward or forward looking rest, or the current game situation. Call this Model C.

The regressions below will test the hypotheses of whether NBA players supply optimal effort as described above, or any one of three forms of sustainable effort. The next section formalizes these theories and moves us toward an empirically testable equation.

Toward an Empirical Model

Consider the following three equation model:

$$P_t = f(E_t, O_t, I_t) \tag{1}$$

$$E_t = g(K_t, R_{t+1}, S_t, H_t, I_t) \tag{2}$$

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[4] An additional, within-season technical constraint that the stock of energy be always non-negative complicates this calculation. I am neither doing the calculation nor contending that players or coaches do the calculation. Rather, I am offering this idea as a hypothesis that, economically speaking, I expect the data to reject.

$$K_t = h(K_{t-1}, E_{t-1}, R_t) \quad . \tag{3}$$

Disregarding subscripts,[5] P is the level of performance by a player in a particular game, O is a set of dummy variables indicating the opposing team for that game, referred to as opposing team effects, I is a set of dummy variables to capture each individual player's talent level, referred to as player effects, E is the effort expended, K is the stock of energy available, R is a vector of effects capturing the rest between games, S is the score differential in the game, and H is a dummy variable signifying whether or not the game is played in front of the home crowd.

This model would be straightforward except for the fact that neither the stock of energy at the beginning or end of each game, K, nor the amount of effort expended, E, are directly observable and measurable. Although this may make it seem hopeless at the outset, progress can be made if one can rely on the assumed existence of a stable, positive relationship between effort and performance, *ceteris paribus*. If such a relationship exists, and if the outside effects that shift the relationship can be controlled for, then the player's performance can be used as a signal of the effort supplied. Equation (1) is posited to be such a relationship.

In equation (1) the performance of a player depends on his own skill, the defensive pressure put forth by the opposing team, and the player's own effort. For the purposes of this paper, a regression of performance on the two sets of dummy variables capturing the player's average skill (and effort) level and the opponent's defense yields predictions of conditional

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[5]The t subscript does not indicate real time. It simply serves to keep each game in chronological order for each player. Subscripts t+1 and t-1 refer to the next game and the preceding game for that player. Individual subscripts, i, are also suppressed.

performance levels. The actual performance levels differ from the predictions (that is the residual errors) because of effort.[6] Thus, the errors in such a regression become a measure of effort. Essentially, performance, when suitably adjusted for differences among players and differences among the strengths of the opponents, becomes a proxy for effort.

Now consider equation (2), which posits that effort is a function of the stock of energy available, the forward looking rest which captures an opportunity cost of supplying effort now, the score differential in the game which relates to the benefit of supplying effort, home team status which encourages the supply of effort, and, possibly, player effects which capture differences among players in the ability to supply effort given the values of the other controls.[7]

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[6]. . . and because of luck. The residuals capture all the unmeasured effects including random luck. Ultimately, it may be impossible to disentangle the effect of luck from the effect of effort. Sometimes players are said to "make their own luck" by putting forth the extra effort. This type of luck can be attributed to effort. Any truly random luck adds an error which is uncorrelated with the underlying measure of effort contained in the residual. The effort variable will be the dependent variable in equation (2) and this random error will cause no problems other than lowering the potential to achieve a high R-squared. But when the recursive equation (3) is substituted into (2), lagged effort will be on the right hand side, and since it is measured with this random error due to luck, its coefficient and significance will be biased toward zero.

[7]Player effects may be unimportant in equation (2) since they were already captured in equation (1), however they will come back again once the recursive K series is introduced in

Equation (2) cannot be estimated because K is unobservable. But by successive substitution of the recursive equation (3), K_t can be eliminated for all t except t=1. Thus, K_t will be a function of K_1 , the stock of energy in the first game, E_1 through E_{t-1}, the effort expended in each game so far, and R_2 through R_t, the season-to-date accumulated rest. Thus, the g function in equation (2) becomes the g* function as follows:

$$E_t = g^*(K_1, E_1, \ldots, E_{t-1}, R_2, \ldots, R_t, R_{t+1}, S_t, H_t, I_t) \quad . \qquad (2^*)$$

