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Fundamentals or Noise? Evidence from the Professional Basketball Betting Market

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ABSTRACT

This paper uses the betting market for professional basketball games to address the issue of unexplained asset price volatility. A pricing model is presented which identifies two components in point spreads for professional basketball games. Both components—the market's estimate of relative team abilities and an idiosyncratic factor—are essentially unobserved, but can be identified ex post. The structure of this market enables tests of competing hypotheses about point spread variation. The tests reject the hypothesis that variation in the two components represents irrelevant noise. The hypothesis that unobserved fundamentals account for this variation is consistent with the data.

IT IS WELL KNOWN that fundamentals-based models explain only a fraction of the variation in prices of financial assets—most of the variation is left in the error term. Two strands in the recent literature address this issue. One strand, in which Shiller's (1989) work is prominent, examines the relation between the present value model, aggregate dividends, and stock prices. These studies typically find that observed price variability exceeds that predicted by the textbook model. Cochrane (1991, 1992) argues that modifications within the confines of rational models can account for these observations. Others see it differently; for example, LeRoy (1989) concludes that "regrettably, it appears as if it is the assumptions of rationality and rational expectations that require reformation."

This paper addresses a second strand of the literature, which attempts to identify the sources of price changes for individual assets. If it could be shown that measurable fundamentals systematically account for the bulk of the variation in prices of individual assets, then the idea that investor irrationality explains the excess volatility result would be suspect. But these studies, best exemplified by Roll (1984, 1988), have been unsuccessful in this regard. Roll attempted to produce a systematic ex post account of the factors which changed stock prices (1988) and orange juice futures (1984). The orange juice study is particularly instructive. Roll selected the orange juice market in the hope of isolating a single predominant source of day to day price variation: exogenous changes in weather. The most intriguing finding of the study

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confirmed this notion: returns in the futures market predicted subsequent errors in the forecasts of the National Weather Service. Nevertheless, Roll concluded that "no factor... can explain more than a small part of the daily price movement in orange juice futures. There is a large amount of inexplicable price volatility." A similar conclusion holds for stock prices.

The inability to provide ex post explanations for price changes has been viewed by many as a failure of the fundamentals-based model. Summers (1986) for example, argues that the "difficulty economists have had in explaining any significant amount of the variation in speculative prices... suggests that valuation errors are being made continuously." On this view, the pricing model's error term is noise that is unrelated to fundamental valuation.

An alternative view holds that the error term represents fundamentals which are known to (some) traders but are unobserved by the econometrician. This view traces back at least to Hayek (1945). Hayek argues that prices summarize complex signals, capturing "the particular circumstances of time and place." To Hayek, the idea that the determinants of prices could be fully identified in a simple model was a vain hope.[1] Thus, a pricing model's error term is packed with fundamental information in this view, although the fundamentals themselves are difficult to identify.

The unobserved fundamentals hypothesis, although a classic view, must be made refutable before it can be a satisfactory explanation for price variability. The stock market suffers from the curse of dimensionality in this regard. In the standard model, stock prices are valuations of expected future cash flows. Abnormal returns—whether due to observable components that can be explicitly modeled or otherwise—correspond to changes in expected cash flows. However, the change of interest can take place at a vast number of future dates (or indeed the changes may not be realized). This makes linking the error term to the hypothesized changes a daunting task. Although event studies draw inferences from the error term, this amounts to a use of the fundamentals-based model, and not a test of it.

The point spread market provides conditions which enable tests of the unobserved fundamentals hypothesis. This paper tests the hypothesis by studying game to game variation in point spreads for professional basketball games. Hayek's view is testable here because the point spread forecasts a single event with an observable outcome: the difference in points scored by opposing teams. Hence, variations in point spreads, whatever their source, face a day of reckoning when the game is played. For the fundamentals-based view to be correct, components in the point spread stemming from unobserved sources must be essential to unbiased prediction of the game's outcome.

[1] Hayek (1945) argues that market-determined prices were essential for a society to make use of the knowledge possessed by individuals. He makes frequent reference to the inability of economists, planners, or "a single mind" to calculate market prices. What is important in prices "is knowledge of the kind which by its nature cannot enter into statistics and therefore cannot be conveyed to any central authority in statistical form." (p. 524).

We use a point spread pricing model developed in Sauer (1991) to test the hypothesis that error terms in pricing models represent unobserved fundamentals. This model decomposes market point spreads (PS) into two components:

$$\mathrm{PS}_t = \delta_t + \epsilon_t. \tag{1}$$

The first component, δ_t, is based on the relative abilities of the opposing teams. The residual component, ϵ_t, comes from a noise source that is unobserved by the econometrician. We show in the paper that variation in δ_t accounts for the vast majority (85 percent) of variation in point spreads between basketball games. Our focus, however, is on the residual component. Suppose we find that ϵ_t is unrelated to game scores. This is but one instance in which an "error term is irrelevant noise" hypothesis would be supported. On the other hand, the hypothesis that the error term represents unobserved fundamentals would be supported only if the residual is related to game scores in a precisely defined way.

