

AUCTIONS WITH CONSTRAINED INFORMATION: BLIND BIDDING FOR MOTION PICTURES

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Abstract—Toward explaining why movie exhibitors have sought legislation requiring distributors to trade-screen films before soliciting bids, a simulation of a Nash equilibrium in an auction suggests that without previews bidders may suffer losses in expected utility. This supports the hypothesis that risk-aversion and competition render exhibitors unable to reduce their bids enough to compensate fully for the dearth of information. An error-components model is used to analyze a unique industry dataset. The results confirm that a component of the bid is lower (raising mean return) while the variance of return is greater for blindly-licensed films.

IN many auction markets, buyers bid for a prize of uncertain value (e.g., outer continental shelf oil leases, art, race horses). An especially intriguing example is the market for exhibition rights of first-run motion pictures. Within a geographically-defined market, theater owners (exhibitors) compete in a sealed-bid, first-price auction. Since audience demand cannot be known with certainty, the value of the film is a random event. In addition to the vagaries of audience taste, distributors (the sellers) frequently force exhibitors to face another uncertainty, namely the film itself. That is, in many states, auctions for some films are held prior to production, so that the exhibitors bid "blind." Over the past few years, this practice has generated a heated controversy, resulting, in other states, in legally required previews. In opposing the practice, exhibitors argue that distributors use blind bids as collateral in financing film production. They view it as unfair, blame it for the bankruptcy of many theaters and claim that it has left them unable to appropriately match films to community mores. Distributors deny these charges. They argue that previews interfere with their ability to release major films during peak attendance seasons, and to coordinate promotional campaigns. The purpose of this work is to explore the basis for and the rationality of this controversy.

If the market for film licenses were competitive, with many buyers and sellers, then blind bidding might be Pareto-superior to a preview regime. This would seem to be the environment envisioned by Kenney and Klein (1983). Distributors' film-inventory costs are probably lower under blind than under preview bidding. Suppose, in addition, that expected return to exhibitors is the same in either blind or preview regimes, but that the variance of expected return is larger under blind bidding. Under risk-neutrality, exhibitors would be no worse-off under blind bidding while distributors would strictly prefer it. In the long run, this preference would shift out the market supply curve, the resulting greater surplus being apportioned to exhibitors and distributors according to the elasticities of supply and demand. With risk-aversion, blind bidding could reduce the utility of exhibitors so that it is no longer Pareto-superior. Then, both supply and demand curves might change position, with the equilibrium apportioning of gains and losses again determined by the relevant elasticities.

In fact, the market for first-run motion picture licenses does not conform to the perfectly competitive paradigm: there are only a few buyers and sellers, the product is not homogeneous, and strategic behavior affecting price is evident. A substantial literature devoted to such environments¹ confirms that buyers facing increased uncertainty about the value of an auction prize will respond, on average, by reducing their bids. So we might expect exhibitors to bid less for blindly-licensed films. Distributors will then pay for their inventory cost savings with smaller rental receipts.

Viewed this way, it does seem reasonable to interpret blind bidding as a mechanism for reallocating risk between exhibitors and distributors.²

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¹ Wilson (1969) has shown that even risk-neutral bidders will reduce their bids under uncertainty. For other evidence of this phenomenon, see Cox (1981), Reece (1979), Rothkopf (1969) and Smiley (1979). For an analysis under risk-aversion, see Milgrom and Weber (1982).

² Contrary to the suggestion of Kenney and Klein (1983), distributors are not "Goliaths" relative to exhibitors. Most U.S. first-run theaters are owned by large circuits.

Assuming rational behavior, the controversy surrounding film auctions suggests that the expected utilities of exhibitors and distributors are not the same in blind and preview regimes. My statistical analysis suggests that exhibitors are risk-averse, and that while they do lower their bids in blind auctions, raising their return, they accept in exchange greater variability of return. Given the sorts of films distributed in these auctions, the analysis suggests that exhibitors do not bid low enough to offset their greater risk. A resulting decline in expected utility then might well drive rational exhibitors to seek legislative relief.

