Information Effects and National Hockey League Betting Market Efficiency

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Abstract:

Previous studies of the National Hockey League (NHL) betting market claim a general movement towards efficiency over the last two decades. These studies, however, assume a homogenous betting market with regards to the time of year in which bets are placed. Differences in available information—information effects—have been shown to distort the Major League Baseball betting market; they produce similar distortions when considered in the NHL market as well. As such, previous claims of market efficiency must be revisited in light of heterogeneous information.

JEL: G14; L83
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1. INTRODUCTION

By definition, betting market efficiency dictates a return on betting not significantly different than the expected value. In spirit, betting market efficiency implies an absence of persistently profitable betting strategies. The forthcoming analysis applies both of these thresholds to re-evaluate claims previously made of the National Hockey League (NHL) betting market.

Previous studies point to a once-inefficient NHL betting market that has, over time, evolved to a state of general efficiency. Woodland and Woodland (2001) first analyzed the nature of the NHL betting market from 1990 to 1996 and found the market to be inefficient. Profitable wagering opportunities existed on underdogs and did not appear to be diminishing over the span of their analysis. Gandar, Zuber and Johnson (2004) revise Woodland and Woodland's calculations to show that returns had been previously overstated, though profitable wagering opportunities on underdogs still existed even under the new methodology. Woodland and Woodland (2011) extend the analysis through 2007 and find that the inefficiency discovered in the initial time period extended into 1999, yet disappears in subsequent seasons .[1] In their estimation, profitable betting opportunities in the National Hockey League ended at the turn of the 21st century.

The analysis herein revisits the claim of the NHL betting market's trend towards market efficiency. Ryan et al. (2011) show that information effects—distortions in available information over the course of a season—have a significant impact on the efficiency of the Major League Baseball betting market in the form of offering persistent profitable betting opportunities. We endeavor to show that, after considering time-of-year effects, similarly persistent profitable betting opportunities exist in the NHL betting market create. In particular, underdogs become significantly profitable bets in the month of February and significantly *un*profitable bets in the month of April. A theoretical justification for such a bias remains elusive; however, no such explanation is required per the goals of this article. As previously mentioned, distortions in the betting market so as to create a simple, persistently profitable betting strategy are sufficient to claim market inefficiency. Betting on all underdogs for an entire month easily meets this qualification.

The analysis continues as follows. Section 2 describes the data. Section 3 outlines a traditional within-lines efficiency test. Section 4 provides a traditional across-lines efficiency test. Section 5

[1] Compared to the other major professional sports leagues in the United States—especially the National Football League—the National Hockey League betting market has received surprisingly little attention. Woodland and Woodland (2010) provide the only other analysis known to the authors, a brief exploration into the nature of the over/under betting market in the NHL.

describes information effects. Section 6 puts forth a new analysis of efficiency in light of information effects. Section 7 concludes.

2. DATA

Our analysis covers 7,383 regular season hockey games from the 2005-2006 season through the 2010-2011 season. Lines were obtained through covers.com. The six seasons match the duration of Woodland and Woodland (2001), and the total number of games actually exceeds their study due to franchise expansion between the two time periods.

A brief note concerning the source of the data is in order. Previous analyses (and the forthcoming analysis) show that the posted lines at covers.com compare very favorably to the posted lines at traditional on-shore sportsbooks in terms of overall market efficiency.[2] As such, the appropriateness of off-shore sportsbooks for betting market study can no longer be reasonably questioned.

In fact, one could argue that the off-shore lines utilized in this analysis are superior to on-shore lines. The vast majority of on-shore lines hold to a ten-, fifteen- or twenty-cent spread in posted odds.[3] Deviations from this general rule lead to the common practice in previous papers of the modification, and subsequent aggregation, of lines that depart from these common spreads.[4] The reason for such data adjustment is clear enough; a dearth of lines at particular posted value prevent the normality assumption from being invoked and, thus, the analysis suffers. Nonetheless, crucial information is lost (or misconstrued, or conjured) when data is modified. Off-shore lines allow a fuller, more robust view of the wagering market by having a sufficient number of observations at many more unique lines. As such, the circle peg of market efficiency analysis is not forced through the square hole of on-shore lines.