In the empirical formulation of equation (2*) note a couple of things. First, K_1, the stock of energy available for the first game, need not be measured. If every NBA player is assumed to start with the same stock of energy, then K_1 is subsumed in the constant term. Alternatively, if each player starts with a different stock of energy, then the K_1 for each player is subsumed in that player's dummy variable in the set of player effects in I_t. Second, as a practical matter, NBA players must be able to recover rather quickly from game to game. It is unlikely that effort expended and rest between games early in the season will have a measurable effect late in the season or even a week later. Instead of including all the lagged amounts of effort and rest back to the beginning of the season, I include only the most immediate lag, which both intuitively and theoretically will have the most effect. Thus, the dynamic nature of the effort provision problem is captured by the backward and forward looking rest variables and the lagged effort variable. If these variables are insignificant, then the dynamic aspects of effort provision wane in importance. It is possible that NBA players can recover completely between games so that the

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equation (3). Ultimately, these player effects were insignificant and dropped from the analysis with no effect on the remaining coefficient estimates.

problem is not really a dynamic one.

We are now ready to describe the data, finalize the regression equations, and list the various testable hypotheses coming from the implications of Models A, B, C, OD, OS, and OM.

The Data

Line scores were retrieved for the top 200 players by scoring average for each NBA game of the 2007-2008 regular season. This list of players includes all of the important players in the league, both starters and reserves, as well as some unimportant players. Over a dozen aspects of each player's game are tracked, including points, rebounds, assists, shot attempts, personal fouls, etc. Additionally, information about the final score in the game, the home team, the opponent, and the team's schedule was gathered. Since each team plays 82 games, this data set has 16,400 observations give or take a few because traded players may end up with more or fewer than 82 eligible games. Player-games with zero minutes played are eliminated as well as the game before (the game in which the player may have been injured) and the game afterward (where a player coming back from injury might be testing his ability to play, and where the lagged effort and backward-looking rest would be misleading). Also dropped from the data were all lines from the first game of the season for each team, (no lagged effort available) and all games in the last week of the season (where star players sometimes rest in meaningless games). The finalized data set contained 12,557 observations. Summary statistics for the variables used in the regressions are provided in Table 1.

Auxiliary regressions were run to separate the players into two types. Minutes played was regressed on the absolute difference between the two team's scores to determine whether a player plays more or less in blowout games. The most important players are those who play less in blowouts and more in close games. So those players with negative coefficients in this regression make up the primary data set. Of the 200 players, 33 were dropped from the primary data leaving 10,428 observations.[8]

This paper uses two basic measures of NBA player performance, the NBA's own index, NBAEFF, which is an ad hoc arithmetic combination of some individual player statistics, and David Berri's "WINSCORE" which is a theoretically derived and statistically calibrated arithmetic combination of most of the same individual player statistics.[9] Berri's measure ought to be superior; if it is, and if the model in this paper is coherent, the results should be better with Berri's measure of performance, since it should have fewer idiosyncrasies adding random noise. Notwithstanding the theoretical superiority of WINSCORE, it is composed of many of the same statistics as NBAEFF and the two measures are highly correlated with a simple correlation coefficient of 0.93.

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[8] The regressions are run on the full data set and the filtered data set with virtually no difference in the overall results.

[9] See Berri, David J., Martin B. Schmidt, and Stacey L. Brook, The Wages of Wins: Taking Measure of the Many Myths in Modern Sports, Stanford University Press, 2006, and Berri, David J., "A Simple Model of Worker Productivity in the National Basketball Association," unpublished manuscript, 2008, for detailed discussions of the differences between the measures.

Both measures have the benefit of scalability. Thus, if you play just as effectively (or ineffectively) for twice as long, your WINSCORE, for example, will double. Thus, dividing WINSCORE by minutes played, WINSCOREPERMIN, gives a measure of the rate of a player's effectiveness, while WINSCORE itself measures overall performance in the game.