Section I sketches the essential institutional features of this market. In section II, I demonstrate the plausibility of incomplete risk-trading, in the context of a simulated Nash equilibrium. Section III presents an empirical study of bids for first-run films. A conclusion is in section IV.

I.

In states where blind bidding is still legal and for a film with a well-known plot, director or star (e.g., an adaptation of a Broadway play or a sequel to a box office hit), the distributor frequently solicits prospective exhibitors before shooting takes place. Exhibitors receive information about the film in a letter, typically including the names of the producer, director and performers, a description of the story line, anticipated production costs, the projected audience, and the expected release pattern. The letter invites bids and suggests as exhibition terms the length of the run, the division of promotional costs between the distributor and the exhibitor and the rental payment. By convention, total payments are the greater of a minimum rental guarantee and the sum of weekly rentals. In turn, weekly rentals are the larger of:

- (1) a percentage (p_i) of box-office gross receipts in week i (G_i), with p_i declining as the run progresses through time; or
- (2) 90% of the difference between G_i and a previously agreed-upon house allowance, referred to as the "nut" (C).

While the house allowance might be construed to reflect the exhibitor's operating costs, in practice it remains fixed over long stretches of time. As a "given," it is more properly viewed as exogenous

to the bidding process. The minimum rental guarantee requested by distributors, which is usually substantial, is collected several weeks *before* the film's release.

Interested theater owners next prepare sealed bids, specifying the screen's seating capacity, the number of weekly showings, a minimum guarantee (A), and a percentage rental schedule. For the entire length of the run (k weeks) the offered rental payment is then:

$$\text{Rental} = \text{Max} \left\{ A, \sum_{i=1}^k \text{Max} [p_i G_i, 0.9(G_i - C)] \right\}^3$$

As a function of weekly gross, the rental is concave (viewed from above).

In selecting winners, distributors are known to consider the previous box-office performance of a screen, as well as the nominal size of the exhibitor's bid. This means that particularly well-located screens may succeed in winning a film with lower bids than screens with poorer track-records.

In states where blind bidding is prohibited, trade screenings are held two or three weeks prior to a film's release. Since exhibitors in states where blind bidding is allowed have by then long committed themselves, there is no opportunity for any exchange of information.

II.

In the model presented here an information constraint can leave risk-averse bidders worse-off in expected utility terms. It is derived from the work of Vickrey (1961), Rothkopf (1969), Wilson (1969, 1977), Holt (1979, 1980), Smiley (1979), Reece (1979), and Milgrom and Weber (1982). Suppose that there are two bidders ($i = 1, 2$) competing for a prize of unknown value, v . Each bidder observes a signal, s_i , containing information about v , and uses it to construct a bid, $p_i = p_i(s_i)$. Each bidder has the same concave utility function, $U(v, p_i)$, and maximizes:

$$L = \int_{-\infty}^{\infty} U(v, p_i) \int_{-\infty}^{\pi(p_i)} h(s_j|v) ds_j f(v|s_i) dv \quad (1)$$

³ In the dataset studied here, the guarantee is binding (i.e., attendance receipts are so small that neither the declining percentage nor the 90/10 formulae satisfy the guarantee) with an approximate frequency of 0.24.

where $h(s_i|v)$ represents the measurement technology (the conditional distribution of the signal, given the prize's true value), $\pi(p_i)$ is the inverse bidding strategy, i.e., $\pi(p_i(s_i)) = s_i$, and $f(v|s_i)$ is the (Bayesian) posterior distribution of the prize's true value, given a particular signal and the prior distribution of v , $g(v)$. Differentiating (1) with respect to p_i yields the following differential equation, whose solution is a Nash equilibrium bidding strategy:

$$p_i'(s_i) = - \int U(v, p_i) h(s_i|v) f(v|s_i) dv / \int U'(v, p_i) H(s_i|v) f(v|s_i) dv. \quad (2)$$

An initial condition for (2) is defined by finding the smallest value of s_i such that the expected utility of the prize, gross of the bid, is equal to zero.

