Research
Macquarie Wealth Management

AUSTRALIA

Horse Most Likely to Win

Rank	Horse	Odds	Probability of Winning
1	6. Hartnell	8.1	9.6%
2	12. Jameka	8.5	8.9%
3	1. Big Orange	13.6	6.6%
4	20. Oceanographer	12.1	6.4%
5	4. Bondi Beach	13.2	6.3%

Source: Macquarie Research, Tabcorp, October 2016

Most Undervalued Horses

Rank	Horse	Odds	Relative Under-valuation
1	18. Assign	33.3	30%
2	3. Curren Mirotic	31.8	20%
3	9. Almoon-qith	22.6	17%
4	7. Who Shot Thebarman	18.5	14%
5	8. Wicklow Brave	16.1	11%

Source: Macquarie Research, Tabcorp, October 2016

31 October 2016
Macquarie Securities (Australia) Limited

Melbourne Cup: Quant Style

Assigning Value

Event

- After a couple of lean years, we've decided that it was time to upgrade our Melbourne Cup quant model. This year we have analysed data from 40,000 participants over 4,000 horse races to give us an extra edge.
- The recent equity market rotation into Value also got us thinking: Are some horses better value than others? By using quant techniques to capture how over- or undervalued horses are relative to their odds, we find the best value horses and estimate each horse's true chances of winning.

Impact

- We launch the **Macquarie Quant *H*alpha Model**, which aims to predict which horses are most likely to be mispriced by the market. The model identifies behavioural biases in betting patterns that systematically distort the odds.
- The data indicates that punters not only have a behavioural bias towards long-shots, but also **incorrectly crowd (i.e. over-pay for)** their bets into:
  - Younger horses
  - Better form ratings
  - Stronger track records
  - Lower handicap weights
  - Horses starting closer to the inner barrier
- We also identify a *Prince of Penzance effect* – **female on jockeys on male horses** win statistically more races after controlling for other variables, and tend to be undervalued. This year, we endow this effect to Assign, ridden by Katelyn Mallyon.
- A strategy of picking undervalued horses using our *H*alpha model wins less often, but when it wins, tends to win big. We tested this by simulating $1 bets on 1,000 actual races, and ended up with $292.

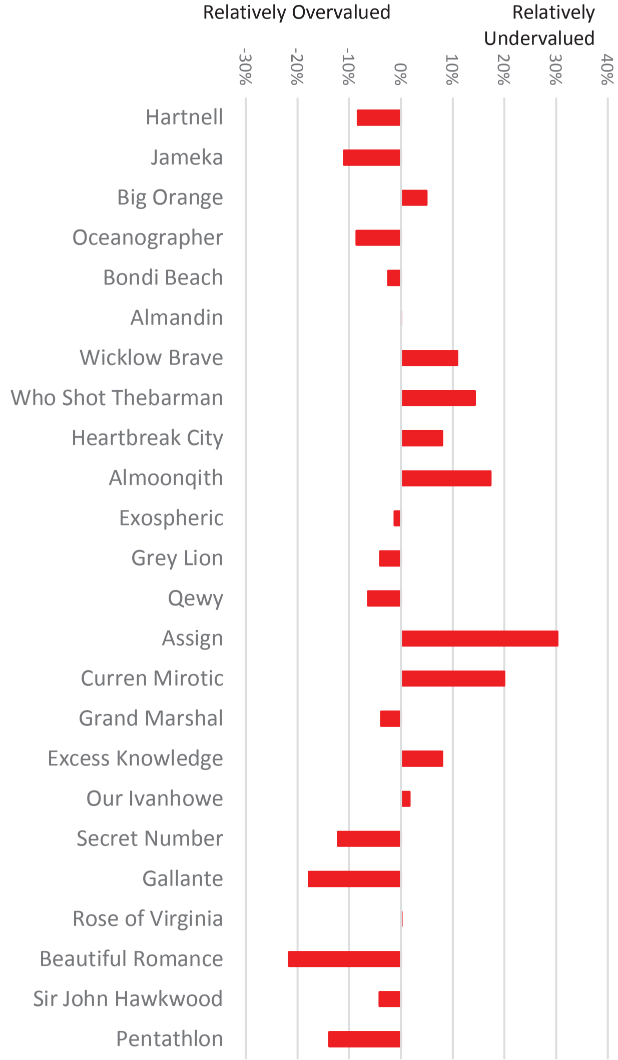
Strategy

- For punters who are out for gold and glory, we use the unbiased odds calculated by our *H*alpha model to pick horses with the highest likelihood of winning. Our top three are **Hartnell** (9.6%), **Jameka** (8.9%) and **Big Orange** (6.6%)
- However, for value investors out for a bargain, the most undervalued horses are **Assign**, **Curren Mirotic** and **Almoonqith**. We think these horses are more likely to win than their odds suggest.
- As always, this report is not meant to be taken seriously and only meant for fun! Horse racing is highly unpredictable (we estimate ~75% random), and we actually know very little about horses. Please use your own good judgement when betting, and happy punting!