For this analysis to be credible it is essential that systematic point spread variation be fully captured by the model. Otherwise we would be mislabeling systematic factors as unobservables. We are thus fortunate that variation in δ_t accounts for such a high percentage of point spread variation. Hence, our problem is not whether we have omitted readily observable factors from the model. Rather, is there anything left in the residual which might be relevant in forecasting game scores?

The following section provides background on the point spread market and the pricing model. In Section II we determine if unobserved fundamentals can account for variation in the noise term. Section III analyzes changes in the team ability estimates. Section IV discusses our findings in the context of current research in financial economics.

I. A Point Spread Pricing Model

A. *A Brief Overview of the Point Spread Market*

Point spreads, like prices in financial markets, can be viewed both as market clearing prices and predictions of outcomes. The outcome of interest here is the score of the game, or more precisely, the difference in points scored by the two teams. Suppose that the Chicago Bulls host the visiting Milwaukee Bucks and that the wagering market clears with a point spread which favors the Bulls by 5 points. This means that bets on the Bulls are winners only if the Bulls win by more than 5 points. Similarly, bets on the Bulls lose if the Bucks either win, or lose by less than 5 points.[2] If the Bulls win by 5 all bettors get their money back.

In an efficient market, the point spread will be an optimal forecast of the difference in points scored by the two teams. Clearly, if the optimal forecast

[2] Winning bets return a profit of \$10 for every \$11 bet. The discussion is brief: see Gandar *et al.* (1988) for more details.

deviates sufficiently from the point spread, informed bettors can capitalize by betting on the appropriate team. As in any market, if the Bulls are underpriced (let the spread be 1 point and the optimal forecast 5), there will be excess demand for this asset: i.e., bettors will want to go long on the Bulls and short on the Bucks. Thus, point spreads which depart from optimal forecasts are profit opportunities, and would not be observed in an efficient equilibrium.

Table I presents some descriptive statistics on the data analyzed in this paper. The data comprise a sample of 5636 games played over six consecutive seasons beginning in 1982. The point spreads (PS) are observations from the Las Vegas betting market, and are recorded in Livingston (1989).[3] The actual difference in the score of a game is denoted by DP. Both DP and PS are ordered on a home team less visiting team basis. Thus, the average value of DP (3.69 points in 1982) is the average number of points by which the home team outscored the visiting team. Since each team plays an equal number of games at home and on the road, DP is a measure of the home court advantage. The average value of PS (3.45 points in 1982) can be interpreted as the betting market's estimate of the home court advantage.

We can see from Table I that the actual home court advantage (DP), and the market's estimate of it (PS), have both increased substantially in recent years. The forecast error is denoted by FE = DP − PS. The mean forecast error is positive (though small) in five of the six years, indicating that home

Table I

Means and Standard Deviations of Home Team–Visiting Team Point Differences

Data are from the *Basketball Scoreboard Book*. N denotes the number of observations for each year. The NBA regular season consists of 943 games; games for which point spreads were not offered are excluded. $\overline{\mathrm{DP}}$ and s(DP) are the sample mean and standard deviation of the difference in points scored between the home and visiting team. $\overline{\mathrm{PS}}$ and s(PS) are the sample mean and standard deviation of the point spreads. The mean forecast error of the point spreads is $\overline{\mathrm{FE}}$; s(FE) is the standard deviation of FE. $p(h_0)$ is the p-value from testing the hypothesis that E(FE) = 0.

Season	N	$\overline{\mathrm{DP}}$	s(DP)	$\overline{\mathrm{PS}}$	s(PS)	$\overline{\mathrm{FE}}$	s(FE)	$p(h_0)$
1982–83	943	3.69	12.4	3.45	6.1	0.24	10.9	0.491
1983–84	941	4.79	11.4	4.33	4.3	0.46	10.7	0.189
1984–85	933	3.63	12.4	3.84	5.0	−0.21	11.3	0.574
1985–86	938	4.57	12.6	4.45	5.5	0.11	11.4	0.761
1986–87	943	5.17	13.2	4.89	6.0	0.28	11.7	0.463
1987–88	938	5.84	12.4	5.29	6.2	0.55	10.9	0.120
All 6	5636	4.62	12.4	4.38	5.6	0.24	11.2	0.113

[3] Livingston reported to us that the data are recorded at 5 P.M. eastern time on a typical weeknight, about 2.5 hours prior to the start of play. There were 943 games played in each of the six seasons. Point spreads were not offered for 22 games over this period, which is why we don't have a complete set of 5658 observations.

teams did slightly better than predicted, on average, by the market. Nevertheless, the hypothesis that the market correctly measured the home court advantage (i.e., that the mean value of FE is zero) is not rejected for any of the six seasons. Although the measures of central tendency coincide, there is a great deal of unpredictability in the score differences. This is indicated by the high standard deviation of point differences relative to point spreads.

Many papers have tested the hypothesis that point spreads are optimal forecasts. Some studies partition point spread samples and test directly for profitable wagering rules (a recent example is Camerer (1989)). While there are published examples of profitable rules, these correlations may be spurious (see Sauer *et al.* (1988)), and in any event tend to fade over time (Tryfos *et al.* (1984) and Gandar *et al.* (1988)). Thus, the optimal forecast hypothesis seems at least a useful first approximation. In the following sections, we use this hypothesis in a model which allows us to focus on the problem of unobserved sources of variation in market point spreads.