Numerical integration is used to simulate a solution to (2). The simulation assumes: (i) a CARA (constant absolute risk-aversion) utility function, $U(v, p_i) = (1 - \exp(-\lambda(v - p_i)))$ where λ is a risk-aversion parameter (Milgrom and Weber, 1982); (ii) that the prior distribution of the true prize value, $g(v)$, is lognormal, with log mean = -2 and log variance = 7.5; and (iii) that the measurement technology, $h(s_i|v)$ is lognormal, and unbiased, with mean v . The parameters of $g(v)$ approximate the relative magnitudes of the mean and variance of weekly box-office gross per screen in the sample.⁴ (ii) and (iii) guarantee that the posterior distribution, $f(v|s_i)$, will also be lognormal (De Groot, 1975). Substituting the indicated utility function, Reece's (1979) FORTRAN program was used to generate estimates of $p(s_i)$ and expected utility at alternative values of s_i . Repeating the simulation with different values of the variance of the measurement technology (SSIGSQ) and setting the risk-aversion parameter at 0.05,⁵ the results are found

in table 1. They suggest an optimal bidding strategy which is concave, with a threshold signal value below which a bid would not be made. In most cases, this threshold declines with SSIGSQ.⁶ Comparing the strategy functions for SSIGSQ values of 2.0 and 2.6, the former appears to dominate everywhere. When a bidder sees a low signal value, his optimal bid increases and his expected utility decreases with more perfect information. On the other hand, when a bidder sees a larger signal value (s_i exceeds 132.970, or roughly one-half standard deviation above the mean), there is a

incomes. However, for the utility function used here, the certainty-equivalent income depends also on the spread between the alternatives and on the starting point. Fortunately, different values of lambda have no appreciable effect on the simulation results.

⁶ This is similar to Reece's findings under risk-neutrality.

TABLE 1.—RISK-AVERSE NASH EQUILIBRIUM

Signal	SSIGSQ	Bid	Expected Utility
39.371	2.0	8.979	.289
	2.2	8.711	.293
	2.4	8.371	.294
	2.6	8.104	.296
59.076	2.0	11.124	.348
	2.2	10.685	.352
	2.4	10.180	.351
	2.6	9.776	.352
88.634	2.0	13.640	.409
	2.2	12.977	.412
	2.4	12.261	.410
	2.6	11.681	.411
132.970	2.0	16.572	.471
	2.2	15.619	.474
	2.4	14.642	.470
	2.6	13.843	.470
199.476	2.0	19.977	.531
	2.2	18.662	.533
	2.4	17.354	.529
	2.6	16.293	.529
299.233	2.0	23.928	.587
	2.2	22.158	.589
	2.4	20.435	.586
	2.6	19.061	.584
448.870	2.0	28.509	.638
	2.2	26.177	.641
	2.4	23.948	.638
	2.6	22.192	.636

Note: prior mean log = -2.0
 prior variance log = 7.5
 risk-aversion parameter = .05
 information parameter, SSIGSQ = 2.0, 2.2, 2.4, 2.6 (smaller values corresponding to more complete information).
 There are two bidders.

⁴ Since the outputs of the simulation (bid and expected utility) are invariant to changes in the unit of measurement, let v be measured in units of \$1450. This implies that the mean and standard deviation of v are about \$8300 and \$9300, respectively.

⁵ Lambda is the Arrow-Pratt measure of absolute risk aversion, $-U''/U'$, expressing the speed with which the (concave) utility function becomes flat. Understandable interpretations of its magnitude are difficult. One possibility, for a given lambda, is the level of certain income yielding the same expected utility as a 50/50 gamble between two alternative

range of uncertainty within which bids and expected utility both increase with better information. Averaging across all signal values (from 0 to infinity), the former result dominates. But, since distributors only select for blind bidding those films whose potential is widely recognized (e.g., a sequel or a screen adaptation), it is indeed plausible that they have high signal values. Thus, exhibitors may well experience lower expected utility, on average, as a result of blind bidding.