Predicted Finishing Order for the 2016 Melbourne Cup

Figure 1 - Predicted Finishing Order

Rank	Horse	Jockey	Odds (4pm 31/10/2016)	Form Rating	Age	Type	Handicap	Barrier	*H*alpha*	Probability of Winning
1	6. Hartnell	James McDonald	8.1	100	6	G	56	12	-8.3%	9.6%
2	12. Jameka	Nicholas Hall	8.5	95	4	M	54.5	3	-11.0%	8.9%
3	1. Big Orange	Jamie Spencer	13.6	85	6	G	57	7	4.9%	6.6%
4	20. Oceanographer	Chad Schofield	12.1	94	5	G	52	11	-8.6%	6.4%
5	4. Bondi Beach	Ryan Moore	13.2	88	5	H	56	5	-2.5%	6.3%
6	17. Almandin	Kerrin McEvoy	14.1	90	7	G	52	17	0.0%	6.0%
7	8. Wicklow Brave	Frankie Dettori	16.1	91	8	G	56	24	10.9%	5.9%
8	7. Who Shot Thebarman	Hugh Bowman	18.5	87	8	G	56	20	14.3%	5.3%
9	13. Heartbreak City	Joao Moreira	18.3	86	7	G	54	23	8.0%	5.0%
10	9. Almoonqith	Michael Walker	22.6	88	7	H	54.5	19	17.3%	4.4%
11	5. Exospheric	Damien Oliver	21	90	5	H	56	13	-1.2%	4.0%
12	19. Grey Lion	Glen Boss	21	92	5	H	52	16	-4.0%	3.9%
13	23. Qewy	Craig Williams	21.6	93	7	G	51.5	15	-6.3%	3.7%
14	18. Assign	Katelyn Mallyon	33.3	87	6	G	52	22	30.3%	3.3%
15	3. Curren Mirotic	Tommy Berry	31.8	87	9	G	56.5	18	20.0%	3.2%
16	11. Grand Marshal	Ben Melham	27.2	90	7	G	54.5	9	-3.8%	3.0%
17	15. Excess Knowledge	Vlad Duric	35.8	90	7	H	53.5	21	8.0%	2.6%
18	2. Our Ivanhowe	Dwayne Dunn	38.3	88	7	H	57	6	1.7%	2.3%
19	21. Secret Number	Stephen Baster	40.3	91	7	G	52	10	-12.2%	1.9%
20	10. Gallante	Blake Shinn	38.3	93	6	G	54.5	2	-17.9%	1.8%
21	24. Rose of Virginia	Ben Thompson	56.4	86	7	M	51	8	0.1%	1.5%
22	16. Beautiful Romance	Damian Lane	48.5	91	5	M	52.5	1	-21.6%	1.4%
23	14. Sir John Hawkwood	Blake Spriggs	59.4	90	8	G	54	14	-4.1%	1.4%
24	22. Pentathlon	Mark Du Plessis	64.5	87	5	G	51.5	4	-13.8%	1.1%



Source: Macquarie Research, Tabcorp, October 2016

* Horses with positive *H*alpha are relatively undervalued (ie, they are more likely to win than their odds imply), while horses with negative *H*alpha are relatively overvalued (i.e. they are less likely to win than their odds imply)

Beating the Odds

Our Melbourne Cup prediction model has had a lean couple of years. After bursting onto the scene with an incredible box trifecta in 2007, the model predicted the outright winner (Shocking) in 2009, picked another box trifecta in 2010, and then picked the winner (Dunaden), again, in 2011. Alas, our success has waned in the four years since then, but this year, we have a secret weapon: Data. Thanks to the *Horses for Courses* data-set made publicly available through Kaggle, this year, we've been able to analyse 40,000 race participants across 4,000 races all over the world.

Using this data, we've devised a completely new approach to predicting the finishing order in the 2016 Melbourne Cup – by modelling behavioural biases in the way that punters place their bets, we're able to identify systematic distortions in the pricing of the odds. Then, by backing out these distortions, we're able to derive odds that more accurately reflect each horse's true probability of winning.