B. The Model

Point spreads for National Basketball Association (NBA) games are typically offered only on the day of the game. Thus, a series of price responses to information events is not observed.[4] Estimates of point spread changes can be constructed with a simple point spread pricing model. The model is designed to produce a base-line point spread that would be observed in the absence of adjustments due to abnormal factors.

The model maintains that the outcome of a game (the difference in score) is a function of luck, the home court advantage, and the relative ability of the two teams. In addition, both observable (e.g., injuries to key players), and unobservable (idiosyncratic) factors also affect scores. Our objective is to obtain parameter estimates of these factors.

Score differences are thus generated by the following:

$$\mathrm{DP} = g\left(S_i^H, S_j^V, v, \omega\right). \tag{2}$$

DP is the points scored by the home team (i) less the points scored by the visitor (j). S_i^H and S_j^V represent the ability of team i when it plays at home, and team j when it plays on the road. v and ω are random components, where ω represents "luck" that cannot be anticipated, and v represents factors that may be known to the market, e.g., injured players, fatigue, match-up problems, etc.

We assume that $g(S_i^H, S_j^V, v, \omega)$ has a linear form given by

$$\mathrm{DP} = S_i^H - S_j^V + v + \omega. \tag{3}$$

[4] For National Football League games, within week point spread changes have been studied by Gandar *et al.* (1988). The typical change in spreads from open to close is generally negligible; it would seem that most of the new information is incorporated at the opening of the market.

Since luck cannot be foreseen, the following condition implies the absence of profit opportunities:

$$\text{PS} = \text{E(DP)} = S_i^H - S_j^V + v \tag{4}$$

This condition, if satisfied, assures that the sign of DP − PS cannot be predicted.[5]

A parsimonious version of the model is obtained if we assume that each team's ability is increased by a common increment (h) over its base line ability (S_i) when playing at home. Thus,

$$S_i^H = S_i + h = S_i^V + h. \tag{5}$$

The estimation technique exploits the fact that each game includes a single home team and a single visiting team. Let $D_{it}^H = \{1$ if team i is the home team for game t, 0 otherwise$\}$ and $D_{it}^V = \{1$ if team i is the visiting team for game t, 0 otherwise$\}$. Let $D_{it} = D_{it}^H - D_{it}^V$. D_{it} is thus a dummy variable with the value of 1 if team i is the home team, −1 if team i is the visitor, and 0 if team i is not a participant in game t. Using (5), the definition of D_{it}, and relaxing the coefficient restrictions between (3) and (4), the model becomes:

$$\text{DP}_t = h_1 + \Sigma_i S_{1i} \cdot D_{it} + v_{1t} + \omega_t \tag{6}$$

$$\text{PS}_t = h_2 + \Sigma_i S_{2i} \cdot D_{it} + v_{2t}. \tag{7}$$

Equations (6) and (7) define a fixed effects regression model which yields coefficient estimates for the home court advantage (h_1, h_2) and abilities ($S_{1i}, S_{2i}, i = 1, \ldots 23$) of the 23 teams. We estimate the model separately for each season since both team abilities and the home court advantage change between seasons.

Table II presents coefficient estimates and summary statistics obtained by OLS estimation of (6) and (7) for the 1982–1983 NBA season. A fact that is immediately apparent is that the point spread equation explains a much greater proportion of its variance ($R^2 = 0.889$) than does the DP equation ($R^2 = 0.274$). This is expected of course, since the DP equation has the additional noise source in unforeseeable luck. Nevertheless, the lower R^2 of the DP equation illustrates the difficulty in predicting what actually happens in a game.

The standard error of the point spread regression is about 2 points. This seems fairly small: it amounts to a single basket scored by one of the two teams. Additional perspective on the model's precision can be obtained by considering the estimates of team abilities. Since the regression uses only 0/1 indicator variables, these estimates are measures of points as well. In Table II, the relative ability estimates have been calibrated such that the

[5] This works only if the DP distribution is symmetric, which is the case for this data (see Sauer (1991)). A better definition of an efficient point spread market requires that $p \in [0.5 - \tau, .5 + \tau]$, where p is the probability of correctly predicting the sign of DP − PS, and τ is a function of the market maker's take (4.55 percent when the book is balanced). This implies PS = MEDIAN(DP) for $\tau = 0$, and PS = E(DP) under symmetry.

