

Time to Unbridle U.S. Thoroughbred Racetracks? Lessons from Australian Bookies

Charles C. Moul · Joseph M. G. Keller

Published online: 29 January 2014
© Springer Science+Business Media New York 2014

Abstract We consider a policy reform that would relax price controls in American pari-mutuel wagering on horse racing by examining bookie behavior in Australia's fixed-odds gambling sector. Descriptive regressions indicate that bookmaker takeouts (the effective prices of races) vary substantially and systematically with race characteristics, though in sometimes counterintuitive ways. Estimates of an explicitly reduced form model of bookie takeout, however, can qualitatively match both intuition and prior findings in the literature. Counterfactuals that use these estimates suggest that regulatory reform that permits racecourses to alter takeout across races would increase variable profit by about 5 %.

Keywords Regulatory reform · Gambling · Horse racing

JEL Classification D22 · L5 · L83

The U.S. horse-racing industry, like many other heavily regulated American sectors, is in decline. Figure 1 shows the annual “handle” (amount wagered), purse (prize money),

We thank Max Kaftal for excellent research assistance including seeking out the data, Tim Ryan (former CEO of the Australian Bookmakers Association) for releasing the data, and Ryan Ruddy for additional research support. We also thank our many Australian acquaintances with first-hand racetrack experience for sharing their field research, as well as many helpful individuals on the supply-side of Australian wagering.

C. C. Moul (✉)
Department of Economics, Miami University Farmer School of Business,
Oxford, OH 45056, USA
e-mail: moulcc@miamioh.edu

J. M. G. Keller
Dunnhumby, Cincinnati, OH, USA
e-mail: jmgkeller@gmail.com

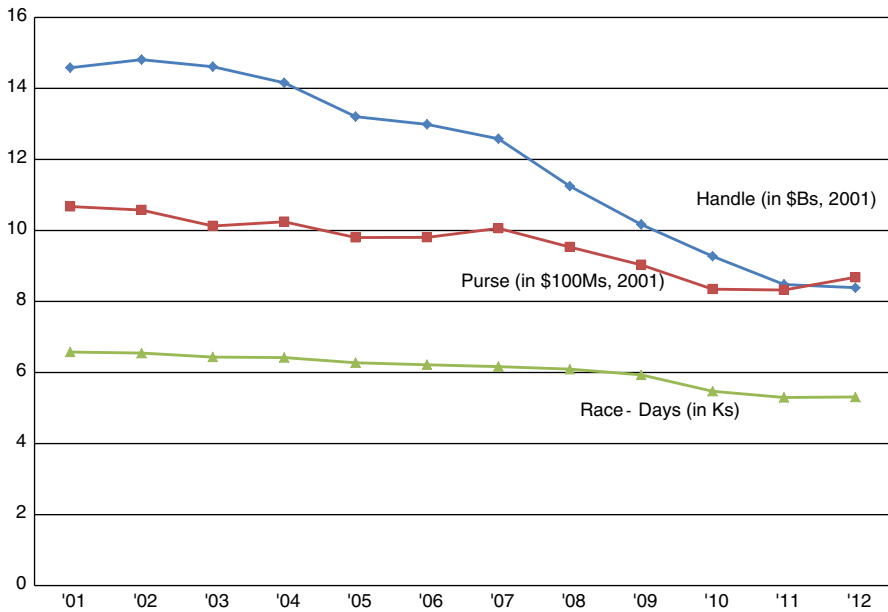


Fig. 1 U.S. thoroughbred racing 2001–2012

and race-days for U.S. thoroughbreds in recent years.¹ Since 2001, all measures are lower, and the annual handle is down by 40 %. An obvious remedy is a change of the state laws that dictate the takeout rate (i.e., price) that tracks charge for all races, and a notable economic literature argues that broadly lowering takeout rates would increase the cumulative takeout (variable profit).

In this paper, we argue for a complementary margin of deregulation: that tracks should be given the authority to set takeout rates that vary across races.² Predicting the effects of such a deregulation is a daunting task; the industry's regulation prevents the empirical variation in U.S. data that would inform the analysis. To sidestep the domestic data limitations, we use Australian data from bookmakers (bookies) who are free to set odds to estimate the impacts of such variable takeout rates. We then link these Australian results to our U.S. policy questions through a counterfactual exercise.

The takeouts that are implied by our observed bookie-odds show substantial variation across races on the same day and at the same track, with a sample standard deviation of 3 percentage points (compared to a mean of 17 percentage points). A revealed preference argument then suggests that American racetracks would benefit from increased flexibility on this dimension. Estimates from descriptive regressions are generally consistent with prior work, in that the takeout is higher for races with larger numbers of horses (field size) and with more evenly matched horses. We address the

¹ These figures are taken from Equibase annual press releases ("Thoroughbred Racing Economic Indicators"). Handle and purse are in 2001 US\$ with inflation-adjustments made using US-CPI data.

² These proposals and others are included in the [National Thoroughbred Racing Association Players' Panel Recommendations \(2004\)](#).

unexpected result that the takeout and purse are negatively related by enabling demand both to rotate and to shift with purse.

We model Australian bookies as selecting the takeout for each race, which is a marked contrast with the U.S.'s pari-mutuel system with uniform takeouts. While quantities wagered are unobserved, we combine observed odds with profit-maximization and with conduct hypotheses to estimate reduced-form pricing equations from which we recover some structural demand estimates. We use these reduced-form estimates to consider the counterfactual of how Australian bookie profits would change if a single uniform takeout rate was set to maximize profits over the entire sample. That is, we consider the implication of depriving bookies of the option of price-discriminating across races. This counterfactual indicates that allowing U.S. racetracks to vary takeout rates across races could boost a racetrack's cumulative takeout by about 5 %.

The rest of the paper is organized as follows: We review the regulatory structure, history, and economics literature that relates to pari-mutuel wagering in the U.S. and fixed-odds wagering abroad in Sect. 1. Section 2 outlines the assumptions and techniques for recovering takeout rates from observed odds. We introduce the data in Sect. 3 and present descriptive regression results that motivate our theoretical model. Section 4 introduces the structural model and its reduced forms under two distinct conduct assumptions. Section 5 showcases our estimates (reduced form and counterfactual), and we conclude with implications of the proposed regulatory change.

1 Background for Gambling on Horse Racing

1.1 Common Institutions

The business models of U.S. and Australian racetracks are generally similar. In both countries, racetrack revenues include the betting handle through the racetrack, as well as nomination and entry fees by racehorse owners. Racetracks in both countries offer pari-mutuel wagering (described in more detail below) in which the track effectively serves as an intermediary for bettors to gamble against each other rather than against the track. Costs are payouts to winning bettors and purses to winning horses. The only difference of note is that Australian racetrack revenues also include fees paid by bookies for the privilege of on-site operation.

Well in advance of race-day, expected purses and entry fees are announced, and horse-owners choose in which races to run. Final purses are then sometimes dependent on actual race-day handle. Withdrawing horses by owners for trivial reasons (e.g., weather) is discouraged, and almost all withdrawals occur because of stated injury or illness.³ Comprehensive data on handle are difficult to find, but casual observation indicates that purses, handle, and entry fees show high and positive correlations. This ordering will serve as our later justification of using purse as a proxy for unobserved characteristics that are set before race-day (e.g., prestige). Crowds tend to grow

³ The owners of horses that are withdrawn because of illness or injury have their entry fees refunded.

throughout the day, and it is common for racetracks to begin with races that draw less betting interest and to improve race-quality with later races.

1.2 U.S. Institutions

After gambling was prohibited in almost all American states in the early 20th century, racetrack-operated pari-mutuel wagering on horse races was re-introduced during the Depression. The revenue-starved states coupled this resurrection with new excise taxes on handle, and most states continue to employ these taxes. As we discuss in our conclusion, the negative welfare consequences of our proposal (detailed by [Schmalensee 1981](#)) can be mitigated by a shift from these revenue taxes on handle to a tax on cumulative takeout receipts (variable profits). For a sense of the magnitudes of handles and the related taxes, Churchill Downs (Kentucky) in the 2011 season had about \$603M in handle on which it paid about \$20M in tax.⁴

Horse racing is categorized as thoroughbred, quarter-horse, or harness, but all horse race gambling in the U.S. exclusively uses the pari-mutuel format. In this format, all payouts are dictated by final odds, which depend on how the handle is distributed across the field of horses at race time. All pre-race posted odds are therefore preliminary, and bettors essentially make wagers for an unspecified price. For straight wagers such as win bets on a particular horse, the racetrack deducts from the handle a percentage equal to the takeout rate and returns the remaining money to the bettors who placed wagers on the winning horse. Odds for any given race are thus determined entirely by how bettors decide to wager. Bettors make these wagers at the racetrack or at off-track betting facilities.⁵

Takeout rates in the U.S. tend to be set by state government or by the state's gambling regulatory body, though some states offer limited discretion to racetracks.⁶ As of 2013, takeout for win bets on thoroughbreds ranged from California's 15.43 % to Arizona's 20.75 %.⁷

Kentucky has a typical structure of regulation and provides the most closely related empirical results to our exercise, and so it warrants special attention: Kentucky has a relatively low takeout rate of 16 % for straight bets such as win (1st place), place (1st or 2nd) or show (1st, 2nd or 3rd). Takeouts for exotic bets on multi-horse outcomes (e.g., exacta, quinella) are also regulated and tend to be several percentage points higher (e.g., Kentucky has a takeout of 19 % for those exotic bets).⁸

⁴ Churchill Downs (2011) annual report, p. 56.

⁵ The Interstate Horseracing Act of 1978 (Public Law 95-515) stipulates that off-track betting facilities must be subject to the same regulations regarding takeout as the racetracks themselves and that such facilities must be at least 60 miles from the nearest racetrack.

⁶ New York, for example, bounds takeout rates for win/place/show bets between 15 and 18 %, though it appears as of 2013 that only Tioga Downs is at the minimum.

⁷ Horseplayers' Association of North America (2013).

⁸ The exacta bet pays if the bettor picks the exact order of the horses that finish first and second; the quinella bet pays if the bettor picks the winners in five races that race-day. Such exotic bets are highly popular and cumulatively make up a large part of handle. The higher takeout rates for exotic bets are thus rationalized by demand arguments.