Wagers in the National Hockey League betting market commonly utilize a moneyline system. Bettors wager upon the outright winner of a given game regardless of score differential. Unlike a traditional point spread wager—where the score differential determines the result of the bet—a winning moneyline wager pays a higher return to the underdog as compared to the favorite. In the general moneyline ($-\beta_1$, $+\beta_2$), a winning favorite bet pays $1/\beta_1$ and a winning underdog bet pays β_2. The spread

[2] See, for example, Paul and Weinbach (2008) and Ryan, Gramm and McKinney (2012).

[3] A ten-cent line shows a difference of ten units (in absolute terms) in a typical moneyline—i.e., (-160, +150). Fifteen-cent and twenty-cent lines differ accordingly.

[4] For example, a posted line of (-152, +141) is changed in the dataset to read (-150, +140).

between the two lines generates the commission for the book, with $|\beta_1|>|\beta_2|$. Following typical moneyline analyses, moneylines where $\beta_2 < 0$ are dropped from the analysis.[5]

One benefit unique to our dataset is the consistency of the moneyline wagering system over the entire span of our games. Prior to the 2005-2006 National Hockey League season, regular season games could end in a tie after an overtime period. Clearly, this causes difficulties for a moneyline wagering system. To rectify the problem, bookmakers incorporate a point-spread line to settle the circumstance of a tie game. For example, a sample hockey line would read:

San Jose Sharks	-½	-160
Pittsburgh Penguins	+½	+130

In this case, either team wins the wager if they win the game outright. In the case of a tie, however, each team's goal total is adjusted appropriately upwards or downwards by half of a goal. In this example, a tie game would yield a winning wager for the Pittsburgh Penguins.[6]

Ultimately, to solve the problem posed by tie games, bookmakers posted a hybrid point spread/moneyline. While interesting in its own regard, analyzing these unique lines moves away from a pure moneyline analysis. Further, pooling combination-style lines alongside the more recent, traditional moneylines could aggregate away palpable differences between the two separate styles of betting line. Our dataset avoids any such problems—in fact, our dataset covers only, and entirely, the traditional moneyline market as it pertains to the National Hockey League (2005-2006 season to the 2010-2011 season).

3. WITHIN-LINES EFFICIENCY TESTS

If moneylines are efficient, then the subjective probability (ρ) of a wager at a given line will not be statistically different than objective probability (π) of winning a wager at that given line. This fact generates a logical null hypothesis to test, namely $\rho_j = \pi_j$, where ρ_j is the subjective probability of an

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[5] Lines fitting this condition constitute 5.41% of the total amount of games played during our time period, and consequently eliminate games where there is no meaningful favorite.

[6] A small number of lines were posted prior to the 2005-2006 season whereby the point-spread portion of line featured adjustments greater than half of a goal; for a fuller description of point spread/moneyline hybrid lines, see Woodland and Woodland (2001).

underdog winning at the jth line, and π_j is the objective probability of an underdog winning at the jth line. Following from Gandar et al. (2002), the subjective probability of an underdog win is

$$\rho = (1 + \beta_1)/(2\beta_1 + \beta_1\beta_2 + 1)$$

where β_1 is the favorite line and β_2 is the underdog line. To satisfy the assumption of a normal distribution, only lines that meet $n_j\rho_j > 5$ and $n_j(1 - \rho_j) > 5$ are analyzed, where n_j is the number of games at the jth line. Lines that do not satisfy these two requirements are excluded from this portion of the analysis. The test statistic for the above null hypothesis is

[Table 1 about here.]

Appendix A contains the complete results of the above statistical test on qualifying lines, and Table 1 presents these results in light of the same statistical tests performed in previous studies. The most important result from the comparison is that our dataset, when viewed as a whole, does not differ significantly from the datasets used in previous studies. If anything, our dataset exhibits a slightly lesser degree of inefficiency. At the 10% level, 11.04% of the lines in our study are inefficient at the 10% level—the second lowest rate of the four datasets. At the 5% and 1% levels, inefficient lines comprise 4.55% and 0.63%, respectively, of the overall number of lines in this study—both rates being lower than any of the previous studies. Admittedly, analyzing efficiency in a line-by-line manner does not conclusively speak to the overall efficiency of the market as a whole; nevertheless, the NHL betting market exhibits a large degree of efficiency when viewed in such broad terms. Moreover, statements made concerning the inefficiency of the National Hockey League betting market must be considered with the mindset that this particular dataset exhibits, arguably, the least amount of overall inefficiency as compared to previous studies.[7]

[7] As mentioned in Section 2, the practice of modifying data could also be conjuring some of the inefficiencies reported in previous studies.