Remember that we are looking for a measure of performance that captures the effort expended. A crude measure of effort expended is given simply by a player's minutes played in a game. However, if the game is not close, a player might not be trying as hard as he would in a tight game. A player's minutes will not capture the intensity of supply of effort over those minutes. One then might consider using WINSCOREPERMIN, which captures this intensity. However, WINSCOREPERMIN might be high because players perform exceptionally well for a short period of time, leading to a blowout win, in which they do not play many minutes and, therefore, do not expend that much energy. The product of minutes played and WINSCOREPERMIN, that is, WINSCORE itself, avoids both of these problems, capturing the overall game performance by the player which should be correlated to the overall effort we are trying to measure.[10]

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[10] A similar issue arises in the measurement of shirking behavior, where "total bases" (TB) was shown to be superior to slugging average (SA) in the context of a baseball player's effort before and after signing a lucrative long term contract. SA does not capture time taken off and is interpreted analogously to WINSCOREPERMIN in this paper, whereas TB captures total effort and corresponds to WINSCORE in this paper. See Scoggins (1993) and Krautmann (1990).

Dummy variables for each opposing team are included in O_t to capture the effect of the opponent's defense on the player's performance. When all 30 dummy variables are included, the constant term in the regression is omitted. In the interest of saving space, the opponent effects are not reported.

Dummy variables for each player are included in I_t to capture individual player effects on performance. Alphabetically, LeMarcus Aldridge is dropped to avoid singularity in the estimation. In the interest of saving space, individual player effects are not reported.

There are several different measurable aspects of the rest variable. First and foremost is the number of days between games, DAYSREST, where games on consecutive days are coded to have one day of rest. If the team played on Tuesday and Wednesday, then DAYSREST = 1 for Wednesday's game. Forward looking rest is also potentially important and is measured as the number of days until the next game in DAYSNEXT. Therefore, in the above example, DAYSNEXT = 1 for Tuesday's game.

A second aspect of player's rest considers the proximity in time of other recent games. The NBA does not schedule a team for three nights in a row, but several times during a season a team will play four games in five nights. A dummy named, FOURINFIVE, equals one if the player-game in question is the fourth game in five nights for the player. This accounts for 3% of the usable player-game observations.

A third aspect of the rest between games is whether the team has to travel between games. A dummy variable, TRAVEL, equals one if the team's last game was in a different city. Thus TRAVEL equals one for all away games (with some exceptions for the two Los Angeles based teams), and for the first home game after completing a road trip. Finally, there may be jet lag effects from changing time zones that interfere with rest between games. This variable, called DELTATIZO, ranges from 3 (the extra hours one gets by going from the east coast to the west coast) to -3 for cross-continental travel from west to east.

HOME is a dummy variable equal to one for a game played at home. This is included to capture the possibility that favorable home town crowds make it easier for players to summon forth effort, or that coaches and players treat home games differently from away games with respect to maintaining sustainability throughout the season.

SCOREDIFF, is the absolute value of the difference in the final game score. A large value of SCOREDIFF indicates a blowout in which it may be optimal to provide less than 100% effort. When SCOREDIFF is low, the return to effort is the highest and more effort should be forthcoming.

It is possible that the effect of scarcity will show up most strongly in the second game of a back-to-back set when the player played many minutes in the first game. Therefore, a variable capturing the minutes logged by a player in the previous game is interacted with a dummy variable, BTOB, indicating a back-to-back game for the player in question. This variable is called MINLAGXBTOB.

Finally, a set of five (November through March with April excluded) monthly fixed effects is included. If players wear down over the course of the season, or if they summon forth more effort as the season progresses and individual games take on more importance, the fixed effects will pick up a positive or negative trend in the effort variable.

The actual statistical tests proceed in two steps, the first of which is to retrieve a series for player effort as the residuals from the estimation of equation (1). The first stage regression is run with each of WINSCORE and NBAEFF as the dependent variable, and the residuals from these (denoted RESIDWINSCORE and RESIDNBAEFF) become the measure of EFFORT for the game in question. There is nothing too remarkable to report from this stage. Superstar players have high positive coefficients and good defensive teams negatively affect opposing player's performances as expected. Overall, player effects and opposing team effects explain 25.3% of the variation in WINSCORE and 32.6% of the variation in NBAEFF.