Table II

Estimates of the Fixed Effects Point Spread Pricing Model, 1982–1983 NBA Season

The coefficients are OLS estimates obtained from independent estimation of

$$\mathrm{DP}_t = h_1 + \Sigma_i S_{1i} \cdot D_{it} + v_{1t} + \omega_t$$
$$\mathrm{PS}_t = h_2 + \Sigma_i S_{2i} \cdot D_{it} + v_{2t}$$

Each equation regresses the point difference DP_t (or point spread PS_t) on a constant and a set of 0–1 dummy variables D_{it} indicating which team is the home team and which team is the visitor. The coefficient on the constant in each regression is the home court advantage (h), and is listed below as Home Court. The coefficients on the dummy variables are estimates of team abilities. These coefficients are labeled as the team nicknames (i.e., Hawks and Celtics) in the table. The fixed effects model identifies only relative team abilities. The Bullets were the omitted team in the regressions and are therefore the numeraire. The coefficients in the table convert the regression estimates from a "relative to the Bullets" to a "relative to the average team" measure. Let S_i^A denote the latter; then the regression delivers $S_i = S_i^A - S_{Bullets}^A$, $i = 1, \ldots, 22$. Since $\Sigma_{i=1}^{23} S_i^A = 0$ the coefficient for the Bullets is $S_{Bullets}^A = -(1/23) \cdot \Sigma_{i=1}^{22} S_i$, and the remaining S_i^A are readily calculated. The coefficients reported below are therefore ability estimates relative to the average team.

	DP Equation $R^2 = 0.274$ Std. Error of Regression = 10.7		PS Equation $R^2 = 0.089$ Std. Error of Regression = 2.06	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
Home Court	3.66	0.349	3.40	0.067
Hawks	−0.73	1.597	0.24	0.309
Celtics	5.31	1.611	6.45	0.311
Bulls	−4.42	1.597	−3.14	0.309
Cavaliers	−6.79	1.606	−6.94	0.310
Mavericks	−0.69	1.659	−0.90	0.321
Nuggets	−0.10	1.674	0.51	0.323
Pistons	−0.18	1.606	−0.47	0.310
Warriors	−3.23	1.654	−2.46	0.320
Rockets	−11.11	1.659	−7.83	0.321
Pacers	−5.32	1.588	−3.93	0.307
Clippers	−4.60	1.659	−4.13	0.321
Lakers	5.07	1.659	6.67	0.321
Bucks	4.31	1.597	3.59	0.309
Nets	2.77	1.597	1.49	0.309
Knicks	2.57	1.597	−1.01	0.309
76ers	7.56	1.597	6.78	0.309
Suns	4.62	1.659	2.98	0.321
Blazers	1.90	1.659	1.31	0.321
Kings	1.05	1.659	0.18	0.321
Spurs	3.22	1.663	2.59	0.322
Sonics	2.90	1.659	3.31	0.321
Jazz	−4.08	1.646	−4.80	0.318
Bullets	−0.03	1.659	0.47	0.321

mythical average team receives an estimate of 0. The estimated home court advantage is 3.4 points. Thus a contest between two teams of equal ability would see the home team favored by 3.4 points (1.7 times the standard error of the regression). The team with the highest ability in both equations for 1982 is the Philadelphia 76ers, who won 60 out of 82 regular season contests and the NBA championship. The Rockets are the worst team in both equations. Given the home court advantage of 3.4 points, the model implies that the 76ers would be favored to beat the Rockets by $3.4 + 6.8 - (-7.8) \approx 18$ points at home. Clearly, the model implies substantial differences between the best and the worst teams in the league. More important, the model's standard error is a small fraction of the range of both predicted and actual point spreads.

We formally test the null of market efficiency by imposing the restriction that the ability coefficients be equal in the two equations. We use two asymptotically equivalent methods for each of the six seasons.[6] The results are summarized in Table III. The first method uses the seemingly unrelated regression estimator and imposes the equality restrictions with joint estimation of the equations. These restrictions are tested with a Wald statistic. In none of the seasons do the p-values call for rejection of the null that the market's estimate of team abilities is the same as the abilities obtained from game scores.

An alternative method of imposing these restrictions regresses the forecast error ($DP_t - PS_t$) on the same set of variables. Efficiency implies that the forecast error be uncorrelated with the teams; i.e., the team dummy coefficients should be zero in this regression. The right-hand columns in Table III contain the R^2, the calculated F-statistic under the zero restrictions, and the associated p-values. The highest R^2 is 0.03, and the p-values are quite close to their counterparts from the Wald tests. Again, the market and the games provide similar estimates of team abilities.

This test of the fixed effects model requires that the market's evaluation of relative team strengths be consistent with game outcomes. Although more burdensome than most tests in the point spread literature, it asks relatively little of the market.[7] But passing these tests is necessary before we proceed to our analysis of the error term.

II. Analysis of the Idiosyncratic Component in Market Point Spreads

In this section we identify and analyze variation in the idiosyncratic component of market point spreads. Identification proceeds in the following

[6] See Abel and Mishkin (1983) for a discussion of these methods.

[7] A common test in this literature examines the hypothesis that $a = 0$ and $b = 1$ in the equation $DP = a + b^*PS + v + w$. Since PS and DP are typically ordered on a home team–away team basis, this test merely identifies if the home court advantage is accounted for properly by the market.