4. ACROSS-LINES EFFICIENCY TESTS

[Table 2 about here.]

To view the entirety of the market from an efficiency perspective, we estimate the following model:

$$\pi_j = \alpha_0 + \alpha_1 \rho_j + \varepsilon_j$$

Due to a significant amount of heteroskedasticity (the White test on the OLS estimation yields $\chi^2 = 8.06$, with a p-value of 0.018), the above model is estimated using weighted least squares, whereby residuals from the jth line are weighted by the number of games at the jth line, n_j. Table 2 provides the results. To test true market efficiency, we jointly test the null hypothesis of $\alpha_0 = 0$ and $\alpha_1 = 1$. The F-statistic from this joint test is 1.16 at (2, 152) degrees of freedom, yielding a p-value of 0.315. This result does not allow for a rejection of the null hypothesis at any respectable level of confidence, therefore market inefficiency cannot be claimed.[8] The results of the across lines efficiency test match well with the within lines results; the National Hockey League betting market, by virtue of these two tests, appears to be operating in general efficiency.

5. INFORMATION EFFECTS

One shortcoming of the existing analyses of the National Hockey League betting market is that all bets throughout a season are lumped together into one large pool. Therefore, all bets made at all points during a season are implicitly viewed equally. As Ryan et al. (2011) show, incorporating this assumption can lead to erroneous conclusions concerning the nature of efficiency within a betting market as well as judgments on the availability (or absence) of profitable betting strategies. These faulty conclusions arise from the effects that changes in information can have on betting markets. Typically, efficient markets are thought to emerge when all available information is incorporated into prices; in the case of a moneyline betting market, all available information would be incorporated into the line, or the price of the bet. However, previous analyses assume that the amount of information to be incorporated into the price is

[8] The estimate for α_1—with $1.0207 > 1$—implies a minor reverse favorite-longshot bias.

unchanging; that is, the amount of information to be synthesized in October is the same as in December is the same as in March. It is preposterous to believe that the information available concerning the true ability of any hockey team is the same in October when the season starts as it would be in April when the regular season ends. The issue, then, extends beyond whether market participants are incorporating all available information; it concerns whether market participants are incorporating all available information *in light of how much information there is to be utilized in betting decisions*. The difference is nontrivial; per Ryan et al (2011), such information effects generate persistent profitable wagering opportunities, whereby ignoring these information effects would leave the set of profitable wagering opportunities empty.

Unique to this analysis is the possibility of another source of information effects. As information about teams and players develops as the season progresses, information about particular matchups between teams develops along with the season as well. One team, while having a worse record, may "match-up" favorably with another team with a better record, and enjoy more success than their record would suggest. Furthermore, success against common opponents may elicit further information about the true ability of a given team. In both cases, as teams play more frequently, additional information is revealed into the betting market. Since uncertainty favors underdogs in a moneyline wagering system (Ryan et al. 2011), the possibility exists that the lack of information available for games between teams from different divisions or different conferences generates profitable betting opportunities.

We capture this possibility by creating two variables that reflect the realities of scheduling within the National Hockey League. The National Hockey League is split into two conferences (the Western Conference and the Eastern Conference), with each conference divided into three divisions (Central, Northwest and Pacific in the Western Conference; Atlantic, Northeast and Southeast in the Eastern Conference). National Hockey League scheduling dictates that teams play more frequently within conferences and more frequently still within divisions. We control for within-division games as well as within-conference games as a potential indicator of additional information effects within the NHL betting market.