Bettor sensitivity to takeout rates has been explored econometrically as well as in several recent experiments. Previous researchers have used cross-sectional variation in takeout rates and amounts wagered to estimate price-elasticities for U.S. pari-mutuel gambling (Gruen 1976; Suits 1979; Mobilia 1993; Thalheimer and Ali 1998; Gramm et al. 2007). These studies have generally found that takeout rates are higher than the revenue-maximizing level, with estimated own-takeout elasticities ranging from -1.6 to -3 . If a track's costs are entirely fixed, then a social planner would prefer that takeout rates be lowered to reach the point of unit-elastic demand. To our knowledge, no studies have considered how race characteristics themselves can affect these price-elasticities—exactly the information that the estimates of our reduced-form model provide. There have also been several recent attempts to learn the responsiveness of bettors to this takeout rate with temporary (Laurel Park, MD 2007a; 2007b) or permanent (Hialeah, FL 2010; Tioga Downs, NY 2010a; 2010b) takeout reductions.⁹

Many empirical studies have examined the determinants of handle, but relatively few have used race-level (rather than year-level or day-level) characteristics as we do. We therefore judge how well our Australian data may illuminate the U.S. regulatory problem by leaning heavily on Coffey and Maloney (2010). That paper uses data from Churchill Downs in 1994 to distinguish the incentive effect from selection in explaining the correlation between performance and reward. More importantly for our purposes, it also includes regression results that show the impact of race characteristics on the amount of money wagered. The authors find that handle is increasing in purse and field size (i.e., number of horses) but is decreasing in dispersion of horse-talent.

1.3 Australian Institutions

Australia, like other countries that were part of the 19th-century British Empire, allows gambling within both a pari-mutuel format and a fixed-odds format. Depending on the state, the pari-mutuel system is either state-run or operated under substantial regulation by a for-profit firm. The state pari-mutuel takeout rate in New South Wales (Sydney) and Victoria (Melbourne) varies by bet type; the pari-mutuel takeout rate for straight win bets is 14.5 % in both states. Pari-mutuel takeout in Queensland (Brisbane) is regulated differently in that the blended takeout (weighted average of straight and exotic bet takeouts) cannot exceed 16 % over a twelve-month period and no takeout rate can exceed 25 %.

Fixed odds gambling in horse racing differs from pari-mutuel wagering in several ways. As the format's name implies, odds offered to a bettor are fixed, though these odds may be changed for subsequent bettors. Key to our exercise, bookies' pricing (i.e., odds-setting) is not regulated. Another obvious contrast with pari-mutuel wagering is the existence of the bookie: an individual who is actively setting odds. Each bookmaker should be thought of as a three-person team: the bookie who sets odds, the penciler who records odds, and the ledger who records bettors' wagers.

⁹ Laurel Park halved its takeouts on thoroughbreds across the board for ten days in August 2007. Hialeah Park lowered its takeout on quarter-horse racing to 12 % for all bet-types in October 2010. Tioga Downs reduced all its takeouts on harness racing to the state minima (15 % for win/place/show bets) at the start of the 2010 season.

The number of bookies depends primarily on the physical size of the racetrack, though cities differ in how the number of bookies varies across race-days (discussed below). Typically between 20 and 40 independent bookmakers at these racecourses compete for bettor business against one another, against the on-site pari-mutuel system, and against all off-site gambling options. These bookies are located either near the track or among the audience.

Racetracks charge bookies for the privilege of operating on site. Daily fees for these locations depend on the quality of location and race-day. For example, Sydney's Australian Racing Club during our sample charged bookies daily stand fees of AUD 110–550. During our sample, racetracks also charged bookies a fee equal to 1 % of handle; this fee was bookies' only noteworthy variable cost. While bookies may represent franchises, only one representative of each franchise is present at a track on a race-day.

While all racetracks nominally charge bookies daily fees for the privilege of operating, conversations with racing club figures indicate that the actual practices differ somewhat across cities. Sydney racetracks appear to be the most aggressive in matching the number of bookies with projected demand, and the number of operating bookies can vary substantially at a track from week to week. Melbourne and Brisbane racetracks, on the other hand, tend to maintain similar numbers of bookies across weeks. These differences are more qualitative than sharp, and so we will not attempt to impose them in our estimation strategies. They do, however, provide context when interpreting later estimates.

In our Australian data, the horses that are slated to race are known in advance of race day. Opening odds from the bookmakers are posted approximately 30 min before race time, and changes to these odds are periodically made prior to the posting of the official starting prices. As shown in [McAlvanah and Moul \(2013\)](#), the takeouts that are implied by these fixed odds start out relatively high (about 30 %) and tend to fall as the race approaches. This decline occurs as the bettor's value of fixed odds wagers relative to pari-mutuel wagers becomes smaller. Under typical circumstances in which no new information is revealed after betting has commenced, one expects fixed odds and pari-mutuel odds to converge as racetime approaches. In the data and throughout this paper, a wager's gross odds is the amount for each dollar wagered that is returned to the bettor in the event of his horse winning. For example, a \$1 wager on a winning horse with listed odds of 4 would pay back \$4 (the original \$1 plus \$3 of winnings).

Two commonly used measures of bookies' profit potential are the margin and takeout.¹⁰ The margin m is defined as the amount of a marginal dollar wagered that is retained by the bookie as a proportion of the amount returned to bettors. It is expressed within the industry as the sum of all wager prices less one: given a field of K horses, $m = \left(\sum_{i=1}^K \frac{1}{O_i} \right) - 1$, where O_i is the odds on horse i . The takeout T is defined as the amount of a marginal dollar wagered that is retained by the bookie as a fraction of the total amount wagered. A 25 % margin therefore corresponds to the bookie's retaining 20 % of the total amount wagered as takeout and paying out 80 %, and the connecting formulae between margin and takeout are $T = \frac{m}{m+1}$ and $m = \frac{T}{1-T}$. Both the margin

¹⁰ An alternate term for the margin is the overround, and alternative, more colorful terms for the takeout are the juice, the vig (short for vigorish), the edge, and the house edge.

and takeout should be weakly positive; otherwise there exists an arbitrage opportunity for bettors to wager on the entire field and earn a positive return without risk.

The choice of which measure to use as the dependent variable is admittedly arbitrary. While bookie margin has instructive parallels with Arrow–Debreu prices that sum to more than one as bookies impose the equivalent of a tax, we prefer the implied takeout in order to facilitate comparisons with the competing and American pari-mutuel regimes. All of our empirical results are robust to employing bookie margin instead of implied takeout rates as the dependent variable.

The takeout is therefore implicitly determined by the set of odds that is chosen by the bookmaker and thus can vary across time, racetracks and races. Shin (1991, 1992, 1993) spearheaded the applicable economic literature that examines bookie profit margins. Our research is somewhat similar to Shin (1993) in that we both use the bookmaker's implied profit margin as the dependent variable and employ race characteristics such as size of field and dispersion of horse-talent as explanatory variables. Unlike our paper, Shin (1993) does not consider the impacts of race quality (as proxied by purse) on margins. An additional difference is that Shin (1993) frames his empirical exercise as identifying the prevalence of insider trading, which he posits is the cause of the recurrently observed favorite-longshot bias in which favorites are underbet and longshots are overbet.¹¹

Our approach, on the other hand, begins with descriptive regressions and then turns to estimating reduced-form models that are explicitly derived from a (simple) structural model. These results serve distinct purposes: The estimates from the descriptive regression are useful for predicting the equilibrium impacts of race characteristics on takeout. The reduced-form estimates illuminate the mechanisms by which those equilibrium impacts arise. The counterfactual exercises that are necessary to address our policy issue are also only possible when empirical results have a reduced-form interpretation.

2 Transforming Odds into Implied Takeout

We now detail the assumptions of a stylized model under which the bookmaker's expected takeout for a race can be constructed from a set of observed odds. The necessary assumptions to do so without additional data are strong, but the payoff is substantial. The results match industry definitions and provide intuition on the transformation of horse-level odds to race-level takeout.

We assume that risk-neutral bettors obtain sufficiently high recreational utility from gambling so that they always wager on a race. These bettors decide on which horse to wager on the basis of the expected monetary payoff. Expected monetary payoffs are equalized in equilibrium, and bettors effectively randomize across horses, choosing a

¹¹ In a broad sense, bookies in Shin's model protect themselves from bettors with inside information on longshots by offering less favorable odds on those horses than the objective probabilities would suggest. Cain et al. (2003) provide additional empirical support that is consistent with the hypothesis. Working against the primacy of this interpretation, recent research has looked to explain the observed longshot bias in pari-mutuel gambling as the result of bettor misperception (Sobel and Raines 2003; Snowberg and Wolfers 2010) or sequential information release (Ottaviani and Sorensen 2009). Peirson and Smith (2010) revisit the insider-trading story without relying on the favorite-longshot bias.

particular horse with probability equal to the probability of that horse winning. Our model of bettors is thus a special case of [Ottaviani and Sorensen \(2010\)](#) without private bettor information so that bettors share common beliefs about race outcomes. This assumption of common beliefs would seem contrary to the idea that the market odds are a synthesis of the disparate beliefs across bettors. Our use of it merely reflects the most direct way to recover the industry's definitions of margin and takeout. This framework also begs the question of why a risk-neutral consumer would choose to make a wager with an expected negative return. We leave these matters to other research and merely point out that local risk-loving preferences over small wagers can rationalize this behavior and are not inconsistent with local risk-averse preferences over large wagers (see [Markowitz 1952](#)).

Unlike their passive pari-mutuel competitors, bookmakers actively set odds O_k , which is the gross payout to a winner of a \$1 wager on horse k to win the race. Let p_k denote the bookie's subjective probability of horse k winning the race. The expected takeout on horse k is thus $t_k = 1 - p_k O_k$. In expectation, the bookie retains t_k of every dollar wagered on horse k and pays out $p_k O_k$.

Letting ρ_k denote a bettor's subjective probability of horse k winning the race, the equilibrium assumption requires that a bettor is indifferent between a wager on any two horses: $\rho_j O_j = \rho_k O_k \forall j, k$. These conditions also correspond to the bookie's maintaining a balanced book: the portfolio under which the bookie is guaranteed a riskless return.¹² When combined with the fact that subjective probabilities sum to one ($\sum_{k=1}^K \rho_k = 1$), our system contains K equations for K horses.