It could be argued that the real-world counterparts of such results are short-run phenomena. Over time, with entry and exit of firms between blind and preview states, differences in return would disappear. Two sorts of replies can be made. First, the location of a theater is an important determinant of its profitability. Given a hierarchy of locations, entering firms would likely have to accept less-desirable locations than already established firms. Second, entry and exit take time to occur. Thus, inframarginal rents can be expected to accrue to exhibitors in preview states.

III.

The econometric model used here is designed to test the following hypotheses:

I. *Ceteris paribus*, exhibitors who face a film-license auction blind will bid lower than exhibitors who have previewed the film.

II. *Ceteris paribus*, the set of information common to both kinds of exhibitors will explain a larger percentage of the variance of bids for blind than for previewing bidders.

III. *Ceteris paribus*, blind exhibitors will realize returns which are larger but more variable than those received by previewing exhibitors. Since direct measures of expected utility are precluded, I assume that the expected utility of a risk-averse exhibitor depends both on the mean and the variance of his return. Demonstrating an increase in mean return accompanied by greater variance would then open the door to diminished expected utility.

The data consist of the terms and actual exhibition experience of 18 films licensed to a national circuit by three major distributors from January through September 1982. Each film was licensed blind in states where permissible, and by previews where not.

Lacking data from losing exhibitors, analysis is confined to winning bids. This is potentially a problem since claiming that blind exhibitors will, on average, bid lower need not imply that the *winning* blind bid will be smaller. Fortunately, a good theoretical argument (Hadar and Russell, 1969) establishes that if exhibitors are risk-averse, preferring more to less information, then winning blind bids *will* be lower (theorem of first-degree stochastic dominance).

Pooling the data, each film is treated as an element of a time-series and each theater in which it is screened is considered a cross-sectional element.

Model

$$\begin{aligned} Bid_{it} = & \beta_0 + \beta_1 SRDensity_{it} + \beta_2 Nut_{it} \\ & + \beta_3 SRBudget_{it} + \beta_4 D_{it} \\ & + \beta_5 XSRBudget_{it} + \beta_6 Runs_{it} \\ & + \beta_7 XRuns_{it} + (\epsilon_{it} + \mu_i) \end{aligned} \quad (3)$$

$$\begin{aligned} Return_{it} = & \beta_0 + \beta_1 SRDensity_{it} + \beta_2 Nut_{it} \\ & + \beta_3 SRBudget_{it} + \beta_4 D_{it} \\ & + \beta_5 XSRBudget_{it} + \beta_6 Runs_{it} \\ & + \beta_7 XRuns_{it} + (\epsilon_{it} + \mu_i) \end{aligned} \quad (4)$$

$i = 1, 2, \dots, 18$ films

$t = 1, 2, \dots, T_i$ screens.

Bid is the sum offered as a guarantee by the exhibitor, in hundreds of dollars, while *Return* is the difference between gross attendance receipts and rental actually paid, in hundreds of dollars.⁷

D is a dummy variable, 0 for blind and 1 for preview observations. It is screen-specific, depending on whether the screen is located in a state which prohibits blind bidding.

SRDensity is the square-root of the number of theaters per one hundred thousand population in this SMSA. It is screen-specific. Included as a measure of competition, it may also capture differences in the relative demand of movie-goers. One strategic response to an increase in *SRDensity* would be higher bids. In a one-shot game, this response would be asymptotic, as no exhibitor would bid more than the film's expected value. Recognition of the winner's curse⁸ likely also

⁷ Analysis focuses on the guarantee because it is the most variable element of the bid vector.

⁸ The winner's curse occurs in auctions when the players do not know the value of the prize with certainty. In a first-price auction, the winner will be the player with the highest estimate of the prize's value. Since the winner's estimate may be highly optimistic, relative both to the estimates of the other players and to the prize's true value, it may well be a "curse" to win.

dampens the tendency for bids to increase with density. Consequently, the relationship is postulated to be concave.

Nut is the house allowance for this screen, in tens of dollars. If *Nut* does capture only costs, then exhibitors would likely experience smaller profits as *Nut* increases and hence would submit lower guarantees. Alternatively, if the *Nut* includes a reward to theaters with good track records, higher values would be associated with larger profits and hence higher guarantees. A linear relationship is assumed.