6. INFORMATION EFFECTS AND THE RETURNS TO BETTING

The effects of information on betting market returns are clear through a Tobit analysis. Analyzing returns in a regression framework necessitates a Tobit model due to the censored nature of the dependent variable.[9] As such, we estimate the following model:

$$R_{tkj} = b_0 + b_1\rho_{tkj} + b_2 AwayUnd + b_3\Delta_{\mathrm{k}} + \varepsilon_{tkj}$$

Following from Gandar et al. (2002), *R* is the actual return to a unit bet on the *t*th team in the *k*th game at the *j*th line. Actual returns are generated from a hypothetical unit bet on every line in our sample; see Section 2 for payoff information for winning favorites and winning underdogs. All losing bets return -1 units. ρ_{tkj} is the subjective probability of team *t* winning game *k* at the *j*th line. Per Gandar et al. (2002), *AwayUnd* is a variable that captures whether the road team is an underdog in the *k*th game. Δ is the matrix of variables which capture information effects. These fall into two broad categories. First, two dummy variables are included to capture whether the *k*th game is a within-division and/or within-conference game. Second, a set of dummy variables control for the time during the hockey regular season in which the *k*th game takes place. These include dummy variables for the months of October, November, December, January, February, March and April. ε_{tkj} is the error term. The expected value for b_1 is positive. The expected value for b_2, following from results in Gandar et al. (2002) and Ryan et al. (2011), is zero. The vector of estimates that comprise b_3 all have expected values of zero, indicating no time-of-year effect on the return to betting. Any non-zero value within b_3 suggests the existence of information effects.

[Table 3 about here.]

Results from the above regression model are in Table 3. As expected, subjective probability is positive and (extremely) significant in all specifications. This result emerges from the fact that teams with higher subjective probabilities generate positive returns more frequently. Simply put, teams expected to win more often *do* win more often. Also as expected, games featuring underdogs as road teams create no significant distortion in the NHL betting market.

Our first measures of information effects—within-conference games and within-division games—generate no significant inefficiencies in the market. While the degree of available information

[9] Analyzing returns in a regression framework requires analyzing every hypothetical bet that could be placed over the duration of our analysis. Therefore, two units bets will be utlitized per game—one per team—leaving every game to have a positive return of some value (depending on the winner and the line) and a negative return of exactly -1.

concerning the matchup of two teams that play infrequently is strictly less than teams that play more frequently, this does not mean that this shortage of information is sizeable enough to generate a significant distortion in the betting market. Furthermore, this lack of direct information between two opponents may be mitigated effectively by virtue of a host of indirect information—be it common opponents, advanced statistical measures, and the like. Ultimately, information effects via scheduling do not distort the NHL betting market.[10]

More interesting, however, are the existence of information effects due to the time of year within the National Hockey League betting market. The strongest information effect emerges in February, when underdog wagers generate significantly higher returns. (Conversely, wagering on favorites in February generates significantly lower returns.) In addition, there is weak evidence to show that wagers on favorites in December and January produce significantly lower returns to favorites.

Table 4 shows the returns to wagering on underdogs by month. For example, should all underdogs be bet throughout the month of October across the six seasons of our sample, the aggregate return for all bets would be 0.25%. This return, however, is not significantly different from the expected return (Z_1) nor significantly different from the zero-profit level (Z_2). These statistical tests translate the results from Table 3 into a more accessible form. Most strikingly, February proves extremely profitable for betting on underdogs. Over the course of our sample, such a betting strategy yielded a 9.40% return—significantly different at the 1% level from both the expected return and the zero-profit level. Conversely, betting on underdogs at the end of the hockey season—in April—generates significant losses. April underdog bets generated a 12.91% loss, significantly different from the expected return (5%) and the zero-profit level (1%). There is also weak evidence that January exhibited returns significantly different from the expected return, yet only at the 10% level of significance.

These findings cast doubt on previous statements concerning the strength of the efficiency of the National Hockey League betting market. Clearly, when viewing the market as homogenous, the hallmarks of efficiency present themselves (Sections 3 and 4). However, when acknowledging the heterogeneous nature of betting markets, profitable wagering opportunities emerge. At this juncture, a point of clarification is in order. While Ryan et al. (2011) provide an economically viable explanation for the information effects that emerge in Major League Baseball betting markets, no such story appears to

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[10] Some models were estimated incorporating an interaction term between time of year effects and scheduling effects, under the hypothesis that scheduling effects could be larger earlier in the season. These interaction terms also failed to generate a significant distortion in the market.