For a given set of observed odds in equilibrium, one can uniquely determine the bettor subjective probabilities:

$$\rho_k = \frac{1/O_k}{\sum_{i=1}^K 1/O_i}. \quad (1)$$

The converse is not true, as bettor subjective probabilities do not correspond to a unique set of odds. Bettor subjective probabilities determine only the ratio of odds; for example, $\frac{O_1}{O_2} = \frac{\rho_2}{\rho_1}$, and $\frac{O_1}{O_3} = \frac{\rho_3}{\rho_1}$ for a three-horse race. The bookie has the capacity to fix the magnitude of the odds for any one horse and thus implicitly the takeout for the race.

Consider the following simple example of a three-horse race: Substituting $O_k = \frac{1-t_k}{p_k}$ into the consumer indifference conditions yields $\frac{(1-t_1)/p_1}{(1-t_2)/p_2} = \frac{\rho_2}{\rho_1}$ and $\frac{(1-t_1)/p_1}{(1-t_3)/p_3} = \frac{\rho_3}{\rho_1}$, which simplifies to $\frac{1-t_1}{1-t_2} = \frac{p_1 p_2}{p_2 p_1}$ and $\frac{1-t_1}{1-t_3} = \frac{p_1 p_3}{p_3 p_1}$. As before, we have more unknowns than equations, and horse-level takeouts are not uniquely identified by the

¹² [Levitt \(2004\)](#) observes both point-spreads and quantities bet from a special wagering tournament based on professional (American) football games and finds evidence inconsistent with such a balanced book assumption. The frequent odd changes (average 37) in the 30 minutes prior to race time observed by [McAlvanah and Moul \(2013\)](#), however, are more consistent with bookies balancing a book than sticking with chosen odds as in [Levitt \(2004\)](#). Furthermore, the data suggest substantial variability across races between the takeouts that are implied by the opening odds and the starting (racetime) odds. Specifically, the observed average ratio of starting odds to opening odds is 1.89, and its standard deviation is 0.62. Such differing odds changes run counter to Levitt's story for our data.

subjective probabilities. Without loss of generality, assume that the bookie sets the odds on horse 1 and thus determines t_1 . The consumer indifference conditions then imply that $t_2 = 1 - (1 - t_1) \frac{p_2 \rho_1}{p_1 \rho_2}$ and $t_3 = 1 - (1 - t_1) \frac{p_3 \rho_1}{p_1 \rho_3}$. These equations indicate that, because of the inter-linking of odds imposed by the bettor equilibrium conditions, a bookie that maintains a balanced book cannot set individual horse-level takeouts independently of each other.

The expected race takeout is then the sum of individual horse-level takeouts, weighted by each horse's fraction of the total amount wagered. We lack data on these weights, and so we must make an assumption as to how that fraction relates to the observed odds. Consistent with our previous assumption with regard to how bettors randomize across horses, we assume that the fraction of the handle that is wagered on a particular horse coincides with the previously inferred bettor subjective probability for that horse. Using these subjective probabilities as weights implies that the takeout for an entire race will be $T = \sum_{k=1}^K \rho_k t_k$. Substituting $t_k = 1 - p_k O_k$ and our prior expression (#1) for equilibrium subjective probabilities yields the formula for takeout:

$$\begin{aligned} T &= \sum_{k=1}^K \left(\frac{1/O_k}{\sum_{i=1}^K 1/O_i} \right) (1 - p_k O_k) = \left(\frac{1}{\sum_{i=1}^K 1/O_i} \right) \sum_{k=1}^K \left(\frac{1}{O_k} - p_k \right) \\ &= 1 - \left(\frac{1}{\sum_{i=1}^K 1/O_i} \right) \end{aligned} \quad (2)$$

Alternatively, the race-margin is given by

$$m = \left(\sum_{i=1}^K \frac{1}{O_i} \right) - 1. \quad (3)$$

These takeout and margin expressions are not limited to racetime odds and can be used for any set of equilibrium odds.

Intuitively, the extent to which the reciprocal gross odds sum to greater than one signifies the bookie's expected profit margin. The above can be viewed as a rationalization of the industry's margin and its interpretation as a race's price. One might alternatively accept the margin as an adequate measure of the price of a race based entirely on its use in industry. In either case, a race's takeout will relate back to the loss that a bettor can expect to face and thus can be interpreted as the price that a bettor faces when wagering on a particular race.

We now link the race takeout T (and implicitly the margin) to the bookmaker's presumed objective function of expected profits. Let Λ_k denote the number of dollars wagered on horse k , and let H denote the total amount wagered on a race with a bookmaker ($H = \sum_i \Lambda_i$). Marginal costs (e.g., fees on handle) are constant and denoted τ . The expected profit for the race will then be $E(\pi) = (\sum_i \Lambda_i t_i) - \tau H$. Using the prior assumption that the amount of money wagered on a particular horse as a share of the total amount wagered coincides with bettor subjective probability on that horse (i.e., $\frac{\Lambda_i}{H} = \rho_i$), $E(\pi) = H (\sum_i \rho_i t_i) - \tau H = H * (T - \tau)$. If the total amount

wagered depends on the takeout so that $H(T)$, then the bookie chooses the level of odds and implicitly the takeout to maximize $H(T) * (T - \tau)$. The bookie's simplified problem is thus analogous to a profit-maximizing firm that faces a downward sloping demand curve.

3 Data

The data set, courtesy of the Australian Bookmakers Association, includes near-complete fixed odds betting information on Saturday races at nine of the largest Australian thoroughbred tracks from November 2, 2002, to August 4, 2007.¹³ While no midweek (Wednesday and Friday) races were provided, Saturdays have the most races and handle in both the U.S. and Australia. We consequently do not expect significant distortion to our policy conclusions that would stem from different types of bettors' being attracted to different days of the week.

These racetracks lie in three different markets and states: four in Sydney, New South Wales; three in Melbourne, Victoria; and two in Brisbane, Queensland.¹⁴ Consistent with being operated by city-wide clubs, major racetracks in the same city rarely operate on the same day.¹⁵ Odds are taken from a randomly sampled bookie for each racecourse and day. We unfortunately have no information regarding bookie identity or characteristics.

The data originally contained 5,213 racing starts. Six races were dropped because of apparently erroneous data (for example, all horses having the same odds). Another 190 races were dropped because they included late scratches when at least one horse dropped out of the race after the bookmaker published opening odds but prior to the start of the race.¹⁶ The remaining 5,017 observations were then matched with the races' total purse value where possible.¹⁷ Because purse data were not available for all races, the final data set includes 5,002 observations. This contrasts favorably with the sample sizes that were employed by Shin (1993) and Cain et al. (2003), which, respectively had 136 and a maximum of 1430 observations.

For each race, we observe the date, racetrack, size of field (i.e., number of horses), ordinal placement of race (e.g., second of day), purse value, and the starting (i.e., racetime) odds on horses from the sampled bookie. We use the starting odds to calculate bettors' subjective probabilities, the bookmaker's takeout, and various measures of dispersion in the field (e.g., Gini coefficients, variance of subjective probabilities, entropy). While all dispersion measures yielded similar results, we will focus on

¹³ The data did not include eight Saturdays, five of which occurred from November 2002 through January 2003. We thus observe 96.8 % of Saturday races over this time.

¹⁴ The nine racecourses are Doomben and Eagle Farm in Brisbane; Caulfield, Flemington, and Moonee Valley in Melbourne; and Canterbury Park, Rosehill Gardens, Royal Randwick, Warwick Farm in Sydney.

¹⁵ In our sample, two racetracks in the same city are open on only two of the 241 Saturdays.

¹⁶ McAlvanah and Moul (2013) consider how this sort of late change to the field might lead to systematic deviation from our profit-maximization assumption.

¹⁷ Purse values were obtained from Racing Information Services Australia, Racing New South Wales, and Queensland Racing.

Table 1 Summary statistics of Australian (2002–2007) horse race data

	All-AUS	Brisbane	Melbourne	Sydney
# Tracks/races	9/5002	2/1703	3/1532	4/1767
Pari-mutuel Takeout ^a	–	~16%/25% ^b	14.5%	14.5%
Implied bookie Takeout ^a				
Mean	17.09%	21.75%	15.92%	13.61%
SD-all	5.22%	3.87%	4.02%	3.82%
SD-by track	3.87%	3.86%	3.96%	3.81%
SD-by track-day	3.25%	3.21%	3.28%	3.26%
Purse ^c				
Mean	91,002	48,673	119,550	107,048
SD	193,960	74,099	224,492	234,222
Min	18,909	22,378	21,554	18,909
Max	3,088,132	1,004,064	2,940,132	3,088,132
Field size				
Mean	11.0	11.9	11.1	10.2
SD	2.9	2.9	2.8	2.7
Min	4	5	4	4
Max	21	20	21	20
VarLogProb ^d				
Mean	0.89	0.79	0.68	1.16
SD	0.51	0.37	0.35	0.62
Min	0.022	0.035	0.077	0.022
Max	4.96	2.67	2.91	4.96
Late ^e				
Mean	0.15	0.12	0.17	0.17

^a All takeouts apply to win-bets^b Pari-mutuel blended takeouts in Brisbane cannot exceed 16% over 12-month period and cannot exceed 25% for any bet-type^c Purses in 2002 AUS \$^d $\text{VarLogProb} = \text{Var}(\ln(\rho))$ where ρ is bettor subjective probability implied by observed odds^e Late is binary indicator for race being eighth or later in day

the variance of the logged subjective probabilities (*VarLogProb*) as this is the best match to Coffey and Maloney (2010). We operationalize the race's ordinal placement by creating indicator variables for each place (e.g., binary for second race of day), omitting the first race of the day category and using it as our baseline. We further consider a *Late* indicator, which denotes when a race is the eighth of the day or later. Finally, we include a week-based time trend over the sample to capture any secular changes in demand.

Table 1 reports summary statistics for the full Australian sample and broken down by market. Of primary interest is the implied bookie takeouts. Takeouts differ markedly in levels across markets, with Sydney bookies retaining 13.6% of money wagered, Brisbane bookies retaining 21.7%, and Melbourne bookies in between

with 15.9 %.¹⁸ While Sydney's average takeout mimics its regulated pari-mutuel takeout of 14.5 %, those of Melbourne and Brisbane both exceed their relevant pari-mutuel takeouts. This may arise if bookies choose to maintain high margins as race-time approaches and accept the lower (or non-existent) sales that result.