The Macquarie Quant *Ha*lpha Model

The Macquarie Quant *H*alpha Model is designed to forecast how under- or overvalued a horse is relative to its pre-race odds. An under-valued horse will, on average, win more frequently than its odds imply, while the opposite holds true for an overvalued horse. For a risk-neutral punter interested in maximising returns, the optimal strategy is actually to consistently bet on the most undervalued horse, rather than the one with the highest probability of winning. This results in less frequent, but much bigger wins. However, we can also use the *H*alpha Model to "correct" the stated odds, and provide a rank prediction as we have done in prior years.

This model detects pricing inefficiencies in horse-betting markets by fitting the realised payoff of horses in past races to a multifactor Ordinary-Least-Squares (OLS) regression model to the following factors:

- Pre-race Odds
- Form Rating
- Last Five Race Outcomes
- Age
- Handicap
- Barrier Number
- Sex of the Horse and Jockey

This allows us detect characteristics associated with horses that systematically pay higher or lower returns than what is priced into their odds. We then optimally combine these characteristics into a quantitative model that forecasts mispricing in a horse's odds: This is the Macquarie Quant *H*alpha Model.

The Macquarie Quant *H*alpha works by capturing behavioural biases in the way that punters make their bets. For example, punters tend to over-value a horse's form rating, pushing the odds for horses with good form even shorter than their actual win rates would dictate. On the other hand, punters over-penalise the handicap weight – highly handicapped horses actually win more frequently than their odds would suggest (and in fact, more frequently overall). There's a theme here. In highly random processes, such as horse racing, our natural tendency is to find patterns (i.e. reasons) that justify the outcome. This means that punters tend to put too much confidence in factors that "should" make a difference, resulting in these factors becoming overvalued. The actual outcome is predictably more random than punters think, and we can take advantage of this.

These behavioural biases are not unique to horse racing. As we discussed in detail in our "Beat the Street" Quantamentals report, over-optimism and over-confidence also drive the mispricing of stocks (albeit with somewhat greater sophistication). By identifying factors that drive the misalignment between expectations and realised outcomes, both equity investors and horse-racing punters can turn the behavioural biases of others to their financial advantage.

Predicting Finishing Positions

Using the Macquarie Quant *H*alpha Model, we predict the direction and magnitude of systematic biases in the pre-race odds. We then estimate the unbiased odds of each horse by backing out the predicted bias. For example, Hartnell's odds imply that it has a 10.5% chance of winning (after adjusting for the bookmaker's margin). However, Hartnell's *H*alpha score suggests that he is overvalued by 8.3%. We therefore estimate that his unbiased probability of winning at 9.6%.

Which Factors Matter?

In this section, we examine the 7 factors in our model individually, and determine how much of a difference each makes to a horse's chances of winning (i.e. its *Relative Win Probability*) and its valuation (i.e. its *Expected Return*).

For each factor, we partition race participants into five fractiles based on that metric. For example, for the *Odds* metric, we sort the horses in each race by their pre-race odds from the shortest odds to the longest. In a 10-horse race, the two horses with the shortest odds are placed into quintile 1, the next two in quintile 2, and so forth. All the horses in quintile 1 across the different races are then aggregated, with the process being repeated across the other quintiles.

Within each quintile, we examine the following metrics:

- **Relative Win Probability:** This is the probability that an individual horse in this fractile wins the race, relative to naïve average (i.e. 1/n, where n is the number of horses in the race). For example, a relative win probability of 1.5 means that the horse is 1.5x as likely to win as the average horse in the race.
- **Average Return:** The average return per race of betting on an individual horse within the fractile. To keep thing simple in the calculation of returns, we consider only whether the horse comes first or not. If the horse wins the race, then the return is the dollar amount of the odds minus one (i.e. the dollar wagered). If the horse does not win, then the return is negative one (i.e. we lose the dollar wagered).

In our analysis of 40,000 race participants across 4,000 races, we find that most factors do have a material impact on a horse's chances of winning a race. However, the effects also appear to be far smaller than punters believe, resulting in significant mispricing within the betting market. We provide detailed analysis below.