the authors pertaining to the National Hockey League at the time of composition.[11] Nonetheless, no such viable economic story is required to cast doubt on the nature of the efficiency within the NHL betting market. Efficiency dictates that deviations exist from the expected return to the degree that persistently profitable betting strategies are present. Placing blanket bets on one half of the market for an entire month certainly qualifies as a viable, simple profitable betting strategy—a successful betting strategy that existed not only over the entire span of our dataset collectively, but also within all six Februarys in our analysis.[12]

7. CONCLUSION

This analysis revisits the claims that the National Hockey League wagering market is strongly efficient. Using existing measures of market efficiency, our updated dataset confirm the previous claims of a broadly efficient market. However, when considering information effects within the National Hockey League wagering market, inefficiencies emerge. Specifically, underdogs are particularly good wagers in February and particularly poor wagers in April. These results cast doubt on the ability to claim efficiency across the entire National Hockey League betting market. Until betting markets are considered heterogeneous with regards to the amount of information available to be incorporated, any claim of efficiency rest upon the assumption that markets are similar throughout all points in time—a far-reaching assumption, to be certain.

[11] A potential explanation may exist for April—perhaps favorites increase effort in light of making the playoffs or pursuing a better seeding when compared to underdogs. However, no plausible explanation exists for the authors at this point.

[12] The lowest return on blanket underdogs bets in a February occurred in the 2010-2011 season (2.80%), while the largest occurred in 2007-2008 season (22.79%). No other month had unanimously positive or negative returns across our sample.

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Table 1: Summary of within-lines efficiency tests

	Appendix A	Woodland and Woodland (2011)	Woodland and Woodland (2001) 30¢ line	Woodland and Woodland (2001) 40¢ line
Initial Season	2005-2006	1996-1997	1994-1995	1990-1991
Final Season	2010-2011	2006-2007	1995-1996	1993-1994
Total number of games	5812	11296	1604	3762
Total number of lines	154	33	16	16
Total number of inefficient lines	17	9	3	1
Percentage of inefficient lines (10%)	11.04%	27.20%	18.75%	6.25%
Percentage of games in inefficient line categories (10%)	13.47%	17.10%	15.27%	4.57%
Percentage of inefficient lines (5%)	4.55%	12.12%	6.25%	6.25%
Percentage of games in inefficient line categories (5%)	4.03%	5.08%	2.56%	4.57%
Percentage of inefficient lines (1%)	0.65%	6.06%	6.25%	6.25%
Percentage of games in inefficient line categories (1%)	0.46%	3.26%	2.56%	4.57%

Table 2: Across-lines bias test

α_0	0.0012	(0.0669)
α_1	1.0207	(0.1574)
R^2	0.2500	
F	1.16	
p	0.3151	

Note : Results from weighted least squares (by n_j). F-statistic, with (2, 152) degrees of freedom, from joint test of $\alpha_0 = 0$ and $\alpha_1 = 1$.

Table 3 - Regression Results: Returns

	All teams		Underdogs only		Favorites only	
Subjective Probability	**1.4090*** (0.2170)**	**1.4101*** (0.2173)**	**2.8038*** (0.6542)**	**2.7271*** (0.6746)**	**1.0953*** (0.2607)**	**1.0655*** (0.2632)**
Away Underdog		0.0010 (0.0076)		0.0439 (0.0823)		-0.0251 (0.0418)
Same Division		0.0091 (0.0086)		0.0684 (0.0794)		-0.0280 (0.0375)
Same Conference		-0.0146 (0.0106)		-0.0773 (0.0987)		0.0252 (0.0480)
October		-0.0028 (0.0135)		0.1044 (0.1273)		-0.0655 (0.0602)
November		-0.0036 (0.0134)		0.0246 (0.1234)		-0.0188 (0.0567)
December		0.0004 (0.0134)		0.1591 (0.1208)		**-0.0944* (0.0567)**
January		0.0054 (0.0138)		0.1846 (0.1228)		**-0.1026* (0.0573)**
February		0.0222 (0.0148)		**0.3133** (0.1284)**		**-0.1603*** (0.0619)**
April		-0.0304 (0.0210)		-0.2555 (0.1782)		0.0958 (0.0715)
Log-likelihood	-19534.62	-19534.36	-9501.24	-9493.44	-9448.15	-9440.09
F	42.17	6.15	18.37	3.33	17.65	3.5
p-value	0.0000	0.0000	0.0000	0.0002	0.0000	0.0001
N	13954	13954	6977	6977	6977	6977

Notes: Tobit regression results, dependent variable is actual return to betting on team *t* in the *k*th game. Standard errors clustered by game. *** = 1%; ** = 5%; * = 10%.