RESIDWINSCORE and RESIDNBAEFF are both lagged one game to appear on the right hand side of equation (4) below. Forming these lags reduces the data set further to 12011 usable observations on the full set of 200 players, and 9984 observations on the reduced data set of 167 top players. Summary statistics for these variables are also listed in Table 1. As the table shows, there is still a lot of variation in these residuals. Glances at some correlations indicate that these residuals are not misbehaving. RESIDWINSCORE is closely correlated (0.87) with WINSCORE, as is RESIDNBAEFF with NBAEFF (0.82). This is simply a confirmation that the opponent effects and the individual player effects in equation (1) leave unexplained a large part of the variation in performance. That is, a large part of the variation in performance is due to game by game differences in effort (and luck). Furthermore, RESIDWINSCORE and RESIDNBAEFF are even more highly correlated (0.95) than the correlation between the performance levels, WINSCORE and NBAEFF, themselves (0.93). However, serial correlation seems to be absent. Indeed, the residuals and their corresponding lags are not closely correlated (0.013 for RESIDWINSCORE and its lag, and 0.04 for RESIDNBAEFF and its lag.) This paper is interpreting this unexplained variation from these equations as measured in the residuals as being due to differences in effort from game to game.

In the second step, these residuals, called "EFFORT," are regressed on a set of variables that can distinguish among models OD, OS, OM, A, B, and C, in the following truncated version of equation (2*):

$$\text{EFFORT} = g^*(\text{EFFORT}_{-1}, \text{DAYSREST}, \text{DAYSNEXT}, \text{TRAVEL}, \text{DELTATIZO}, \text{HOME}, \text{SCOREDIFF}, \text{FOURINFIVE}, \text{MINLAGXBTOB}, \text{NOV}, \text{DEC}, \text{JAN}, \text{FEB}, \text{MAR}, \text{I},) \quad . \qquad (4)$$

Model A captures the hypothesis that sustainable effort means a complete emptying of the tank of energy in each game. Therefore, EFFORT should depend on backward looking rest variables, (DAYSREST, FOURINFIVE, MINLAGXBTOB). EFFORT may also depend on travel schedules or time zone changes (TRAVEL, DELTATIZO), but should be unaffected by the other variables on the right hand side.[11]

Model B captures the hypothesis that sustainable effort means that coaches and players attempt to assure that there is the same available stock of energy for each game. Therefore, EFFORT should depend positively on forward looking rest (DAYSNEXT) but be unaffected by the other variables.

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[11]HOME may or may not be significant, but if it is, it should be positive. For example, one could modify Model A to posit that all energy be used in home games, perhaps to maximize home attendance, but that some energy be reserved in away games. Similar arguments can be made for the other models.

Model C captures the hypothesis that sustainable effort means a constant amount of effort and none of the variables in equation (4) should be significant.

Model OS captures optimal static effort. Only the current game situation, as captured in SCOREDIFF, is important. The other variables will be insignificant because players can recover sufficiently even in back-to-back games so that the problem is not really a dynamic one.

Model OM captures "optimal" effort with no foresight. The current game situation (SCOREDIFF) is important as are the variables that capture the backward-looking rest and lagged effort variables. However, the forward-looking rest variable will not correlate to current effort because of the lack of foresight by the myopic decision makers.

Finally, OD captures optimal, dynamic effort. Theoretically, any or all of the right hand side variables can affect the effort given in each game. Effort expended in the previous game should negatively affect the ability to supply effort in the current game. Backward and forward looking rest and travel schedules can affect the supply of effort. As in the other optimal models, the current game situation should have a major effect; the closer the game, the more effort. Thus, SCOREDIFF should be negatively correlated with effort.

Table 2 lists the variables and their theoretically expected effects in each of the models.

Results

Table 3 lists the results for several runs of equation (4).[12] The results do not provide

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[12]The individual player effects in I were not significant and are not reported. Dropping

overwhelming support for any of the models in the sense that only a very small percentage of the variation in the residuals is explained in the models. However, the pattern of the coefficient estimates matches the pattern of Model OS, that is, optimal effort supply in a static setting. Game scheduling effects and travel do not seem to matter. Only two variables, HOME and SCOREDIFF, are consistently significant in all the equations. None of the variables capturing rest (forward or backward looking), travel, or jet lag seem to be important. And the lagged effort variable, which is expected to be negative, if heroic effort in one game diminishes the ability to supply effort in the next game, is consistently positive and sometimes significantly so.

Nevertheless, the following tentative inferences can be supported. First of all, Models A, B, and C, which capture different ways to think about sustainable effort, can be rejected based on the significant negative effect of SCOREDIFF. Under the null hypotheses of Models A, B, and C, SCOREDIFF should be insignificant. That is, if providing sustainable effort is what guides player behavior, then the game situation should have no effect on the amount of effort forthcoming. But the data proves that the larger the final score differential, the smaller amount of effort is forthcoming from the players.