SRBudget is the square-root of the film's production cost, in millions of dollars. It is film-specific. Its relationship to the bid of one screen is assumed to be concave, based on the underlying concave relationships between bid and expected return,⁹ return and gross receipts, and gross receipts and budget: $Bid = B\{\text{expected return}[\text{gross}(\text{budget})]\}$. Since films with greater production cost are likely to be shown in more theaters, the proportionality of return per screen to *SRBudget* may be entirely consistent with total return (per film) being proportional to *Budget*.¹⁰

Runs, another film-specific variable, is the number of first, same-day screen openings. Distributors select large values for films expected to have immediate audience appeal and smaller values for films expected to need time to develop. If distributors estimate the time paths of expected gross correctly and if these time paths do not themselves influence the total volume of audience demand, then one would expect no relationship between *Return* and *Runs*, and, hence, no systematic effect on *Bids*. However, if films with immediate audience appeal on average do produce more revenue, then the number of screen openings may itself communicate important information to exhibitors, resulting in positive relationships between *Runs* and both *Bid* and *Return*.

The remaining three regressors are interaction terms for separating the responses of blind and previewing exhibitors. The sign of the coefficient on the first interaction term, *D*, indicates whether the intercept of the bidding function of blind exhibitors is smaller than that of previewing ex-

hibitors. The second and third interaction terms, *XSRBudget* and *XRuns* (whose coefficients are the slopes of the "treatment" bidding functions), capture whether blind exhibitors use budget and runs information differently than do previewing exhibitors.

The *Return* equation contains the same variables, entered with the same functional form as the *Bid* equation.

Bid, *Nut*, *Gross*, and *Rental* were obtained from the theater circuit.¹¹ Numbers of theaters by SMSAs came from the 1977 Department of Commerce Census of Service Industries. Population by SMSA was obtained from the 1980 Census. The costs of producing film negatives (i.e., the *Budgets*) and *Runs* were obtained from *Variety*.

An error-components estimator was constructed, assuming that the slope coefficients remain constant across films, while each film's intercept is a random variable.¹² Note that since there is no intra-film variability for either *SRBudget* or *Runs*, estimators for β_3 and β_6 are available only from the between estimate. Results of the between, within and GLS estimates are in table 2.

One of the assumptions underlying the unbiasedness of the GLS specification is that the individual film effects are orthogonal to the other regressors. Hausman (1978) suggests that this is so if the within and the GLS estimates are approximately equal. Computation of the relevant test statistic confirms the unbiasedness of the *Bid* equation specification but not that of the *Return* equation.¹³ In this case, the within estimate, which assumes fixed rather than random effects, is preferable (unbiased).

The goodness-of-fit measures, while small, are respectable, given the limited nature of the data. Examination of the residuals from both the *Bid* and the *Return* equations indicates that the functional forms are appropriate.

Note that in the empirical model adopted here, the first two hypotheses imply opposing impacts of blind licensing on the level of bids: while we expect blind exhibitors to respond to the additional uncertainty with lowered bids, we also

⁹ See my dissertation for a simple risk-averse model in which the optimal bid increases with expected return, at an eventually decreasing rate.

¹⁰ For example, suppose that the number of screens is proportional to *SRBudget*. Then total return (return per screen \times number of screens) would be proportional to *Budget*.

¹¹ The data to replicate this research are available on request to the author.

¹² The GLS estimator is a weighted average of the between and within estimators.

¹³ Hausman's statistic (*QMQ*) is distributed Chi-square, with 5 degrees of freedom. For the *Bid* equation, *QMQ* = 7.30 while for the *Return* equation, *QMQ* = 326.57.