Table 4: Returns to betting on underdogs by month

	N	R_U	$E(R_U)$	Z_1	Z_2
October	950	0.0025	-0.0201	0.6770	0.0756
November	1128	-0.0262	-0.0217	-0.1446	-0.8403
December	1181	0.0256	-0.0214	1.5744	0.8571
January	1114	0.0372	-0.0195	**1.8194***	1.1928
February	900	0.0940	-0.0199	**3.3135*****	**2.7351*****
March	1257	-0.0321	-0.0201	-0.4046	-1.0791
April	447	-0.1291	-0.0199	**-2.4712****	**-2.9215*****

Notes: Z_1 is the test statistic for H_o: $R_u = E(R_U)$. Z_2 is the test statistic for H_0: $R_U = 0$.
***, and ** denote significance at the 1% (5%) level.

Appendix A: Within Lines Bias Test

(β_{1j}, β_{2j})	ρ_j	n_j	w_j	π_j	z_j	(β_{1j}, β_{2j})	ρ_j	n_j	w_j	π_j	z_j
(-108, +100)	0.4906	42	25	0.5952	1.3569	(-150, +140)	0.4098	95	38	0.4000	-0.1949
(-110, +100)	0.4884	77	39	0.5065	0.3181	(-152, +140)	0.4086	26	11	0.4231	0.1506
(-109, +101)	0.4882	55	31	0.5636	1.1190	(-151, +141)	0.4082	37	17	0.4595	0.6345
(-111, +101)	0.4861	53	32	0.6038	1.7147*	(-153, +141)	0.4069	19	6	0.3158	-0.8087
(-110, +102)	0.4859	30	11	0.3667	-1.3065	(-152, +142)	0.4066	52	23	0.4423	0.5249
(-112, +102)	0.4838	51	21	0.4118	-1.0287	(-154, +142)	0.4053	27	12	0.4444	0.4142
(-111, +103)	0.4836	43	28	0.6512	2.199**	(-153, +143)	0.4049	26	12	0.4615	0.5880
(-113, +103)	0.4815	59	33	0.5593	1.1967	(-160, +140)	0.4037	27	18	0.6667	2.7847***
(-113, +104)	0.4802	41	21	0.5122	0.4094	(-155, +143)	0.4037	22	9	0.4091	0.0515
(-114, +104)	0.4792	44	21	0.4773	-0.0258	(-154, +144)	0.4033	22	7	0.3182	-0.8141
(-120, +100)	0.4783	20	9	0.4500	-0.2530	(-155, +145)	0.4017	62	21	0.3387	-1.0122
(-114, +105)	0.4780	45	21	0.4667	-0.1522	(-157, +145)	0.4005	25	9	0.3600	-0.4136
(-115, +105)	0.4770	75	44	0.5867	1.9018*	(-156, +146)	0.4002	16	5	0.3125	-0.7156
(-115, +106)	0.4758	41	18	0.4390	-0.4711	(-158, +146)	0.3990	18	8	0.4444	0.3941
(-116, +106)	0.4748	42	22	0.5238	0.6365	(-157, +147)	0.3986	38	12	0.3158	-1.0424
(-116, +107)	0.4736	33	15	0.4545	-0.2188	(-159, +146)	0.3984	16	9	0.5625	1.3410