Table III

Tests of the Equality Restrictions on the Team Ability Coefficients

We conduct tests of the restrictions $h_1 = h_2$, $S_{1\iota} = S_{2i}$ $i = 1, \ldots, 22$ imposed by the null hypothesis that $\text{PS}_t = \text{E}(\text{DP}_t)$ in the equations

$$\text{DP}_t = h_1 + \Sigma_\iota S_{1\iota} \cdot D_{\iota t} + v_{1t} + \omega_t$$

$$\text{PS}_t = h_2 + \Sigma_\iota S_{2\iota} \cdot D_{\iota t} + v_{2t}$$

The Wald statistic imposes the equality restrictions directly in joint GLS estimation of the two-equation system and is distributed $\chi^2_{[23]}$ under the null. The F-statistic is based on the 23 exclusion restrictions in an OLS regression of the forecast error ($\text{DP}_t - \text{PS}_t$) on the constant and team dummies. p-value is the probability under the null of obtaining a test statistic greater than the reported value. The two tests are asymptotically equivalent and here give similar results.

	GLS Estimation		OLS Estimation of Forecast Error		
Season	Wald	p-Value	R^2	F	p-Value
1982–83	31.6	0.11	0.031	1.34	0.13
1983–84	27.2	0.51	0.022	0.94	0.54
1984–85	25.4	0.33	0.026	1.08	0.36
1985–86	19.0	0.70	0.020	0.81	0.73
1986–87	21.3	0.56	0.022	0.90	0.59
1987–88	30.9	0.13	0.029	1.31	0.15

manner. Estimates of the home court advantage and team abilities are used to make out of sample predictions of point spreads for upcoming games. Games in which star players are injured—an important and potentially observable factor—are omitted from the forecast sample (these games are the focus of Sauer (1991)). The difference between the actual and predicted point spread for the forecast sample is the idiosyncratic factor. This factor is thus constructed in the same fashion as an abnormal return in the event study literature.

The structure of this market enables an ex post evaluation of the idiosyncratic factor. This is the reverse of the reasoning used in event studies. Event studies use abnormal returns to draw inferences from stock price changes. In an event study the researcher knows what the information is, has a theory of its consequences, and examines abnormal returns to evaluate the theory. Once again, the actual consequences—changes in expected future cash flows—are difficult to measure. This makes it difficult to test the event study method directly (but by the same token it is the reason why event studies are useful in the first place).

In the point spread market, the actual event being forecast is singular and readily observed. Hence, here we can examine the relation between the idiosyncratic factor (abnormal return) and actual outcomes. Under the fundamentals-based theory, the presence of an idiosyncratic component in the point spread entails an equivalent adjustment in the expected score difference of the basketball game itself. In the stock market, the lack of simple outcomes makes it difficult to determined if unexplained price variation is irrelevant noise, or rather an amalgam of factors based on complex fundamentals. In the point spread market these characterizations are testable hypotheses.

A. Diagnostic Tests of the Point Spread Pricing Model

Before conducting these tests we run diagnostics on the point spread pricing model. We need to know how well the model predicts point spreads out of sample. It turns out that its predictions are remarkably accurate, especially when compared with models used in the finance literature.

The method we use is to estimate (7), thereby obtaining estimates of h_2 and S_{2k}, $k = 1, \ldots, 23$. We use an estimation period designed to cover the 20 most recent games of each team.[8] The estimates are then used to predict subsequent point spreads out of sample. The predicted point spread for a game where team i is host to team j is:

$$\text{ESTPS} = h_2 + S_{2i} - S_{2j}. \tag{8}$$

For each set of estimates, point spread forecasts (ESTPS) are generated for the next five games. Games in which a star player was injured were removed from the set of forecasts.[9] The 20-game window is then shifted ahead five games, and the process is repeated.

This procedure yields 3567 predicted point spreads. The variance of actual point spreads for these games is 31.4 points (squared). The residual variance of the predictions is 4.2 (roughly the same as it is in sample). Hence, out of sample, the model explains more than 85 percent of game to game variation in point spreads. This is almost an order of magnitude greater than what market models used in event studies achieve in sample.[10] The mean value of the prediction error is -0.003. Less than a quarter of the forecast errors are more than 2 points away from zero. Hence, the distribution of the forecast errors is concentrated on a narrow interval around zero.

These diagnostic checks tell us that the fixed effects model of point spread pricing does a remarkably good job of predicting point spreads out of sample. We therefore need not be shy about using the model to identify variation in point spreads from unobserved sources.

[8] The vagaries of the NBA schedule keep this procedure from being exact: some teams play 21 games in the same period that others play 19. Hence, the sample used to construct coefficient estimates is the most recent 230 games (23 teams · 20 games/2) played in the season.

[9] Sauer (1991) recorded and analyzed these games. We retain these games in the estimation sample. Since we have injury information, we added a dummy variable to (7) which indicates the presence or absence of an injured player for the home and/or visiting team. This eliminates an omitted variable bias which would otherwise affect the estimates of the team strength coefficients.

[10] Brown and Warner's (1985) analysis of event study methods found that the average R^2 for estimates of the market model was 0.10.

B. Is There Information in the Idiosyncratic Component?

The estimation procedure detailed above yields 3567 values of ESTPS for noninjury games. ESTPS is based on relative team abilities, and is the fixed effects component of equation (1). Given the actual market point spread, the unobserved, or idiosyncratic component is obtained from (1) as $\epsilon_t = \mathrm{PS}_t - \mathrm{ESTPS}_t$. In the diagnostic tests we were concerned with the ability of the model to predict point spreads in general. If its predictive power were negligible, there would be little point in analyzing the idiosyncratic component. Fortunately, the evidence indicates that game to game variation in ESTPS explains most of the variation in point spreads.