On the other hand, the significant coefficient of SCOREDIFF is consistent with the predictions of the models capturing the optimal supply of effort. Thus, the data support confirmation of the belief that optimal effort is being supplied, albeit in a static setting where only the current game situation is important (Model OS). There is no support for dynamic effects either recognized (Model OD) or unrecognized (Model OM).

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the player effects did not affect the other coefficients

From the consistently positive and significant effect of HOME, one concludes that players perform better at home, controlling for their own average performance and the average defensive intensity put forth by opponents. This begs the question of why. It may be easier to translate effort into high performance at home due to familiar surroundings, or it may be easier to supply effort at home due to enthusiastic crowds, or players may be "luckier" at home. This variable really does not distinguish among the models which with slight modification could be reinterpreted to support higher optimal levels of effort at home (to impress local fans increasing both home attendance and the player's future bargaining power in salary negotiations) or to support a bifurcated sustainability that favors extra effort at home for the same reasons.

From the insignificance of the coefficients of the travel and rest variables, one cannot claim support for Model A, B, OD, or OM. These models predict that the rest between games, either forward looking, backward looking, or both should affect the effort level. If these effects do exist, they are too small to pick up in this approach. Some support is given to Model C which posits constant effort, but this model is already rejected due to the significance of SCOREDIFF.

The positive coefficient of the lagged effort variable presents a puzzle. The effect is predicted to be zero in the sustainable effort models and negative in the optimal effort model if using up energy in one game lowers the amount of energy and potential effort in the next game. I offer two possible explanations for the results.

The first possibility notes that the coefficient of lagged effort, although positive, is insignificant when WINSCORE is used to create the data series for effort.. Thus, the significant coefficient when NBAEFF is used can be dismissed as an anomaly due to the ad hoc nature of the formulation of the performance variable. The insignificant result using WINSCORE is consistent with theory if the effect of using up energy in one game does not have a measurable effect on the amount of energy available in the next game as hypothesized in Model OS.

The second possibility centers on the possible existence of streaky performance or a new type of "hot hand" effect.[13] For reasons that are not well understood, players can go through slumps or hot spells during the season. NBA players are not immune from personal problems, biorhythms, or a myriad of other psychological influences that can affect their play for better or for worse. Nagging injuries or other health concerns may last for several games in a row in which the player underperforms. Then, when fully healthy again, a string of relatively improved performances can ensue. These effects are player specific and idiosyncratic, but if they are quantitatively important, they could explain the positive coefficient on the lagged effort variable.

Finally, the monthly fixed effects do show a trend of increasing performance/effort as the season goes on. This is understandable for several reasons. Most players improve over the course of the season as they mature, as they learn the tendencies of their teammates, and as they become more familiar with the coach's systems and expectations. Indeed, players who do not improve will find themselves playing fewer minutes as the season progresses so that the remaining players will have to supply the effort that their non-performing teammates are not supplying. Furthermore, as the season progresses, the remaining games take on additional importance as the relative position of the teams in the standings becomes clearer.

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[13]The usual "Hot hand" literature in basketball focuses on consecutive shots made within a game as opposed to stellar performance in a string of games. See Gilovich, et. al. (1985).

Summary and Discussion

This paper examines performance by NBA players over the course of the 2007-2008 season. A first stage regression "explains" performance as a function of individual player effects and opposing team effects. Once controlling for the skill of the player and the defensive tenacity of the opponent, the residual performance is used as a proxy for the effort that the player expended in each particular game. In a second stage, these effort levels were used as the dependent variables to determine which, if any, independent effects have an important influence on effort.

A variety of definitions of what constitutes sustainable effort are rejected by the data because the closeness of the game is an important determinant of the effort provided. In contrast, the view that NBA players supply optimal effort with no dynamic feedback from one game to the next is supported by the data. Indeed, when extra effort is required in a close game, the NBA players can and do provide it.