TABLE 2.—ESTIMATION OF BID AND RETURN

	Between		Within		GLS	
<i>BID</i>						
Constant	-1513.67	(-2.53)	-----	-----	-115.47	
<i>SRDensity</i>	248.38	(1.06)	-3.80	(-1.78)	-3.81	(-1.78)
<i>Nut</i>	1.59	(2.36)	1.06	(5.76)	1.13	(6.44)
<i>D</i>	1716.26	(1.51)	98.17	(0.59)	169.85	(1.04)
<i>SRBudget</i>	89.79	(1.61)	-----	-----	-----	-----
<i>Runs</i>	0.29	(1.58)	-----	-----	-----	-----
<i>XSRBudget</i>	-128.61	(-0.47)	-38.58	(-1.25)	-38.38	(-1.26)
<i>XRuns</i>	-1.25	(-1.82)	-0.04	(-0.29)	-0.10	(-0.72)
	$R^2 = .47$		$R^2 = .17$		$R^2 = .20^a$	
	10 df		205 df		205 df	
<i>RETURN</i>						
Constant	-1254.36	(-2.37)	-----	-----	-15.51	
<i>SRDensity</i>	209.95	(1.02)	-1.54	(-1.50)	-1.50	(-1.46)
<i>Nut</i>	3.19	(5.33)	0.58	(6.52)	0.68	(7.70)
<i>D</i>	1329.67	(1.32)	-168.48	(-2.09)	-143.15	(-1.79)
<i>SRBudget</i>	-30.71	(-0.62)	-----	-----	-----	-----
<i>Runs</i>	0.01	(0.03)	-----	-----	-----	-----
<i>XSRBudget</i>	-221.19	(1.32)	15.34	(1.04)	13.14	(0.89)
<i>XRuns</i>	-0.37	(-0.61)	0.05	(0.72)	0.06	(-0.84)
	$R^2 = .766$		$R^2 = .191$		$R^2 = .1403^a$	
	10 df		205 df		205 df	

Note: *t*-statistics are in parentheses.

^a R^2 is calculated as the square of the correlation coefficient between actual bid (or return) and estimated bid (or return).

expect them to pay more attention to *SRBudget* and *Runs*. Testing a weak version of hypothesis I (the intercept of the blind bidding function is smaller), we have:

$$\text{Bid intercept} = \Gamma_0 + (\Gamma_1 - \Gamma_0)D,$$

so that when $D = 0$, the intercept is Γ_0 and when $D = 1$, it is Γ_1 . The GLS constant is a measure of Γ_0 and the GLS coefficient on D ($0.10 < \alpha < 0.25$, with α the probability of a Type I error) is a measure of $(\Gamma_1 - \Gamma_0)$. By subtraction, Γ_1 is 54.38. As expected, the blind intercept is smaller.

An alternative explanation of this difference could be that the sample is biased, most of the films "better" than blind exhibitors believed them to be, given the information available. Since previewing exhibitors had more information and likely "knew" this, their bids could be higher. If so, then the ex post difference between per screen return (gross - rental) and per screen budget (*budget/runs*) should be positive and, as a proportion of per screen budget, greater than 1. On the other hand, if the film is poorer than the information available to blind exhibitors would imply, then this ratio will be less than -1. Calculating it for all 18 films, only 3 were surprise smash hits and

none was unexpectedly poor. Since the average preview bid for each of the surprise smashes was less than or equal to the average blind bid, this alternative explanation seems unlikely.

Regarding hypothesis II, neglecting the other regressors, we have $\text{Bid} = \Gamma_2 \text{SRBudget} + (\Gamma_3 - \Gamma_2) \text{XSRBudget} + \Gamma_4 \text{Runs} + (\Gamma_5 - \Gamma_4) \text{XRuns}$. Estimates of Γ_2 ($.05 < \alpha < .10$) and Γ_4 ($.05 < \alpha < .10$) come from the between estimator, while the GLS coefficients on *XSRBudget* ($\alpha = .10$) and *XRuns* (not significant) give us $(\Gamma_3 - \Gamma_2)$ and $(\Gamma_5 - \Gamma_4)$, respectively. Solving, $\Gamma_3 = 51.4092$ and $\Gamma_5 = 0.1938$. Evidently blind exhibitors do attach greater weight to both the size of the film's budget and the number of first-run screen openings: a blind exhibitor will bid approximately \$8900 more while a previewing exhibitor will bid only \$5100 more for every one million dollar increase in a film's negative cost, *ceteris paribus*.