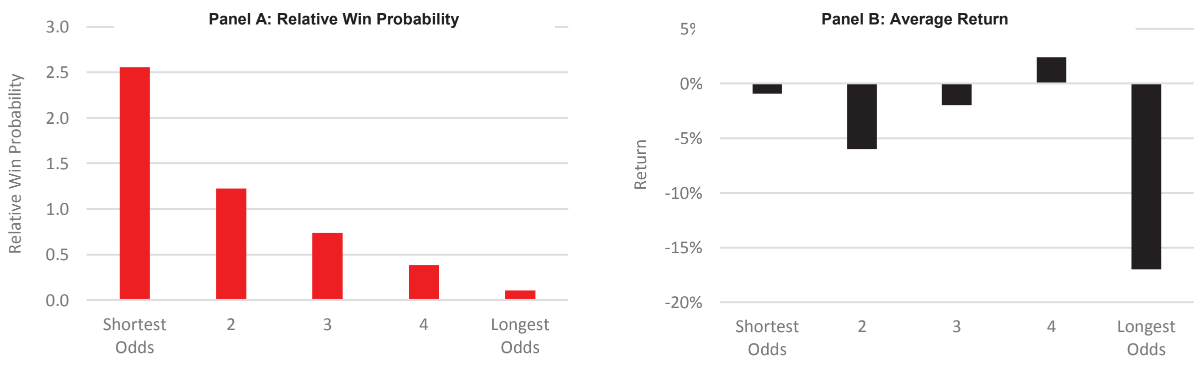
Odds

The odds, much like stock prices, should theoretically reflect all publicly available information about the underlying assets (a horse's running potential, in this case). As such, we find that odds are generally strong predictors of which horse is most likely to win the race. Horses in the top fifth of shortest odds are individually 2.6x as likely to win the race as the naïve average, while those in the bottom fifth are only 0.1x as likely to win.

The data gets interesting when we look at the expected returns of each odds fractile. The middle three fractiles are actually fairly consistent with risk aversion in a behavioural economics context – as horses become more risky (i.e. less likely to win), punters place their odds at a steeper "discount". The ends of the spectrum, however, are dominated by a behavioural anomaly known as the favourite-longshot bias. At one end of the extremes, punters tend to undervalue the favourites (though not enough to overcome the bookmaker's margin), while at the other end, they tend to massively overvalue the long-shots. Economists will recognise this as the left tail of Kahneman and Tversky's Prospect Theory (1979).

Be wary of the long shot. Our empirical evidence suggests that on average, punters lose three times as much money betting on a long-shot as picking a horse out of a hat. The sweet-spot in the odds spectrum actually appears to be in fractile 4. Here, you can capitalise off economic risk aversion while at the same time avoiding the strong lottery preferences that dominate fractile 5.

Figure 2 - Odds

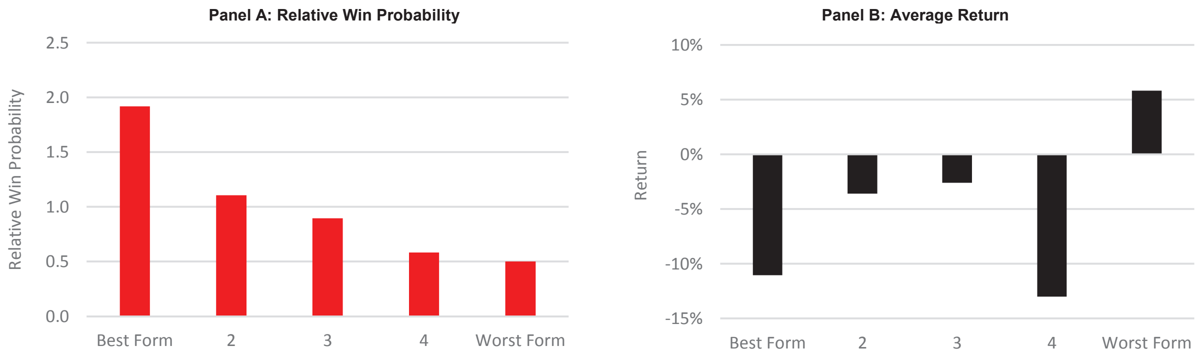


Source: Macquarie Research, Kaggle, October 2016

Form

How much should you trust the opinions of experts? Actually, they're pretty good, if relative win probabilities are anything to go by. The problem is that other punters think so as well, which leads to the crowded trade (or crowded bet, in this case) being in horses with good form. If you're concerned with maximising expected returns based on form alone, the data suggests that you should do the opposite – back horses with *the poorest form*. Individually, these unloved beauties are only about 0.5x as likely to win as the average horse, but when they do, they pay off handsomely! To boost your odds, diversification will be your friend.