There is substantial variation in takeouts across markets, and it appears to be primarily related to variation in race characteristics. Comparing the market-specific standard deviation of implied takeout over different subsamples, over four-fifths of the variation within markets occurs in races on the same day at the same track. To the extent that weather is relatively constant within a day, this strongly suggests that our observed race characteristics may play an important role in the takeouts that bookies set.

Race characteristics other than price also differ across cities. Races at Melbourne and Sydney racetracks offer substantially higher purses than those held at Brisbane. Field sizes appear to be similar across the three Australian markets, but there are substantial differences in the ex ante dispersion of the field (measured by the variance of the implied log-subjective probabilities). Brisbane racetracks are also much less likely to have late races (defined as the eighth race of the day or later). This resurfaces in our regressions when we must make allowances for an insufficient number of Brisbane observations of ninth and tenth races of the day.

Table 2 presents simple correlations among the observed variables of interest and means conditioning on whether a race is late in the day for the entire Australian sample and broken down by market. Perhaps the most striking figures are the large and positive correlation coefficients between field size and takeout. While consistent with the story of insider trading that is argued by Shin (1993), these correlations could also reflect better demand for races with more horses (as found in Coffey and Maloney 2010) or field size capturing unobserved race-quality measures.

The negative correlation between takeout and purse for Melbourne is counterintuitive and appears to run against the results of Coffey and Maloney (2010).¹⁹ Even when that correlation is positive as for Brisbane and Sydney, it is of a smaller magnitude than one might expect. The means of each variable that condition on whether a race is late in the day indicate that late races have higher takeouts, larger fields, and (weakly) less dispersion of horse-ability. While late races have larger purses in Melbourne, the data surprisingly indicate that late races have smaller purses in Brisbane and Sydney.

Table 3 displays the sample-level and city-level descriptive results and t-statistics when takeout is regressed on various race characteristics. These estimates should be interpreted as the equilibrium impact of the characteristic on bookie takeout. Given the widely differing levels of takeout across markets, we estimate our regression using market-specific samples as well as the full sample. All regressions include racetrack fixed effects. Preliminary estimates indicated an increasing and concave relationship

¹⁸ We have no compelling explanation for the elevated Brisbane takeouts, but better composition may be important. Anecdotal observations indicate that Brisbane bettors are almost exclusively domestic Australians, while Sydney and Melbourne tracks have more (potentially wealthier and more price-sensitive) bettors from southeast Asia.

¹⁹ The negative correlation between purse and takeout for the entire sample is primarily driven by the fact that Brisbane has low purses and high takeouts while Melbourne and Sydney have high purses and low takeouts.

Table 2 Correlations and conditional means

	Takeout	Purse	Field Size	VarLP	Trend		Late = 0	Late = 1
All markets (n = 5,002)								
Takeout	1.00	-0.09	0.54	-0.24	-0.11	Takeout	16.75 %	18.92 %
Purse	-0.09	1.00	0.15	0.11	0.01	Purse	0.092	0.088
Field size	0.54	0.15	1.00	-0.07	0.02	Field size	10.8	12.6
VarLogProb	-0.24	0.11	-0.07	1.00	0.08	VarLogProb	0.89	0.83
Trend	-0.11	0.01	0.02	0.08	1.00			
Brisbane (n = 1,703)								
Takeout	1.00	0.02	0.38	-0.03	-0.09	Takeout	21.46 %	23.83 %
Purse	0.02	1.00	0.32	0.12	0.11	Purse	0.050	0.040
Field size	0.38	0.32	1.00	0.06	0.10	Field size	11.8	13.2
VarLogProb	-0.03	0.12	0.06	1.00	-0.04	VarLogProb	0.79	0.79
Trend	-0.09	0.11	0.10	-0.04	1.00			
Melbourne (n = 1,532)								
Takeout	1.00	-0.06	0.54	-0.16	-0.18	Takeout	15.54 %	17.79 %
Purse	-0.06	1.00	0.18	0.16	0.01	Purse	0.117	0.130
Field size	0.54	0.18	1.00	0.05	-0.03	Field size	10.8	12.5
VarLogProb	-0.16	0.16	0.05	1.00	0.17	VarLogProb	0.69	0.62
Trend	-0.18	0.01	-0.03	0.17	1.00			
Sydney (n = 1,767)								
Takeout	1.00	0.07	0.67	-0.19	-0.15	Takeout	13.02 %	16.48 %
Purse	0.07	1.00	0.19	0.10	-0.02	Purse	0.111	0.085
Field size	0.67	0.19	1.00	-0.04	-0.02	Field size	9.7	12.3
VarLogProb	-0.19	0.10	-0.04	1.00	0.13	VarLogProb	1.18	1.05
Trend	-0.15	-0.02	-0.02	0.13	1.00			

Takeouts implied by racetime win-bet odds. Purses in 2002 AUS \$Ms. VarLogProb = VarLP = $\text{Var}(\ln(\rho))$ where ρ is better subjective probability implied by observed odds. Late is indicator for race being eighth or later in day

between takeout and field size that was well accommodated by including field size in logs, and so we proceed using that transformation.

All estimates indicate that takeout falls with purse (insignificant for Sydney) and field dispersion (insignificant for Brisbane) but rises with field size and being later in the race-day (insignificant for Melbourne). Because we observe few Brisbane races that are ninth or tenth of the day (three and one, respectively), we combine those race-number categories with the eighth race. Time-trend polynomial estimates are essentially nuisance variables for our exercise, but we graphically present their implications from the all-market sample beneath the table. These estimates imply a secular pattern in which takeout falls early in the sample, stabilizes and then falls again toward the sample's end. The time-trend implications for the specific markets (not shown) are similar, though the transition points vary across markets.

We highlight two points from these descriptive regressions: First, the coefficients appear to differ enough across markets to warrant market-specific, rather than pooled,

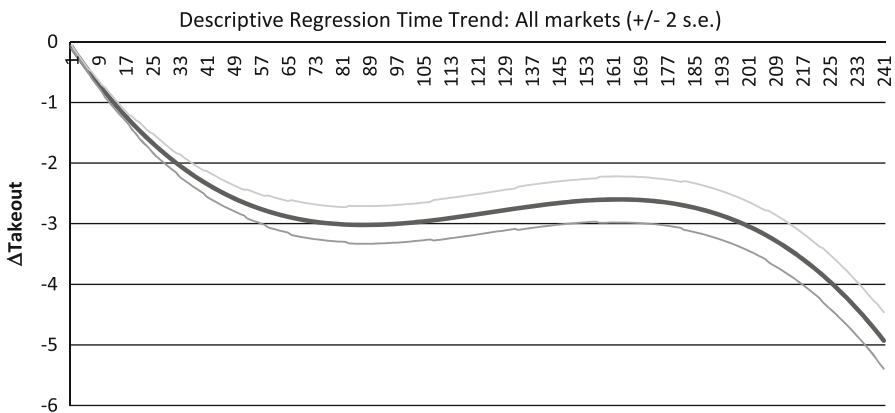
Table 3 Descriptive regressions (OLS) on implied win-bet takeout T (in percentage points)

Sample # Tracks/races E(T)	All-AUS 9/5002 17.09 %		Brisbane 2/1703 21.75 %		Melbourne 3/1532 15.92 %		Sydney 4/1767 13.61 %	
	b	t/t	b	t/t	b	t/t	b	t/t
Purse	-1.34	4.78***	-3.40	3.66***	-2.63	7.38***	-0.34	1.15
ln(FieldSize)	7.69	36.27***	6.51	17.20***	8.40	25.16***	7.83	19.81***
VarLogProb	-0.89	10.32***	-0.22	0.92	-1.34	6.34***	-0.86	9.21***
Race #2	0.04	0.21	0.61	1.68	-0.56	1.51	-0.02	0.10
Race #3	-0.17	0.86	-0.29	0.79	-0.94	2.63***	0.73	2.72***
Race #4	-0.17	0.91	-0.26	0.79	-0.68	1.88	0.43	1.89
Race #5	-0.08	0.42	-0.27	0.77	-0.61	1.70	0.62	2.56**
Race #6	-0.03	0.13	-0.18	0.51	-0.57	1.58	0.84	3.43***
Race #7	0.36	1.81	0.26	0.72	0.09	0.24	0.94	3.48***
Race #8	1.20	5.96***	1.53	4.20***	0.39	1.09	1.75	5.94***
Race #9	1.33	4.88***	— ^a		0.04	0.10	2.33	6.54***
Race #10	0.31	0.47	— ^a		-0.61	0.81	2.69	8.13***
Trend	-8.43	9.91***	-8.64	5.89***	-3.78	2.79***	-13.23	10.06***
Trend ²	7.41	9.80***	8.04	6.05***	4.80	3.94***	10.06	8.83***
Trend ³	-1.98	10.12***	-2.19	6.30***	-1.65	5.20***	-2.31	7.94***
R ²	0.6458		0.2269		0.4113		0.5396	

All results use track fixed effects. Purse deflated to 2002 AUS \$Ms. Trend reflects number of weeks since start of sample (divided by 100). All t-statistics reflect White correction

, *95 and 99 % levels of significance

^a Insufficient observations, combined with Race #8 category (i.e., Late)



regressions. A Chow test indicates that the null of non-intercept coefficients being the same across markets can be rejected with high confidence ($F = 7.70$, $p < 0.0001$). Second, with the exception of the negative impact of purse on takeout, these results are largely consistent with the extant literature. Coffey and Maloney (2010) find on-site

pari-mutuel handle to be increasing in field size but decreasing in field dispersion. As stated above, [Shin \(1993\)](#) and the related papers have already documented the positive relationship between field size and takeout.

The purse coefficient, however, stands out. In addition to being counterintuitive, it appears to contradict our primary purpose for its inclusion: to serve as a proxy for unobserved (to the econometrician) ex ante race quality. While difficult to reconcile with a model of perfect competition, this result can arise in markets in which firms have market power if increases in demand elasticity swamp the outward demand shifts in the resulting mark-ups. It is this apparent paradox and the potential resolution proposed by [Nevo and Hatzitaskos \(2006\)](#) that motivates our particular structural model and its reduced form.