Distinguishing between optimal effort and sustainable effort is important when it comes to identifying shirking behavior in a dynamic model. Shirking usually means the provision of a reduced level of effort as part of a principle-agent problem with asymmetric information and costly measurement of underlying effort. In the language of this paper shirking would correspond to the provision of less than 100% of "optimal" effort. In a dynamic setting, it is crucial to realize that the time series of optimal, as opposed to sustainable, effort be the benchmark to which actual effort is compared in trying to identify shirking. Unfortunately, not a whole lot can be said about shirking based on the data in this paper because the lagged effort variable and the rest, travel, and scheduling variables, which would be evidence of the dynamic setting, were all insignificant.

TABLE 1

Summary Statistics

Variable name	mean	standard deviation	minimum	maximum	n
DAYSREST	2.08	0.94	1	7	12557
DAYSNEXT	2.08	0.94	1	7	12557
TRAVEL	0.748	0.43	0	1	12557
DELTATIZO	0.003	0.89	-3	3	12557
FOURINFIVE	0.03	0.17	0	1	12011
BTOB	0.25	0.43	0	1	12011
HOME	0.499	0.50	0	1	12557
SCOREDIFF	11.53	8.12	1	52	12557
MINUTES	30.82	8.94	1	56	12557
NBAEFF	15.27	9.54	-11	56	12557
WINSCORE	6.11	6.02	-12.5	32	12557
WINSCOREPERMIN	0.185	0.19	-1	1.2	12557
RESIDWINSCORE	0.010	5.22	-17.6	23.9	12011
RESIDNBAEFF	0.031	7.86	-29.8	36.4	12011

TABLE 2

Expected Effects by Model

Variable	Model A	Model B	Model C	Model OS	Model OM	Model OD
EFFORT-1	0	0	0	0	-	-
DAYSREST	+	0	0	0	+	+
DAYSNEXT	0	+	0	0	0	+
TRAVEL	-	0	0	0	-	-
DELTATIZO	+	0	0	0	+	+
SCOREDIFF	0	0	0	-	-	-
FOURINFIVE	-	0	0	0	-	-
MINLAGXBTOB	-	0	0	0	-	-
HOME	+?	+?	+?	+?	+?	+?
Monthly effects	0	0	0	?	?	?

TABLE 3
Equation (4) Coefficient Estimates and (t-statistics)

Dependent variable	RESIDWINSCORE		RESIDNBAEFF	
Sample	top 200	top 167	top 200	top 167
Constant	0.158 (0.51)	0.250 (0.71)	0.875* (1.87)	1.158** (2.21)
Lagged dependent	0.012 (1.29)	0.009 (0.92)	0.039*** (4.26)	0.032*** (3.24)
DAYSREST	-0.079 (-1.22)	-0.081 (-1.12)	-0.143 (-1.47)	-0.168 (-1.56)
DAYSNEXT	-0.028 (-0.52)	-0.057 (-0.95)	-0.064 (-0.79)	-0.088 (-0.98)
TRAVEL	0.208 (1.52)	0.295* (1.93)	0.221 (1.08)	0.326 (1.44)
DELTATIZO	0.011 (0.20)	0.012 (0.20)	0.040 (0.50)	0.036 (0.40)
HOME	0.912*** (7.67)	1.069*** (8.09)	1.294*** (7.26)	1.508*** (7.66)
SCOREDIFF	-0.019*** (-3.18)	-0.031*** (-4.71)	-0.071*** (-8.03)	-0.099*** (-10.11)
FOURINFIVE	0.370 (1.27)	0.432 (1.33)	0.537 (1.23)	0.551 (1.14)
MINLAGXBTOB	-0.007 (-1.50)	-0.009* (-1.77)	-0.006 (-0.87)	-0.010 (-1.33)
NOV	-0.673*** (-2.93)	-0.618** (-2.38)	-1.074*** (-3.11)	-0.976** (-2.52)
DEC	-0.536** (-2.36)	-0.480* (-1.86)	-0.744** (-2.18)	-0.618 (-1.61)
JAN	-0.248 (-1.09)	-0.234 (-0.91)	-0.340 (-1.00)	-0.315 (-0.82)
FEB	-0.029 (-0.12)	-0.165 (-0.63)	0.054 (0.15)	-0.137 (-0.35)
MAR	-0.002 (-0.01)	-0.069 (-0.27)	0.063 (0.19)	-0.062 (-0.16)
N	12,011	9,984	12,011	9,984
Adj. R-squared	0.009	0.011	0.014	0.018

*, **, *** indicated significance at the 0.10, 0.05, 0.01 levels, respectively

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