But is there information in the error term? Suppose that $\epsilon = 5$ points. In this case, the fixed effects of the spread (ESTPS) ignores a potentially large factor in the game outcome. Recall that an efficient market implies $\mathrm{E(DP - PS)} = 0$. Thus, in the class of games for which $\epsilon = \mathrm{PS} - \mathrm{ESTPS} = 5$, $\mathrm{E}\{(\mathrm{DP} - \mathrm{ESTPS})|\epsilon = 5\} = 5$ is also implied. We have already documented that the unconditional mean forecast error (MFE) of ESTPS is -0.003; it is unbiased. However, conditional on the noise term, the fundamentals-based model implies that $\mathrm{MFE(ESTPS)}|\epsilon) = \epsilon$.

The mean forecast errors of actual and estimated point spreads for the 3567 point spread forecasts are presented in Table IV. They are grouped according to the magnitude of ϵ. (Note that all negative values of ϵ and their associated forecast errors have been multiplied by -1, which conserves table space and statistical power.[11] As noted earlier, there are very few large prediction errors, which makes conclusions obtained by eyeballing the tail of the distribution somewhat tenuous. Nevertheless, as suggested by the fundamentals-based hypothesis, there is a marked tendency for MFE $(\mathrm{ESTPS}|\epsilon)$ to increase with ϵ.

Three formal hypothesis tests on the correspondence between MFE $(\mathrm{ESTPS})|\epsilon)$ and ϵ compactly summarize what we learn from this analysis:

1. *Pure noise*. This hypothesis corresponds to the "error term is irrelevant noise" notion discussed earlier. It asserts that the error term arises exclusively from factors which are unrelated to the outcome of the game itself. If this is true, ϵ contains no information relevant to the outcome. This implies that $\mathrm{E}\{\mathrm{DP} - \mathrm{ESTPS}|\epsilon)\} = 0$ for all values of ϵ.

   The alternative is a fundamentals-based hypothesis, which predicts that the sign of the forecast error DP − ESTPS is the same as the sign of the error term. Given our transformation of the data, the

[11] This procedure would throw away information only under conditions that are difficult to imagine. A psychological story that could generate problems is that $\upsilon > 0$ represents excessive enthusiasm for the home team and $\upsilon < 0$ represents excessive pessimism. But if the degree of excess is symmetric about zero no information is lost by the procedure. That is, let $\upsilon = 3$ indicate that $\mathrm{E(DP - PS)} = 3$ and $\upsilon = -3$ that $\mathrm{E(DP - PS)} = -3$. Multiplying the latter values by -1 loses no information. If the degree of excess were not symmetric, information would be lost. The two-sided version of Table IV shows no evidence of asymmetry. Copies of this table are available from the authors upon request.

Table IV

Forecast Errors of the Model's Predicted Point Spread When Actual Point Spreads Differ from the Model's Predicted Point Spread

The fixed effects point spread model is estimated for a 20-game period of the season. The ability estimates for each team (S_i) are recorded. These are used to generate predicted point spreads for the subsequent 5-game period. The 20-game window is then shifted ahead 5 games and the process is repeated. ESTPS is the predicted point spread for the game based on the ability estimates of the participating teams. ϵ = PS − ESTPS is the unexplained component in the market point spread. The mean forecast error of ESTPS in predicting actual game score differences is MFE(ESTPS). N is the number of observations for each value of ϵ. Std. Error is the standard deviation of the forecast error. Note that negative values of ϵ (and the forecast errors) have been multiplied by −1 and grouped with their positive counterparts to conserve table space and statistical power.

ϵ	N	MFE(ESTPS)	Std. Error
0.0	432	−0.35	10.14
0.5	744	0.92	11.19
1.0	624	0.88	10.17
1.5	535	1.26	11.37
2.0	398	1.07	11.06
2.5	307	2.61	11.77
3.0	211	2.75	11.34
3.5	162	1.44	10.53
4.0	90	2.98	12.27
4.5	57	2.97	9.60
5.0	35	5.69	12.35
5.5	21	5.88	8.84
6.0	14	2.29	12.65
6.5	7	−0.74	7.05
7.0	5	8.00	4.85
7.5	8	4.50	13.69
≥ 8.0	4	−3.50	6.90

fundamentals-based alternative implies E{DP − ESTPS} > 0. A positive mean forecast error would indicate the presence of relevant information in the error term. The mean forecast error is 1.49 for nonzero changes in the point spread, with a standard error of 0.195. The pure noise hypothesis is thus rejected (t = 7.64, p-value < 0.001).

2. *Pure fundamentals.* This is the hypothesis proposed in the discussion: that the mean forecast error of the estimated point spread is the difference between it and the market-determined point spread. The test is thus: H_0: $\epsilon - (\text{DP} - \text{ESTPS}|\epsilon) = 0$. The mean value is 0.29 (t = 1.51). Hence, one cannot reject this hypothesis at conventional levels (the p-value is 0.131). Since the difference is positive, one might interpret this as very weak evidence that game to game changes in point spreads are excessive. On the other hand, the excessive change (0.29) is quite small relative to the minimum possible change in the outcome (a full

point).[12] Furthermore, on examination of the table, it is immediately apparent that had the spread not changed at all (the pure noise case above), forecast power would have been much worse.