4 Model of Bookie Behavior

Given the institutional detail that bookies face very low marginal costs (e.g., 1 % in Australia), the observed takeout rates require that bookies have some form of market power. We consider two extreme cases to accommodate this. In the first case, bookies will compete against one another, but market power will be generated by consumers having a distaste for travel from their locations to the spatially differentiated bookies. We employ a new model that extends [Salop \(1979\)](#) to accommodate the estimation of reduced-form pricing equations using data from a single firm (see [Moul 2013](#)).²⁰

In the second case, bookies collude and jointly set takeout rates. Bookies engaging in (perhaps tacit) collusion with such a large number of rivals may seem unlikely, but repeated interaction combined with the bleak prospect of minimal margins under the competitive equilibrium may make this possible. [Shin \(1991, 1992, 1993\)](#) and [Peirson and Smith \(2010\)](#) make the same assumption regarding bookies in the United Kingdom given the easy observation of odds by rivals and the repeated nature of the game.²¹ Our choice between these models will be dictated by how well their estimates fit the data and match results from the extant literature.

Both models are based on a common structure. We posit quasilinear utility among a continuum of consumers who are uniformly distributed along a Salop circle of M_{cr} circumference for race r at course c . There are N_{cr} evenly spaced bookies on the circle. The circle assumption not only mimics the idea of bookies located along the main ring but also spares us a treatment of endpoints that would break our necessary symmetric bookies assumption. Consumer size M_{cr} is assumed to be unaffected by takeout rates and therefore exogenous to bookies. All consumers wager on all races, but the amount wagered may vary across races. Given our previous assumption of better indifference and randomization across different horses in equilibrium, the amount to wager becomes the bettor's only choice variable.

²⁰ We are grateful to the Editor for encouraging us to develop this approach.

²¹ The tourist trap model of [Diamond \(1971\)](#) could also rationalize the result of monopoly prices, though the bookies being in such close proximity at the racetrack makes a search cost explanation unlikely.

Consumer i who wagers q dollars at racecourse c with bookie k on race r derives utility

$$U_{ickr} = \alpha_{cr} q_{ickr} - \frac{1}{2} \beta_{cr} q_{ickr}^2 - \delta d_{ik} + y_i, \quad (4)$$

where d_{ik} denotes the distance from consumer i to bookie k and y_i denotes i 's numeraire consumption. Parameters (α, β, δ) are all assumed to be strictly positive. If we let T_{ckr} denote bookie k 's takeout (price) for race r at course c and I_i consumer i 's income, the consumer's utility maximization problem can be expressed as

$$\max_{q_{ickr}} U_{ickr} = \alpha_{cr} q_{ickr} - \frac{1}{2} \beta_{cr} q_{ickr}^2 - \delta d_{ik} + I_i - T_{ckr} q_{ickr}. \quad (5)$$

Conditional on a consumer's bookie choice, consumer i 's demand and indirect utility are then

$$q_{ickr}^D = \frac{\alpha_{cr}}{\beta_{cr}} - \frac{1}{\beta_{cr}} T_{ckr}. \quad (6)$$

$$V_{ickr} = \frac{1}{2} \frac{\alpha_{cr}^2}{\beta_{cr}} + \frac{1}{2} \frac{1}{\beta_{cr}} T_{ckr}^2 - \delta d_{ik} + I_i - \frac{\alpha_{cr}}{\beta_{cr}} T_{ckr}. \quad (7)$$

A consumer must choose the bookie with which to wager and will do so by selecting the bookie who yields the highest indirect utility. Surrounding any of the N_{cr} bookies will be an arc of consumers who find that bookie to be the best option. Consider an arbitrary bookie (denoted bookie 2 at location L) with adjacent bookies (denoted bookies 1 and 3 at locations $L - \frac{M_{cr}}{N_{cr}}$ and $L + \frac{M_{cr}}{N_{cr}}$). There exists a consumer between bookies 1 and 2 who is indifferent between the two, and likewise for the consumer who is between bookies 2 and 3. Denoting these marginal consumer locations as x ($V_{ic1r} = V_{ic2r}$) and y ($V_{ic2r} = V_{ic3r}$),

$$\begin{aligned} x &= L - \frac{M_{cr}}{2N_{cr}} - \frac{1}{2} \frac{\alpha_{cr}}{\delta \beta_{cr}} (T_{c1r} - T_{c2r}) + \frac{1}{4} \frac{\alpha_{cr}}{\delta \beta_{cr}} (T_{c1r}^2 - T_{c2r}^2) \\ y &= L + \frac{M_{cr}}{2N_{cr}} - \frac{1}{2} \frac{\alpha_{cr}}{\delta \beta_{cr}} (T_{c2r} - T_{c3r}) + \frac{1}{4} \frac{\alpha_{cr}}{\delta \beta_{cr}} (T_{c2r}^2 - T_{c3r}^2). \end{aligned} \quad (8)$$

All consumers between these locations will choose to visit bookie 2, so bookie 2's demand is

$$\begin{aligned} q_{c2r}^D &= (y - x) q_{ic2r}^D \\ &= \frac{1}{\delta \beta_{cr}^2} \left(\frac{\delta \beta_{cr} M_{cr}}{N_{cr}} - \alpha_{cr} \left(T_{c2r} - \frac{T_{c1r} + T_{c3r}}{2} \right) \right. \\ &\quad \left. + \frac{1}{2} \left(T_{c2r}^2 - \frac{T_{c1r}^2 + T_{c3r}^2}{2} \right) \right) (\alpha_{cr} - T_{c2r}). \end{aligned} \quad (9)$$

In a symmetric equilibrium in which all bookies charge identical takeouts, each bookie captures $\frac{1}{N}$ of the available M consumers.

The above demand is a straightforward extension of the traditional [Hotelling \(1929\)](#) and [Salop \(1979\)](#) models in which consumers face unit demand. While in those models the only benefit of cutting price is the attraction of new consumers, this benefit is magnified by consumers' also buying more in our model. This addition is what will enable demand rotation to explain the perverse descriptive results.

We observe only prices and not quantities, so we must specify the supply-side in order to construct a reduced-form pricing equation. To this end, we consider the two extreme hypotheses of Bertrand–Nash competition with spatially differentiated sellers and perfect collusion. Given its relative simplicity, we begin with the cartel solution and then turn to the Bertrand–Nash competitive solution.

The cartel seeks to set a single price for each race at a racecourse that maximizes cumulative profits retained by all bookies. Assuming no spillovers across races,

$$\max_{T_{ckr}} \Pi_{cr} = \sum_{k=1}^{N_{cr}} M_{cr} (T_{ckr} - \tau) q_{ckr}^D. \quad (10)$$

Given the assumption of a common price across bookies, this reduces to

$$\max_{T_{cr}} \Pi_{cr} = N_{cr} (T_{cr} - \tau) \left(\frac{M_{cr}}{N_{cr}} \right) \left(\frac{\alpha_{cr}}{\beta_{cr}} - \frac{1}{\beta_{cr}} T_{cr} \right) \quad (11)$$

and is solved at

$$T_{cr} = \frac{\alpha_{cr}}{2} + \frac{\tau}{2}. \quad (12)$$

This is the familiar condition that a profit maximizing monopolist facing linear demand will price at the simple average of demand's vertical intercept and marginal cost. We discuss later how our specification of α_{cr} will enable us to identify both demand shifters and demand rotators.

For the competitive model, bookie k seeks to set a takeout rate for each race that maximizes his profits:

$$\max_{T_{ckr}} \pi_{ckr} = M_{cr} (T_{ckr} - \tau) q_{ckr}^D. \quad (13)$$

Taking the first-order condition and imposing symmetric takeouts across bookies (eventually) yields the following reduced-form pricing (implicit) function:

$$\left(\alpha_{cr} \hat{\beta}_{cr} + \alpha_{cr}^2 \tau + \hat{\beta}_{cr} \tau \right) - \left(2\hat{\beta}_{cr} + \alpha_{cr}^2 + 2\alpha_{cr} \tau \right) T_{cr} + (2\alpha_{cr} + \tau) T_{cr}^2 - T_{cr}^3 = 0, \quad (14)$$

where $\hat{\beta}_{cr} = \beta_{cr} \delta \left(\frac{M_{cr}}{N_{cr}} \right)$. [Moul \(2013\)](#) shows that a unique real takeout satisfies this cubic equation if $\alpha_{cr} > \tau \geq 0$ and $\hat{\beta}_{cr} > 0$. Parameters that define α_{cr} and $\hat{\beta}_{cr}$ will imply an equilibrium takeout, and this predicted takeout can then be compared to the observed takeout. Monte Carlo simulations in [Moul \(2013\)](#) indicate that, when data

are generated by this process and these data mimic the level of noise suggested by real-world estimates, all estimates are generally precise and goodness-of-fit greatly exceeds that of simple descriptive regressions.

To guide our specification choices, we begin by considering the most general case of a bookie's profit-maximization problem: A bookmaker chooses his takeout T to maximize expected profits $\pi = (T - \tau) H$, where H denotes the relevant residual demand for win bets. The first-order condition for the profit maximization problem is then

$$\frac{\partial E(\pi)}{\partial T} = H + \frac{\partial H}{\partial T} (T - \tau) = 0. \quad (15)$$

If race characteristics X are exogenous to the bookmaker, appealing to the Implicit Function Theorem yields the comparative statics of race characteristics on bookmaker takeout at the optimum:

$$\frac{\partial T}{\partial X} = - \frac{\frac{\partial H}{\partial X} + \frac{\partial^2 H}{\partial T \partial X} (T - \tau)}{2 \frac{\partial H}{\partial T} + \frac{\partial^2 H}{\partial T^2} (T - \tau)}. \quad (16)$$

The denominator is negative by necessity to ensure a maximum.

The sign of $\frac{\partial T}{\partial X}$ (that is, the sign of a coefficient in our descriptive regressions) depends on the sign of $\frac{\partial H}{\partial X} + \frac{\partial^2 H}{\partial T \partial X} (T - \tau)$. If the impact of X on the slope of the demand of betting is insignificant (i.e., $\frac{\partial^2 H}{\partial T \partial X} \approx 0$), descriptive estimates $\frac{\partial T}{\partial X}$ will be the same sign as the impact of race characteristics on the amount of money wagered $\frac{\partial H}{\partial X}$. If, however, changes in X affect the slope of the demand curve (i.e., $\frac{\partial^2 H}{\partial T \partial X} \neq 0$), $\frac{\partial T}{\partial X}$ may not mimic $\frac{\partial H}{\partial X}$ in sign. Nevo and Hatzitaskos (2006) use this framework to explain why, for example, tuna goes on sale during Lent. The underlying story is that consumer composition changes and the aggregate effect is that consumer demand becomes more elastic even as it increases. Profit-maximizing firms with market power respond to the more elastic demand by lowering mark-ups. We hope to explain the counterintuitive results in our descriptive regression with a similar story, and our specification choices must therefore allow for demand rotation as well as demand shifts.