Figure 3 - Form

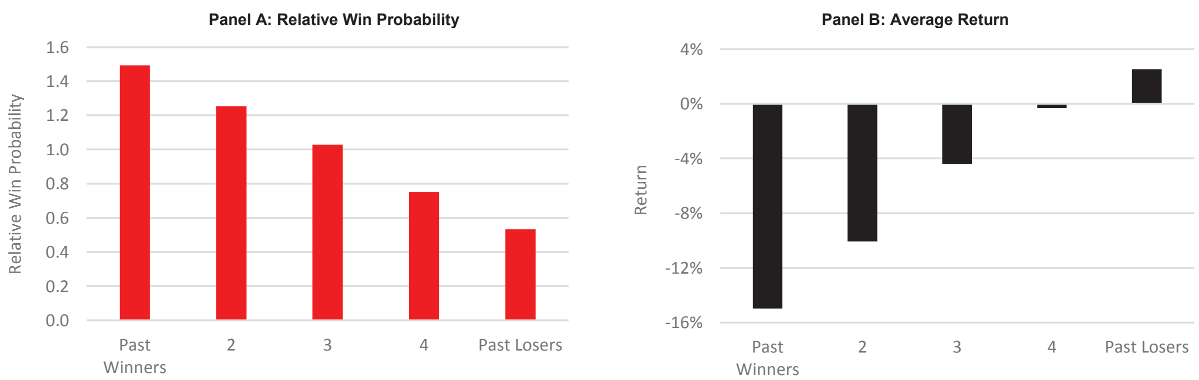


Source: Macquarie Research, Kaggle, October 2016

Last Five Race Results

In horse racing, past performance is a fair indicator of future performance[1]. In general, horses that ranked better in previous races also tended to rank better in the upcoming race. There's also a direct linear relationship between the past performance of a horse and its expected return – but it's negative! On average, betting on past losers has actually been a much more profitable strategy than betting on past winners. Punters appear to place excessive confidence in the explanatory power of past performance, and further, underestimate the pervasiveness of this behavioural fallacy in others. To maximise expected returns, the optimal strategy is therefore to go against the herd. Sound familiar? Our Quantamentals Report, "Stalking the Herd", show that crowding in equities markets can also lead to similar underperformance, and there too, the profitable trade is against the direction of the herd.

Figure 4 – Last Five Race Results



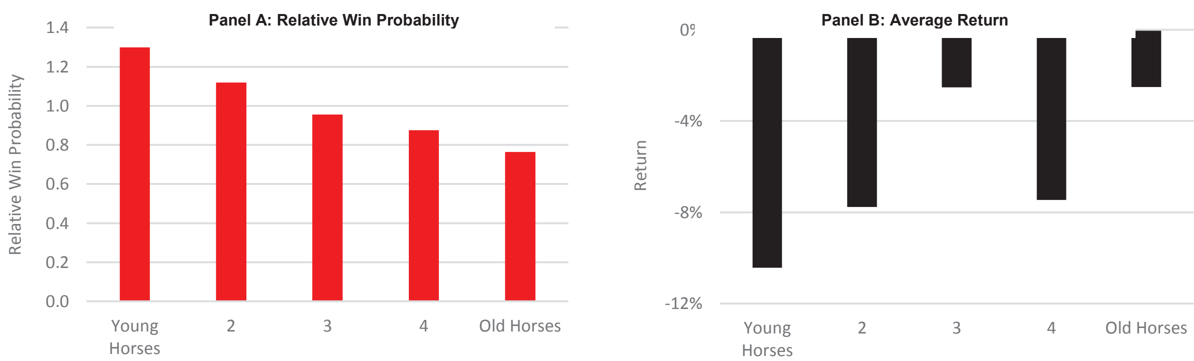
Source: Macquarie Research, Kaggle, October 2016

[1] In our case, we've consolidated historical performance into a single metric that represents the average rank of the horse in the past five races. Horses that were scratched or failed to finish were assumed to have a rank of 10.

Age

"Age before beauty" or so the saying goes, though not, apparently, when it comes to horse racing. Younger horses are, on average, faster than older horses. The margin, however, isn't as great as punters tend to think. The youngest horses tend to win about 1.3x as often as the average horse, while the oldest horses win about 0.8x as often. The crowded bet in the youngest horses, though means that betting on these will lose you about twice as much money as randomly picking a horse. While no age bracket systematically beat the odds, punters can reduce their expected losses by avoiding over-valued, younger horses.