3. *Strong fundamentals*. An ANOVA procedure can be used to check for fundamentals-related information in the following manner. Define classifications according to the values of ϵ. The nonfundamentalist null hypothesis states that MFE(ESTPS) does not differ across these classifications.[13] This hypothesis is not rejected ($F = 1.5$, p-value $= 0.19$).

   Recall from our earlier discussion that there is a great deal of unpredictability in game outcomes. It therefore asks quite a bit of the data to distinguish between point spreads which differ by as little as 0.5 points. A less-demanding test (with more power against a nonfundamentalist null) is obtained by partitioning the sample into two roughly equal sized groups, x^1: $\epsilon = \{0.5, 1.5\}$ and x^2: $\epsilon = \{2.0, 8.0\}$. The mean forecast errors of ESTPS in the two partitions are 1.00 and 2.19, respectively. The hypothesis that the two means are the same is rejected ($t = 4.25$, with p-value < 0.001) in favor of the fundamentals-based alternative that MFE(ESTPS) is larger in the x^2 partition.

There is a straightforward interpretation of these test results. Relevant information is embedded in the idiosyncratic component of point spreads, although the results do not distinguish 2-point differences from say, 2.5 points. The preponderance of positive values of MFE(ESTPS) in Table IV indicates that the idiosyncratic factor in the point spread improves the prediction of outcomes. In this sense, the idiosyncratic component of point spreads (the error term) is closely related to fundamentals.

III. Changes in Team Ability Estimates between Seasons

In the previous section, we found that high-frequency variation in point spreads can be linked to unobserved fundamentals. On the other hand, there was a hint that a small amount of excess reaction may exist in the data. Depending on the exact nature of the process, overreaction at high frequency could build up into significant departures from fundamentals over time. Alternatively, these effects may be entirely transitory (or nonexistent), and therefore have no long-run significance.

In this section, we examine adjustments in point spreads between seasons, based on revisions of the market's estimate of team abilities. The question is

[12] Hence, even if this is an excessive reaction it would be difficult to exploit. Note also that misreported point spreads could lead to this result. Measurement error would infect PS, which is unfiltered, to a greater degree than ESTPS. ESTPS is created through a regression filter, in which the error is only a small part of a 230-game estimation sample. In the case of misreported spreads, ESTPS could be a more accurate forecast of the outcome.

[13] There are very few observations with values of ϵ in excess of 5.5 points. Given the large random component in scores, we restricted the analysis to values in the range $\{0.5, 5.5\}$, yielding 11 classifications.

whether the market's reevaluation of team strengths represents an unbiased estimate of the true change, or rather reflects fads and trends in the wagering market which may be unrelated to changes in team abilities.

We allow the market the first 30 games (37 percent) of each season to develop new estimates of team abilities. The point spread pricing model is estimated using the subsequent 30-game period. The coefficients obtained are interpreted as the market's current estimate of team abilities. For the subsequent 20-game period, forecast errors (of the actual outcome) using both the current (ESTPS) and previous season's predicted point spread (PSPS) are constructed.[14] The sample we analyze consists of all games in the forecast period (a) involving teams which experienced changes in ability estimates of 2 or more points, and (b) for which ESTPS $-$ PSPS ≥ 2. This yields a sample of 501 games in which ability estimates changed and were not self-canceling in their impact on the point spread. The question we ask of this sample is quite simple: are revisions imbedded in the current season's ability estimates informative?

Table V presents the mean forecast errors of game outcomes using ability estimates from the current (ESTPS) and previous season (PSPS).[15] The forecast errors are ordered according to the difference between ESTPS and PSPS. As before, if the revision is fundamentals-based, MFE(PSPS) should equal the revision, and MFE(ESTPS) should equal zero. If ability estimates merely bounce around due to fads and trends, then both mean forecast errors would be zero.

It is clearly evident that the updated ability estimates are far better predictors of score differences. Twelve of the thirteen mean forecast errors of PSPS are positive, and they increase markedly with the size of the adjustment. This is strong evidence that the market changes its estimate of team abilities in the right direction at long horizons.

Formal tests of the pure noise, simple and strong fundamentals hypotheses yield results parallel to those in the previous section. Pure noise is decisively rejected. This hypothesis implies that the mean forecast error of PSPS is zero. The calculated value is 3.48 ($t = 7.10$, p-value < 0.001).

In this case, simple fundamentals reduces to the statement that MFE (ESTPS) = 0. This hypothesis—that the change in estimated abilities is on the money—is not rejected. The mean is -0.61 ($t = 1.26$), indicating that teams whose perceived ability increased did slightly worse than predicted by the spread. Though statistically insignificant, this hints that the adjustment might be about a half point too much. Again however, the amount by which the adjustment is off is relatively small: the average change in (ESTPS $-$ PSPS) is a nontrivial 4.09 points for the sample.

[14] The NBA season consists of 82 games in this period. Thus, we use 80 of the 82 games in this procedure. We ignore the last two games because these are often "garbage games" in which star players are rested because their teams have already determined their playoff berth, and so on.