A strong version of hypothesis I (blind bids are lower than preview bids), is not supported. The linear combination

$$Z = (\Gamma_1 - \Gamma_0) + (\Gamma_3 - \Gamma_2) \text{SRBudget} \\ + (\Gamma_5 - \Gamma_4) \text{Runs},$$

evaluated at the mean of the preview observations, is negative.¹⁴

Two other implications of the results are interesting. The first is that bids *decrease* as the density of theaters increases ($\alpha = .05$). If density captures the level of market competition, then exhibitors might bid lower as their number increases. However, this would be surprising (Holt, 1979, 1980) unless they are unusually concerned about the winner's curse. On the other hand, if density measures market size (inversely), then perhaps exhibitors believe films are less valuable in smaller markets. Second, the significant positive relationship between *Bid* and *Nut* implies that *Nut* is *not* simply a measure of operating cost.

For the *Return* equation, the GLS specification is biased but, qualitatively, yields the same results as the within estimator. That is, substituting the within specification has no impact on the rank ordering of either the level or the variability of blind and preview observations. Analyzing the GLS results, the intercept for blind exhibitors, as expected, exceeds that of previewers (-15.51 versus -158.65, with $\alpha = .05$). Furthermore, the contributions of the slope coefficients on *XSRBudget* and *XRuns*, evaluated at the preview mean, do *not* swamp this effect. Blind returns are larger. Finally, paralleling the results from the *Bid* equation, *Return* falls as theater density increases ($\alpha < 0.10$) and *Return* is positively related to *Nut* ($\alpha < 0.05$).

For the third hypothesis, the results are supportive. Seven films were selected for study, each of which had at least three blind and three preview observations. For each film, the GLS parameters from the *Return* equation were used to adjust return per screen for differences in *Nut* and density:

$$\text{Adjusted return}_{it} = \text{Return}_{it} + 1.501 \text{SRDensity}_{it} - .6758 \text{Nut}_{it}.$$

In five films, the standard deviation of adjusted return is greater for blind observations, significant for two films at $\alpha = 0.05$. Finally, I estimate the extent of risk-aversion amongst exhibitors bidding on the four films with the most observations. Assuming the quadratic utility function, $U(Y) =$

TABLE 3.—ESTIMATES OF ABSOLUTE RISK-AVERSION

Film	$-U''/U'$
A	.004
B	.034
C	-.012
D	.000

$a_1Y - a_2Y^2$, expected utility is given by

$$E[U(Y)] = a_1(\text{mean } Y) - a_2(\text{var } Y) - a_2(\text{mean } Y)^2.$$

For each film, setting $a_1 = 2$ and using the data on actual mean return and variance of return, I first solve for the value of a_2 such that the expected utilities of blind and previewing exhibitors are equal. Then, I evaluate the absolute risk-aversion measure, $-U''/U'$ (here, $2a_2/(a_1 - 2a_2Y)$), at the mean blind return. The results are in table 3. Since these estimates are based on the assumption that exhibitors were indifferent between the blind and preview return distributions when, in fact, they are not, these may be fairly interpreted as lower bounds on true risk-aversion. Recall that in the Nash equilibrium simulation, a risk-aversion parameter only slightly larger than the one estimated for Film B ($\lambda = .05$) was "enough" to generate an expected utility loss for blind bidders.

IV.

The purpose of this research has been to rationalize the battle between exhibitors and distributors over blind bidding. The explanation offered is that while blind exhibitors do deal with the information constraint by lowering their bids, they are unable, because of their risk-aversion and the inherent competitiveness of these auctions, to reduce them enough. Consequently, on an expected-utility basis, blind exhibitors do more poorly. The theoretical simulation reported here does lend support to this explanation.

Empirically, the analysis confirms that, *ceteris paribus*, there is a bid component which blind exhibitors reduce. It also supports the hypothesis that blind exhibitors pay more attention to the scant information available to them. And, it suggests that blind exhibitors are compelled to accept greater variance in exchange for larger mean return. Estimated relative risk-aversion parameters are then shown to be consonant with expected utility losses under blind bidding.

¹⁴ For a lengthier discussion of this matter, see my dissertation.

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