(-117, +107)	0.4726	50	25	0.5000	0.3885	(-158, +148)	0.3970	36	17	0.4722	0.9222
(-117, +108)	0.4714	39	16	0.4103	-0.7646	(-160, +147)	0.3968	24	10	0.4167	0.1987
(-118, +108)	0.4704	66	29	0.4394	-0.5046	(-159, +149)	0.3955	16	6	0.3750	-0.1675
(-118, +109)	0.4692	26	15	0.5769	1.1006	(-160, +150)	0.3939	63	23	0.3651	-0.4688
(-119, +109)	0.4682	35	12	0.3429	-1.4865	(-161, +151)	0.3924	23	10	0.4348	0.4161
(-125, +105)	0.4675	15	8	0.5333	0.5108	(-163, +150)	0.3922	32	17	0.5313	1.6105
(-119, +110)	0.4671	46	19	0.4130	-0.7342	(-162, +152)	0.3909	40	14	0.3500	-0.5302
(-120, +110)	0.4661	80	44	0.5500	1.5043	(-164, +151)	0.3907	25	11	0.4400	0.5048
(-120, +111)	0.4649	36	20	0.5556	1.0903	(-163, +153)	0.3894	27	10	0.3704	-0.2028
(-121, +111)	0.4640	39	22	0.5641	1.2537	(-165, +152)	0.3892	28	10	0.3571	-0.3484
(-121, +112)	0.4628	28	15	0.5357	0.7737	(-170, +150)	0.3885	16	11	0.6875	2.4539**
(-122, +112)	0.4619	61	29	0.4754	0.2119	(-164, +154)	0.3879	18	6	0.3333	-0.4752
(-122, +113)	0.4607	36	18	0.5000	0.4729	(-166, +153)	0.3878	14	7	0.5000	0.8619
(-123, +113)	0.4598	43	24	0.5581	1.2939	(-165, +155)	0.3864	57	24	0.4211	0.5367
(-123, +114)	0.4586	24	8	0.3333	-1.2320	(-166, +156)	0.3850	32	11	0.3438	-0.4792
(-124, +114)	0.4577	36	16	0.4444	-0.1601	(-168, +155)	0.3848	19	5	0.2632	-1.0901
(-130, +110)	0.4573	19	9	0.4737	0.1437	(-167, +157)	0.3835	31	16	0.5161	1.5185
(-124, +115)	0.4566	19	8	0.4211	-0.3109	(-170, +156)	0.3829	19	8	0.4211	0.3424
(-125, +115)	0.4557	147	63	0.4286	-0.6603	(-168, +158)	0.3821	28	10	0.3571	-0.2715
(-126, +116)	0.4537	58	20	0.3448	-1.665*	(-169, +159)	0.3806	16	5	0.3125	-0.5613
(-127, +117)	0.4517	131	52	0.3969	-1.2584	(-172, +158)	0.3800	17	8	0.4706	0.7694
(-128, +118)	0.4497	99	42	0.4242	-0.5086	(-170, +160)	0.3792	48	18	0.3750	-0.0602
(-129, +119)	0.4477	41	20	0.4878	0.5165	(-171, +161)	0.3778	24	8	0.3333	-0.4493
(-135, +115)	0.4474	15	8	0.5333	0.6693	(-174, +160)	0.3772	15	7	0.4667	0.7149
(-130, +120)	0.4457	164	74	0.4512	0.1413	(-172, +162)	0.3764	33	15	0.4545	0.9266