The cartel model's specification is straightforward:

$$\alpha_{cr} = \left(\frac{X_{cr}}{1 + Z_{cr}\gamma} \right) \psi. \quad (17)$$

Referring back to the above consumer structure, this is consistent with consumer demand for wagering with an equilibrium bookie taking the form

$$q_{cr} = X_{cr}\theta - \phi T_{cr} (1 + Z_{cr}\gamma), \quad (18)$$

which implies that $\psi = \frac{\theta}{\phi}$. By de-meaning Z_{rc} , we ensure that ϕ represents the average price sensitivity. To the extent that Z is a subset of X , a variable may then have two channels by which it can affect the price.

The requirements that $\alpha_{cr} > 0$ and $\hat{\beta}_{cr} > 0$ to ensure the existence of the competitive model's solution force that model's specification to be somewhat more complex.

We specify α_{cr} and $\hat{\beta}_{cr}$ as

$$\alpha_{cr} = \exp(X_{cr}\psi - Z_{cr}\gamma) \quad (19)$$

$$\hat{\beta}_{cr} = \exp(\Omega_{cr} - Z_{cr}\gamma). \quad (20)$$

The price coefficient in this specification for α_{cr} is subsumed into the intercept term ψ_0 . When $\Omega_{cr} = \frac{\delta}{\phi} \frac{M_{cr}}{N_{cr}}$, this is consistent with demand for a bookie's service taking the form

$$q_{cr} = \exp(X_{cr}\psi) - \exp(\phi - Z_{cr}\gamma) T_{cr}. \quad (21)$$

Our estimation of this competitive model assumes that track-operators maintain a constant ratio of bettors to bookies throughout the sample (i.e., Ω is constant across races at a given track). Given our previous discussion of racing club policy across the different cities, this assumption seems a better fit for Sydney than the other two markets. Extensions may consider further parameterizing Ω_{cr} to depend on characteristics beyond racecourse indicators.

Disturbances must be modeled to accommodate the model's imperfect fit with the observed data. An obvious concern is bias that arises from omitted variables that may influence the horses that comprise the race-field. Specifically, higher prestige races may generate larger and more even fields, and the econometrician would then be unable to distinguish bettors' preferences on the race's prestige from those on field size and talent dispersion. While bettors are unlikely to care directly about a race's purse, purse and prestige are presumably highly positively correlated. We therefore address this concern by using race-purse as a proxy for race-prestige and henceforth subsume purse into our X and Z matrices. If this fully addresses the omitted variable concern, then idiosyncratic disturbances are all that remain.

Both models can readily accommodate a measurement error interpretation of this idiosyncratic disturbance (in logs for the competitive model and in levels for the cartel model). In this context, the observed bookie achieves an unbiased approximation of the profit-maximizing takeout but does not always reach the ideal. The cartel model can also readily accommodate an interpretation of unobserved product characteristics (e.g., race-day weather) in X , though not in Z . Moul (2013) shows that, when the measurement-error competitive model is estimated with data that are generated with unobserved product characteristics, point estimates are biased toward zero. Significant estimates may therefore be meaningful even in this plausible mis-specified scenario.

The implicit nature of the competitive model's pricing function precludes a ready expansion. The expansion of the cartel model, though, yields the following equation to be estimated by NLLS:

$$T_{cr} = \frac{1}{2} \left(\frac{X_{cr}}{1 + Z_{cr}\gamma} \right) \psi + \frac{\tau}{2} + U_{cr}. \quad (22)$$

In the special case when $\gamma = 0$, this reduces to the descriptive regression with shifted intercepts to allow for the marginal cost.

We therefore work around our inability to observe the representative bettor's money wagered (or any information regarding handle) by assuming that any observed takeout

is the equilibrium solution to the individual bookie's or the cartel's profit-maximization problem. Conditional on any functional form for which a solution to the profit-maximization problem exists, observed takeout can be matched against observable characteristics based on the competitive model's equilibrium (#14) or the cartel's first-order condition of equation (#22).²² Such an approach puts substantial stress on the choice of functional form and is another reason we choose the original (straight-forward) utility specification.

Our reduced-form solution is then a takeout (i.e., pricing) equation. With it, we can identify the structural parameters that are interacted with takeout (i.e., demand rotating γ s). Depending on the model, demand shifting ψ s are either identified (Salop competitive model) or identified only up to scale (cartel model). Residuals will be heteroskedastic by construction if disturbances are unobserved determinants of demand, as $q_{cr} = X_{cr}\theta - \phi T_{ckr} (1 + Z_{cr}\gamma) + \varepsilon_{cr}$ implies $U_{cr} = \frac{\varepsilon_{cr}}{2\phi(1+Z_{cr}\gamma)}$. As residuals are also likely to be heteroskedastic even under the measurement-error specification of the disturbance, we will employ robust standard errors.

5 Results

5.1 Empirics

We estimate our Salop-competitive model using MATLAB and a simplex search method. Conditional on initial parameter values that specify values of α_{cr} and $\hat{\beta}_{cr}$ consistent with (#19) and (#20), MATLAB's 'solve' function yields the implied real takeout for each race that solves equation (#14). The residual is defined as the difference of the log(observed takeout) and this log(implied takeout), so that $U = \ln(T) - \ln(\hat{T})$. The search algorithm then minimizes the sum of squared residuals. The cartel model is more straightforward to estimate, inasmuch as it requires non-linear search over only the demand-rotating parameters γ and has no cubic equation to solve. To facilitate comparison with the descriptive regressions, the goodness-of-fit from the competitive model is based on observed takeout instead of its log.

The repeated solving of the cubic equation for the competitive model is computationally burdensome. We consequently consider a reduced set of explanatory variables, using only the *Late* indicator in lieu of binary indicators for each ordinal placement and a first-order (i.e., linear), rather than third-order, polynomial for the time trend. Even with this more tractable parameter search, the search algorithm often sends the estimate of Ω to positive infinity. This problem precludes the application of the model to city-wide samples, as well as to most of the track-specific samples.²³ We are, however, able to obtain results for Doomben in Brisbane and Flemington in Melbourne.

Those track-specific estimates of the descriptive regression, the competitive model, and the cartel model are presented in Table 4. For both tracks, the cartel model gener-

²² Thomadsen (2005), for example, uses this approach and a relatively complex discrete choice model of demand in his pricing analysis of fast food restaurants.

²³ The source of this problem is unclear. One possibility is suggested by appealing to the Implicit Function Theorem. As $\Omega \rightarrow \infty$, $\frac{dp}{d\Omega} \rightarrow 0$, so there is little guard against a large value of Ω becoming larger.

Table 4 Track-specific results of descriptive (OLS) and reduced form (NLLS) regressions

Descriptive	Reduced Form-competition			Reduced form-cartel		
	b	t/t	b	t/t	b	t/t
<i>Doomben Racecourse, Brisbane (n = 858)</i>						
Purse	–		γ_{Purse}	2.15**	γ_{Purse}	0.83
ln(FieldSize)	–		$\gamma_{lnFieldSize}$	0.05	$\gamma_{lnFieldSize}$	0.84
VarLogProb	–4.44	2.29**	ψ_{Purse}	2.14**	ψ_{Purse}	0.73
Late	6.36	12.44***	$\psi_{lnFieldSize}$	0.65	$\psi_{lnFieldSize}$	2.29**
Time	0.27	0.74	$\psi_{VarLogProb}$	0.31	$\psi_{VarLogProb}$	0.73
Constant	1.91	5.08***	ψ_{Late}	2.12**	ψ_{Late}	4.92***
	–1.06	5.56***	ψ_{Time}	2.77***	ψ_{Time}	5.60***
	21.89	173.83***	ψ_0	45.55***	ψ_0	138.55***
	–		Ω	16.76***	–	
R ²	0.1953		R ²	0.1892	0.1971	
<i>Flemington Racecourse, Melbourne (n = 477)</i>						
Purse	–		γ_{Purse}	1.22	γ_{Purse}	3.15***
ln(FieldSize)	–		$\gamma_{lnFieldSize}$	6.29***	$\gamma_{lnFieldSize}$	1.13
VarLogProb	–3.77	4.54***	ψ_{Purse}	0.49	ψ_{Purse}	2.71***
Late	8.50	14.64***	$\psi_{lnFieldSize}$	3.54***	$\psi_{lnFieldSize}$	1.54
Time	–1.27	2.90***	$\psi_{VarLogProb}$	2.59***	$\psi_{VarLogProb}$	3.82***
Constant	1.04	3.00***	ψ_{Late}	1.95	ψ_{Late}	2.81***
	–0.70	2.71***	ψ_{Time}	2.62***	ψ_{Time}	2.29**
	16.91	115.43***	ψ_0	65.56***	ψ_0	85.98***
	–		Ω	81.06***	–	
R ²	0.3544		R ²	0.3563	0.3764	

Time reflects number of weeks (in 100s) since start of sample. All t-statistics reflect White correction

, *95 and 99 % levels of significance

ates slightly better goodness-of-fit than does the competitive model. Furthermore, the competitive estimates are unsatisfactory when compared to results from the extant literature and the descriptive regressions. At Doomben, goodness-of-fit falls compared to the descriptive regression despite having three additional parameters. This is contrary to Moul (2013), in which competitive reduced-form regressions notably outperform descriptive regressions in fit. At Flemington, the competitive model slightly improves on the descriptive regression's fit but generates a statistically significant negative coefficient for field size, which contradicts the literature.