[15] We are interested in comparing only the fixed effects components of the spread in this analysis. Hence, we do not use the actual point spread, which also contains the idiosyncratic component. In the previous section we found that it imbeds significant information of its own.

Table V

Forecast Errors When Ability Estimates Change

The point spread model is estimated for the 30-game period spanning the 31st through the 60th game of each season. Point spread forecasts are generated for the subsequent 20-game period. ESTPS is the predicted point spread for a game using the current estimates of team abilities. PSPS is the predicted point spread for a game using the previous season's estimated team abilities. Forecast errors are calculated for games in which (1) either or both of the teams' ability estimates changed by 2 or more points between seasons, and (2) $|ESTPS - PSPS| \geq 2$ points. N is the number of games in each category. MFE(ESTPS) is the mean forecast error of (DP − ESTPS); MFE(PSPS) is the mean forecast error of the previous season's ability estimates.

ESTPS − PSPS	N	MFE(ESTPS)	MFE(PSPS)	Std. Error
2.0	47	−2.17	−0.17	10.92
2.5	69	−1.25	1.25	11.24
3.0	60	0.37	3.37	10.83
3.5	59	−1.50	2.05	12.21
4.0	80	1.46	5.46	11.43
4.5	33	−0.30	4.47	10.73
5.0	49	−2.41	2.59	8.75
5.5	26	0.52	6.02	9.13
6.0	20	−0.75	5.25	13.54
6.5	18	0.47	6.97	9.29
7.0	13	−2.89	4.12	9.16
7.5	13	−1.81	5.69	10.51
≥ 8.0	14	−0.07	8.43	9.97

As for the strong fundamentals hypothesis, the data again do not discriminate between point spread adjustments that differ by small amounts. However, even the least likely single partition of the sample rejects the nonfundamentals-based null that the size of ESTPS − PSPS is irrelevant. The partition is based on ESTPS − PSPS and separates $\{2, 4\}$ from $\{4.5, 8\}$.[16] MFE(PSPS) is 2.66 for the former and 4.88 for the latter, the difference being significant ($t = 2.26$, p-value $= 0.012$).

Thus, the market's perception of team abilities changes over time. We conjecture that it would be an arduous task to explain even a fraction of the variation in the ability estimates. But we needn't do this, for in this market we can document the close correspondence between these changes and the outcomes (game scores). It is clearly evident that the point spread forecasts would have been much poorer had the ability estimates not changed. Again, we find that an unobserved source of variation in point spreads is an important predictor of score differences.

IV. Conclusion

Speculative prices are noisy, a fact that has caused considerable consternation among researchers. Investigating the source of this noise has not been an

[16] An unusually large forecast error is included in the first partition.

easy task. Consider a simple example: stock prices react on day 1 to information that will affect cash flows $n - 1$ days hence, and on day 2 to information that will affect cash flows $n - 2$ days hence. If the first news is good and the second bad by the same amount, after n days it appears that nothing has changed except the stock price. Without knowing the information itself, when it is received in the market, and its relation to cash flows, we have unexplained volatility. Since it is the task of empirical science to explain things, this seems less than satisfactory.

Fama's (1970, 1976) efficient markets approach successfully deals with this problem at one level. In particular, it accounts for two stylized facts which were once thought incompatible with fundamentals-based pricing (LeRoy (1990)). First, stock selection based on fundamentals does not deliver superior returns (the information already being present in prices). Second, to a first approximation, stock returns are not forecastable (new information is random). Although this is a remarkable synthesis, critics (Shiller (1989) and Summers (1986)) have pointed out that most tests of market efficiency have low power against alternatives, such as the noise trader model of DeLong, Shleifer, Summers, and Waldmann (1990).

The crux of the issue is whether noise is better characterized by unobserved fundamentals or irrelevant, perhaps psychologically determined factors. The nature of these two constructs make testing between the alternatives difficult. They are no more observable in the betting market than in the stock market. But the betting market does differ in a way which allows for tests which discriminate between alternatives. The betting market, like the stock market, is a vehicle which allows information about expected outcomes to be captured in a price. In contrast however, the event being forecast is singular; at some point the game is played, and the focus of all the information is evaluated.

The model in this paper identifies a noise component in market point spreads. Although this component is small relative to its systematic counterpart, it is not irrelevant. In its absence, point spread forecasts of game outcomes would be significantly biased. This implies that the noise component is essential to predicting the outcome of the game itself.

We conclude that the noise term represents unobserved fundamentals in this setting. Unfortunately, this finding does not transfer seamlessly to other markets. The fact that basketball games provide determinate outcomes allows us to analyze the relation between the outcome and the error term in our pricing model. But in this market, the rational bettor faces only those risks directly related to the basketball game itself; noise trader problems limiting profitable arbitrage possibilities are ruled out by the design of a point spread wager. Controversy over the error term in stock price models will remain until tests which distinguish between plausible alternatives are developed. We were able to do this for the betting market. Thus, at a minimum, we have demonstrated that information known to a market but not the econometrician can be mislabeled as irrelevant noise. Noise is news in the point spread betting market.

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