Appendix A: Within Lines Bias Test (cont.)

(β_{1j}, β_{2j})	ρ_j	n_j	w_j	π_j	z_j	(β_{1j}, β_{2j})	ρ_j	n_j	w_j	π_j	z_j
(-131, +121)	0.4438	56	21	0.3750	-1.0362	(-175, +161)	0.3758	21	9	0.4286	0.4992
(-132, +122)	0.4419	107	57	0.5327	1.8921*	(-173, +163)	0.3750	14	7	0.5000	0.9660
(-133, +123)	0.4400	70	36	0.5143	1.2527	(-174, +164)	0.3736	16	7	0.4375	0.5282
(-134, +124)	0.4381	45	22	0.4889	0.6871	(-177, +163)	0.3731	15	3	0.2000	-1.3859
(-140, +120)	0.4380	30	11	0.3667	-0.7870	(-175, +165)	0.3723	52	28	0.5385	2.4794**
(-135, +125)	0.4362	123	63	0.5122	1.6997*	(-176, +166)	0.3709	24	9	0.3750	0.0417
(-136, +126)	0.4343	65	30	0.4615	0.4425	(-180, +165)	0.3699	22	6	0.2727	-0.9439
(-137, +126)	0.4336	41	17	0.4146	-0.2447	(-177, +167)	0.3695	23	7	0.3043	-0.6477
(-137, +127)	0.4325	62	24	0.3871	-0.7215	(-178, +168)	0.3682	31	13	0.4194	0.5906
(-138, +127)	0.4317	31	14	0.4516	0.2234	(-182, +167)	0.3672	21	11	0.5238	1.4887
(-138, +128)	0.4307	34	13	0.3824	-0.5689	(-180, +170)	0.3655	47	10	0.2128	-2.1748**
(-139, +128)	0.4299	37	21	0.5676	1.6913*	(-185, +170)	0.3633	24	8	0.3333	-0.3051
(-145, +125)	0.4289	17	10	0.5882	1.3275	(-182, +172)	0.3629	33	7	0.2121	-1.8015*
(-139, +129)	0.4288	33	14	0.4242	-0.0534	(-187, +172)	0.3607	22	10	0.4545	0.9165
(-140, +129)	0.4281	22	12	0.5455	1.1123	(-185, +175)	0.3591	52	16	0.3077	-0.7721
(-140, +130)	0.4270	92	35	0.3804	-0.9038	(-187, +177)	0.3565	15	7	0.4667	0.8906
(-141, +130)	0.4263	25	9	0.3600	-0.6705	(-193, +177)	0.3540	15	3	0.2000	-1.2475
(-141, +131)	0.4253	39	16	0.4103	-0.1895	(-191, +178)	0.3540	53	17	0.3208	-0.5065
(-142, +131)	0.4245	32	10	0.3125	-1.2823	(-193, +180)	0.3516	31	11	0.3548	0.0381
(-142, +132)	0.4235	57	25	0.4386	0.2308	(-201, +183)	0.3460	27	6	0.2222	-1.3525
(-143, +132)	0.4228	42	17	0.4048	-0.2364	(-203, +185)	0.3437	27	11	0.4074	0.6969
(-143, +133)	0.4217	29	12	0.4138	-0.0866	(-206, +186)	0.3418	17	6	0.3529	0.0965
(-144, +133)	0.4210	25	10	0.4000	-0.2131	(-207, +187)	0.3407	23	11	0.4783	1.3920
(-150, +130)	0.4202	30	15	0.5000	0.8859	(-210, +190)	0.3373	35	13	0.3714	0.4268
(-144, +134)	0.4200	34	11	0.3235	-1.1397	(-212, +192)	0.3351	24	13	0.5417	2.1438**
(-145, +134)	0.4193	14	6	0.4286	0.0703	(-215, +195)	0.3318	22	3	0.1364	-1.9472*
(-145, +135)	0.4183	91	37	0.4066	-0.2258	(-220, +200)	0.3265	25	13	0.5200	2.0628**
(-146, +135)	0.4176	25	9	0.3600	-0.5838	(-222, +202)	0.3245	19	3	0.1579	-1.5507
(-146, +136)	0.4166	35	17	0.4857	0.8300	(-225, +205)	0.3214	22	6	0.2727	-0.4887
(-147, +136)	0.4159	24	7	0.2917	-1.2346	(-230, +210)	0.3164	29	11	0.3793	0.7285
(-148, +136)	0.4152	16	6	0.3750	-0.3265	(-232, +212)	0.3144	16	4	0.2500	-0.5552
(-147, +137)	0.4149	51	19	0.3725	-0.6132	(-235, +215)	0.3116	18	9	0.5000	1.7263*
(-149, +137)	0.4135	21	5	0.2381	-1.6325	(-240, +220)	0.3069	19	7	0.3684	0.5818
(-148, +138)	0.4132	49	20	0.4082	-0.0711	(-245, +225)	0.3023	23	11	0.4783	1.8375*
(-150, +138)	0.4119	24	8	0.3333	-0.7817	(-260, +240)	0.2894	21	8	0.3810	0.9253
(-149, +139)	0.4115	26	8	0.3077	-1.0756	(-300, +270)	0.2649	27	8	0.2963	0.3697

Notes: $\beta 1_j$ and $\beta 2_j$ are the jth favorite and underdog lines, while ρ_j, n_j, w_j and π_j are the subjective win probabilities, number of games number of underdog wins and the objective probabilities at the jth line, respectively.

$\Sigma n_j = 5812$

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.