The track-specific estimates of the cartel model suffer virtually no such defects for these samples. The negative coefficient between purse and takeout from the descriptive regression is rationalized for these tracks by demand both shifting out and becoming more elastic. This increased elasticity could result if everyday bettors have relatively inelastic demands and the bettors who are drawn to high-purse, high-prestige races have relatively elastic demands. To the extent that American bettors share the same characteristics, this would mitigate against the concern that racetracks would "gouge" bettors on the most visible race-days. Other coefficients that are estimated from the cartel model match intuition and are generally significant for Flemington though not for Doomben. Given these results, we conclude that our observed bookie takeouts are better explained by the (admittedly less appealing) cartel model than by our competitive model. We proceed using the cartel model and the full set of explanatory variables.

We display our nonlinear least squares estimates for the reduced-form model for the entire sample and the particular cities in Table 5. As discussed above, our maintained hypothesis is that the observed bookie is part of a bookmaker-cartel, and so our linear demand implies that the observed takeout (less one-half the observed marginal cost) is simply one-half of the market demand's vertical intercept (i.e., choke price). The prior descriptive regressions are merely special cases of the reduced form in which $\gamma = 0$ for all variables.

The estimates for the entire sample, for Brisbane, and for Melbourne reconcile our prior expectations and purse's descriptive impact on demand. In those regressions, increases in purse shift demand outward but also increase price sensitivity. In the presence of market power, firms may reduce markups (here takeout rates) as demand becomes more elastic, even if demand increases at the same time. As with the descriptive regression, a Chow test decisively rejects equal parameters across cities ($F = 8.34$, $p < 0.0001$), and we will emphasize our city-specific estimates accordingly.

Brisbane's estimates all have the expected sign, but only the *Late* race indicator is statistically significant among the race characteristics. While not shown, when $\gamma_{\ln FieldSize}$ is set to zero in the Brisbane regression, $\psi_{\ln FieldSize}$ is positive and highly significant (t-stat ≈ 17). Many Melbourne parameters, however, are estimated precisely. Furthermore, Melbourne's estimates nicely showcase the value of the reduced-form model. Those estimates show that, while purse's net impact is a combination of countervailing forces (outward shift and greater price sensitivity), field size's net impact is a combination of two forces that work in the same direction (outward shift and less price sensitivity).

The estimates that use the Sydney races, though, are less satisfactory. While not highly significant, the estimates indicate that increasing the purse shifts demand

Table 5 Cartel reduced form estimates (NLLS) on implied win-bet takeover T (in percentage points)

$q = X\theta - \phi(1 + Z\gamma)T + \varepsilon$		Structural demand					
$T^* = 0.5 + (X/(1 + Z\gamma))(1/2)\psi + U$, where $\psi = \theta / \phi$		Profit-maximizing takeover					
Sample	All-AUS	Brisbane		Melbourne		Sydney	
#Tracks/Races	9/5002	2/1703		3/1532		4/1767	
$E(T^* - 0.5)$	16.59 %	21.25 %		15.42 %		13.11 %	
	b	t/t	t/t	b	t/t	b	t/t
Purse	0.31	3.27***	1.34	0.87	3.21***	-0.09	1.49
ln(FieldSize)	0.06	1.85	-0.09	-0.18	1.85	-0.40	3.39***
Purse	5.45	1.98**	49.84	16.60	2.21**	-3.81	2.02**
ln(FieldSize)	17.38	16.88***	9.10	11.42	3.87***	5.54	2.16**
VarLogProb	-1.73	10.10***	-0.44	-2.85	6.53***	-1.64	8.39***
Race #2	0.04	0.11	1.22	-1.15	1.59	0.25	0.53
Race #3	-0.41	1.06	-0.57	-1.80	2.56**	2.15	3.20***
Race #4	-0.40	1.12	-0.54	-1.27	1.81	1.40	3.05***
Race #5	-0.24	0.65	-0.53	-1.13	1.60	1.93	3.99***
Race #6	-0.03	0.08	-0.33	-0.79	1.09	2.16	4.46***
Race #7	0.72	1.86	0.51	0.09	0.13	2.27	4.44***
Race #8	2.32	5.82***	2.94	0.73	1.06	3.67	6.27***
Race #9	2.55	4.67***	^a	-0.08	0.10	4.76	6.77***
Race #10	0.46	0.34	^a	-1.52	1.14	5.82	9.26***
Trend	-16.44	9.72***	-17.23	-6.68	2.50**	-25.45	9.93***
Trend ²	14.51	9.65***	16.13	8.79	3.66***	19.32	8.75***
Trend ³	-3.87	9.98***	-4.41	-3.07	4.91***	-4.43	7.88***
R ²	0.6470		0.2278	0.4175		0.5499	

Table 5 continued

$q = X\theta - \phi(1 + Z\gamma)T + \varepsilon$			Structural demand		
$T^* = 0.5 + (X/(1+Z\gamma))(1/2)\psi + U$, where $\psi = \theta / \phi$			Profit-maximizing takeout		
Sample	All-AUS	Brisbane	Melbourne	Sydney	
#Tracks/Races	9/5002	2/1703	3/1532	4/1767	
E(T* - 0.5)	16.59 %	21.25 %	15.42 %	13.11 %	
	b	b	b	b	/t/
	/t/	/t/	/t/	/t/	/t/
$\Gamma - 1$ (s.e.)	10.47	3.47	7.37	(0.70)	-

Purse deflated to 2002 AUS \$Ms. Trend reflects number of weeks (in 100s) since start of sample. All t-statistics reflect White correction

, *95 and 99 % levels of significance

^a Insufficient observations, combined with Race #8 category (i.e., Late)

inward. This runs counter to both intuition and the results of Coffey and Maloney (2010). Our best explanation of this failure is the previously stated Sydney policy of deliberately matching the number of bookies with the number of bettors, which is a policy that was less apparent in Melbourne and Brisbane. This variable composition of bookies in Sydney would make tacit collusion even more difficult. It is also possible that this matching of bookies to demand could generate the equivalent of the horizontal long-run supply curve in which price is unrelated to demand factors. Regardless, these results imply that a representative bettor that might be inferred from Sydney bookie takeouts would be irreconcilable with our priors on the U.S. market. We therefore focus our counterfactual exercises on the Brisbane and Melbourne estimates.

5.2 Counterfactuals

We now use observed takeouts, our estimated parameters, and the residuals from our reduced-form cartel model to return to the model and its case when the disturbance is an observed determinant of demand. Recall from above that $\psi = \frac{\theta}{\phi}$ and $U_{cr} = \frac{\varepsilon_{cr}}{2\phi(1+Z_{cr}\gamma)}$ under these assumptions. If we substitute in the implications for θ and ε , the representative consumer's betting demand for race r at course c becomes

$$q_{cr} = X_{cr}\psi\phi - \phi T_{cr}(1 + Z_{cr}\gamma) + 2\phi(1 + Z_{cr}\gamma)U_{cr}. \quad (23)$$

Substituting in our expression for the profit-maximizing takeout rate and simplifying yields

$$q_{cr} = \phi(1 + Z_{cr}\gamma) \left(\left(\frac{X_{cr}}{1 + Z_{cr}\gamma} \right) \left(\frac{1}{2} \right) \psi + U_{cr} - \frac{\tau}{2} \right) = \phi(1 + Z_{cr}\gamma)(T_{cr} - \tau). \quad (24)$$

If we aggregate these quantities to account for the population of M_{cr} bettors, betting profits over all races in the observed variable takeout regime are then

$$\sum \pi_{cr}^{Variable} = \sum M_{cr}(T_{cr} - \tau)q_{cr} = \phi \sum M_{cr}(1 + Z_{cr}\gamma)(T_{cr} - \tau)^2. \quad (25)$$

We are interested in the gains from variable takeout rates that are distinct from those that would come from a profit-maximizing fixed takeout rate. Our proposed counterfactual therefore must first specify that profit-maximizing uniform takeout rate:

$$\begin{aligned} \max_T \sum \pi_{cr} &= (T - \tau) \sum M_{cr}q_{cr} \\ &= (T - \tau) \sum M_{cr}(X_{cr}\theta - \phi(1 + Z_{cr}\gamma)T + \varepsilon_{cr}) \end{aligned} \quad (26)$$

$$T^* = \frac{\sum M_{cr}(X_{cr}\theta + \varepsilon_{cr})}{2\phi \sum M_{cr}(1 + Z_{cr}\gamma)} + \frac{\tau}{2}. \quad (27)$$

If we use our prior parametric linkages and simplify, this becomes

$$T^* = \frac{\sum M_{cr} (X_{cr} \psi (\frac{1}{2}) + (1 + Z_{cr} \gamma) U_{cr})}{\sum M_{cr} (1 + Z_{cr} \gamma)} + \frac{\tau}{2} = \frac{\sum M_{cr} (1 + Z_{cr} \gamma) T_{cr}}{\sum M_{cr} (1 + Z_{cr} \gamma)}. \quad (28)$$

We could therefore identify the uniform profit-maximizing takeout rate entirely from our estimates if we observed bettor populations M_{cr} . This specification also highlights the importance of the γ parameters: When $\gamma = 0$, the profit-maximizing uniform takeout rate is the average of the observed takeout rates weighted by bettor populations.

Substituting this solution back into the representative consumer's demand and summing over all races yields

$$\sum M_{cr} q_{cr} = \phi \sum M_{cr} (1 + Z_{cr} \gamma) \left(\left(\frac{X_{cr}}{1 + Z_{cr} \gamma} \right) \left(\frac{1}{2} \right) \psi + U_{cr} \right) \quad (29)$$

$$= \phi \sum M_{cr} (1 + Z_{cr} \gamma) (T_{cr} - \tau). \quad (30)$$

This is the same result as above under race-varying takeout and matches the result of [Robinson \(1969\)](#) that aggregate quantity with linear demand doesn't change with price discrimination. Profits from the representative bettor over all races for the uniform takeout regime are then

$$\sum \pi_{cr}^{Uniform} = (T - \tau) \sum M_{cr} q_{cr} = \phi \frac{(\sum M_{cr} (1 + Z_{cr} \gamma) (T_{cr} - \tau))^2}{\sum M_{cr} (1 + Z_{cr} \gamma)}. \quad (31)$$

Because ϕ appears linearly in both profit expressions, the ratio of profits will not depend on its value. Let Γ denote the ratio of variable takeout profits to uniform takeout profits. That ratio is then

$$\Gamma = \frac{\sum \pi_k^{Variable}}{\sum \pi_k^{Uniform}} = \frac{(\sum M_{cr} (1 + Z_{cr} \gamma)) (\sum M_{cr} (1 + Z_{cr} \gamma) (T_{cr} - \tau)^2)}{(\sum M_{cr} (1 + Z_{cr} \gamma) (T_{cr} - \tau))^2}. \quad (32)$$

This ratio conveys exactly the information that we seek: How much would Australian bookmaker profits rise if they went from a profit-maximizing uniform-takeout regime to a variable-takeout regime.

Unfortunately, we do not observe these bettor populations. The unsatisfying assumption that $M_{cr} = M$ for all races within a market leads to all population measures canceling out, and in this case Γ can be identified from our estimates and data. Without data on how the number of bettors changes with race characteristics, it is difficult to approximate the magnitude of bias from this assumption. Simple experiments indicate that gains from switching from uniform to variable takeouts are always overstated, and this overstatement grows with the variance of M_{cr} . These experiments also indicate that the bias is most severe when bookie takeouts are directly correlated with bettor populations but is much more modest when takeout moves opposite bettor population. Fortunately, our descriptive results showed a negative relationship between purse and takeout. The reasonable assumption of a strong positive correlation between

purse and better population then suggests that our estimates of Γ are inflated but still informative. This overstatement was by less than 10 % when the better population's standard deviation was 40 % of its mean but rose to 60 % when the better population's standard deviation equaled its mean.

We restrict consumer populations to be equal across all races within a market and calculate the estimated percentage point increase (i.e., $\Gamma - 1$) and standard errors.²⁴ We consider the natural case in which the profit-maximizing uniform takeout rate is set for all racetracks in a market. As mentioned above, the reduced form estimates from Sydney do not qualitatively match the estimates of Coffey and Maloney (2010), and so we consider only the Brisbane and Melbourne results.

Our relaxed regulatory regime is estimated to boost bookmaker variable profits by 3.5 % (s.e. 0.5) in Brisbane and 7.4 % (s.e. 0.7) in Melbourne. Both figures are more modest than the 10.5 % (s.e. 0.3) increase implied by the entire sample's estimates. Ratios are estimated relatively precisely, and t-statistics exceed 6. It is reassuring that these implied variable profit gains are quite similar to the roughly 5 % gains from price discrimination in Broadway theater found by Leslie (2004). To further put these figures into context, the Thalheimer and Ali (1998) takeout elasticity estimate of -1.85 implies that dropping Kentucky's takeout for win bets from 16 to 14 % would raise cumulative takeout at racetracks by 7.7 %. Such a reduction of uniform takeout rates would presumably yield larger gains than our proposal, but variable takeout's benefits to racetracks on top of that reduction are not inconsequential.

6 Conclusions

While bookies have no role in pari-mutuel wagering in the U.S., we have provided a model to link our Australian estimates to a potential reform of the American horse racing industry. Our estimates give some idea of the impacts that would follow a reform that grants racetracks flexibility in setting takeouts. These estimates also highlight the value of the incorporation of theory into empirical work and provide more support for the idea that many observations that appear paradoxical within a model of perfect competition can be readily reconciled in a model that allows market power.

We illustrate the implications of our proposed reform by returning to Kentucky. Similar to other states, the state of Kentucky levies an excise tax on handle on live races of 3.5 % for large tracks and 1.5 % for small tracks, where \$1.2M of daily average handle is the size-threshold (KRS 138.510). Our linear functional form implies that moving from a fixed to variable takeout would have no impact on cumulative handle, and so the current excise tax regime would yield no gains to the state from such a reform.

If, however, Kentucky were to tax cumulative takeout instead of handle, then some of the gains would go to the state government where they could displace or prevent other taxes with greater negative welfare consequences. Given the current fixed takeouts, this change is largely semantic, in that the 3.5 % excise tax on a large track's money wagered

²⁴ Standard errors are constructed using the delta method with finite perturbation of all estimated parameters.

is equivalent to a 21.875 % tax on cumulative takeout on straight win/place/show bets. Any costs of implementing such a reform would therefore be borne by racetracks as they devise methods to set optimal takeout rates.

The parlous state of the domestic horse racing industry, driven both by increased competition in gambling markets and recent macroeconomic conditions, highlights the need for radical reform. It is a fortunate situation where such a reform can be deregulatory in nature. Allowing racetracks to set race-specific takeout rates prior to the commencement of on-site wagering and changing the tax structure in the industry would appear to have exactly this potential, and this policy reform merits further consideration.

References

- Cain, M., Law, D., & Peel, D. (2003). The favourite-longshot bias, bookmaker margins and insider trading in a variety of betting markets. *Bulletin of Economic Research*, 55(3), 263–273.
- Churchill Downs Incorporated Annual Report. (2011). Retrieved December 31, 2013, from <http://ir.churchilldownsincorporated.com/annuals.cfm>.
- Coffey, B., & Maloney, M. (2010). The thrill of victory: Measuring the incentive to win. *Journal of Labor Economics*, 28(1), 87–112.
- Diamond, P. (1971). A model of price adjustment. *Journal of Economic Theory*, 3, 156–168.
- Equibase Company. (2002–2012). *Thoroughbred racing economic indicators*. Retrieved December 31, 2013, from <http://www.equibase.com/news/pressarchive.cfm>.
- Gramm, M., McKinney, C. N., Owens, D. H., & Ryan, M. E. (2007). What do bettors want? Determinants of pari-mutuel betting preference. *American Journal of Economics and Sociology*, 66(3), 465–491.
- Gruen, A. (1976). An inquiry into the economics of race-track gambling. *Journal of Political Economy*, 84(1), 169–178.
- Hialeah Park Racing & Casino. (10/6/2010). *Hialeah cuts takeout rate to 12% for all bets*. Retrieved December 31, 2013, from <http://www.bloodhorse.com/horse-racing/articles/59227/hialeah-cuts-takeout-rate-to-12-for-all-bets>.
- Horseplayers Association of North America. (2013). *Track ratings 2013 by overall score*. Retrieved December 31, 2013, from <http://www.horseplayersassociation.org/hanatrackratingsbyoverallscore2012.html>.
- Hotelling, H. (1929). Stability in competition. *Economic Journal*, 39(153), 41–57.
- Laurel Park Racecourse. (7/18/2007a). *Laurel Park to feature 10 percent takeout*. Retrieved on December 31, 2013, from <http://www.brisnet.com/cgi-bin/editorial/article.cgi?id=8531>.
- Laurel Park Racecourse. (9/17/2007b). *Jury still out on recent takeout-reduction experiments*. Retrieved on December 31, 2013, from <http://www.bloodhorse.com/horse-racing/articles/40837/jury-still-out-on-recent-takeout-reduction-experiments>.
- Leslie, P. (2004). Price discrimination in Broadway theater. *RAND Journal of Economics*, 35(3), 520–541.
- Levitt, S. (2004). Why are gambling markets so differently organized from financial markets? *Economic Journal*, 114(495), 223–246.
- Markowitz, H. (1952). The utility of wealth. *Journal of Political Economy*, 56, 151–154.
- McAlvanah, P., & Moul, C. C. (2013). The house doesn't always win: Evidence of anchoring among Australian bookies. *Journal of Economic Behavior and Organization*, 90, 87–99.
- Mobilia, P. (1993). Gambling as a rational addiction. *Journal of Gambling Studies*, 9(2), 121–151.
- Moul, C. C. (2013). *Estimating demand for spatially differentiated firms with unobserved quantities and limited price data*. Miami University, working paper.
- National Thoroughbred Racing Association Players' Panel Recommendations. (2/19/2004). Retrieved December 31, 2013, from <http://www.horse-races.net/library/article-ntrapanel.htm>.
- Nevo, A., & Hatzitaskos, K. (2006). *Why does the average price paid fall during high demand periods?* Working Paper, Northwestern University, <http://faculty.wcas.northwestern.edu/~ane686/research/tuna3>.
- Ottaviani, M., & Sorensen, P. N. (2009). Surprised by the parimutuel odds? *American Economic Review*, 99(5), 2129–2134.
- Ottaviani, M., & Sorensen, P. N. (2010). Noise, information, and the favorite-longshot bias in parimutuel predictions. *American Economic Journal: Microeconomics*, 2(1), 58–85.

- Peirson, J., & Smith, M. A. (2010). Expert analysis and insider information in horse race betting: Regulating informed market behavior. *Southern Economic Journal*, 76(4), 976–992.
- Robinson, J. (1969). *The economics of imperfect competition* (2nd ed.). London: Macmillan.
- Salop, S. C. (1979). Monopolistic competition with outside goods. *Bell Journal of Economics*, 10(1), 141–156.
- Schmalensee, R. (1981). Output and welfare implications of monopolistic third-degree price discrimination. *American Economic Review*, 71(1), 242–247.
- Shin, H. S. (1991). Optimal betting odds against inside traders. *Economic Journal*, 101(408), 1179–1185.
- Shin, H. S. (1992). Prices of state contingent claims with insider traders, and the favourite-longshot bias. *Economic Journal*, 102(411), 426–435.
- Shin, H. S. (1993). Measuring the incidence of insider trading in a market for state-contingent claims. *Economic Journal*, 103(420), 1141–1153.
- Snowberg, E., & Wolfers, J. (2010). Explaining the favorite-long shot bias: Is it risk-love or misperception? *Journal of Political Economy*, 118(4), 723–746.
- Sobel, R. S., & Raines, T. (2003). An examination of the empirical derivatives of the favourite-longshot bias in racetrack betting. *Applied Economics*, 35(4), 371–385.
- Suits, D. B. (1979). The elasticity of demand for gambling. *Quarterly Journal of Economics*, 93(1), 155–162.
- Thalheimer, R., & Ali, M. M. (1998). *An economic analysis of a parimutuel racetrack-racebook*. Working paper for Equine Industry Program, University of Louisville.
- Thomadsen, R. (2005). The effect of ownership structure on prices in geographically differentiated industries. *RAND Journal of Economics*, 36(4), 908–929.
- Tioga Downs Casino. (3/26/2010a). *NY board approves Tioga Downs take-out reduction*. Retrieved December 31, 2013, from <http://xwebapp.ustrotting.com/absolutenm/templates/?z=1&a=36219>.
- Tioga Downs Casino. (6/21/2010b). *Tioga Downs take-out reduction yielding positive results*. Retrieved December 31, 2013, from <http://xwebapp.ustrotting.com/absolutenm/templates/?z=1&a=37537>.