Figure 5 – Age

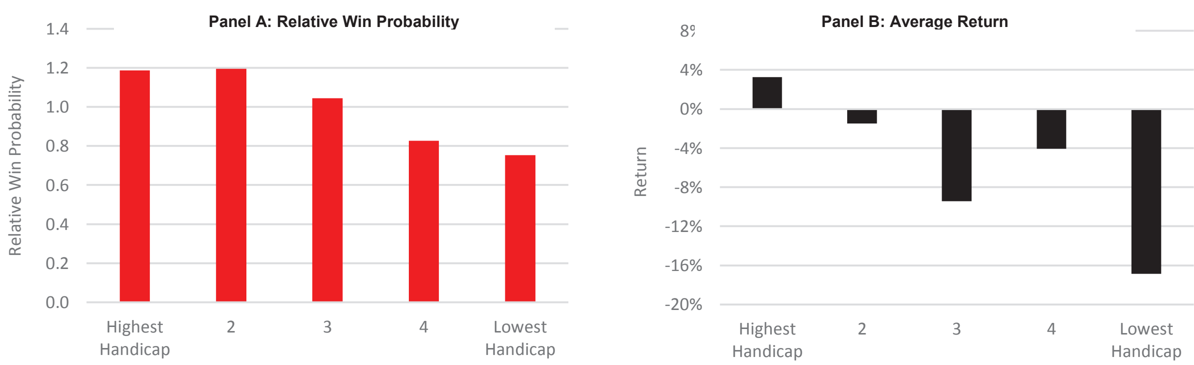


Source: Macquarie Research, Kaggle, October 2016

Handicap Weight

The handicap weight of a horse is a somewhat unusual factor in that horses with higher handicaps are more likely to win, but also tend to be more undervalued in their odds. Insofar as handicapping is supposed to even out the playing field, the empirical evidence suggest that handicappers systematically under-handicap good horses and over-handicap poor horses. Having said that, handicapping does appear to even the odds within the subset of above-average horses (i.e. the top 40%). Punters, however, appear to over-estimate the effect of the handicap, and systematically overvalue horses with the lowest handicap while undervaluing those with the highest. Under rational preferences, betting on the most highly handicapped horses is the dominant strategy. Not only are these horses most likely to win, but they also provide the highest expected return.

Figure 6 – Handicap Weight

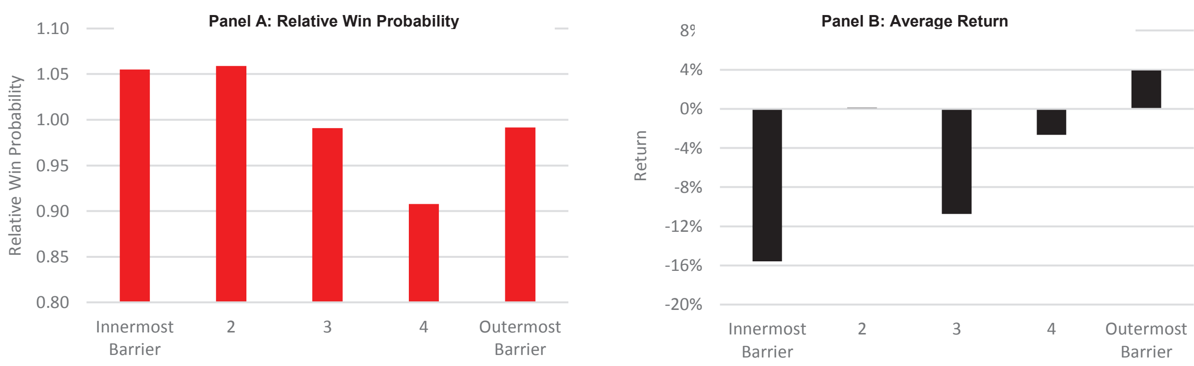


Source: Macquarie Research, Kaggle, October 2016

Barrier

Relative to other factors, the barrier number doesn't actually make a tremendous difference to the outcome of the race. Racing at the inner-most barrier appears to give a 5% advantage to the horse while the outermost barrier is disadvantaged by about 1%. Punters, however, overwhelmingly favour the inner-most barrier, and this results in severe bet-crowding here. The profitable bet is actually in the outer-most barrier. Being on the outside has a very small impact on the horse's chances of winning, but because of punters' behavioural biases, produces a +4% return per race.

Figure 7 – Barrier



Source: Macquarie Research, Kaggle, October 2016

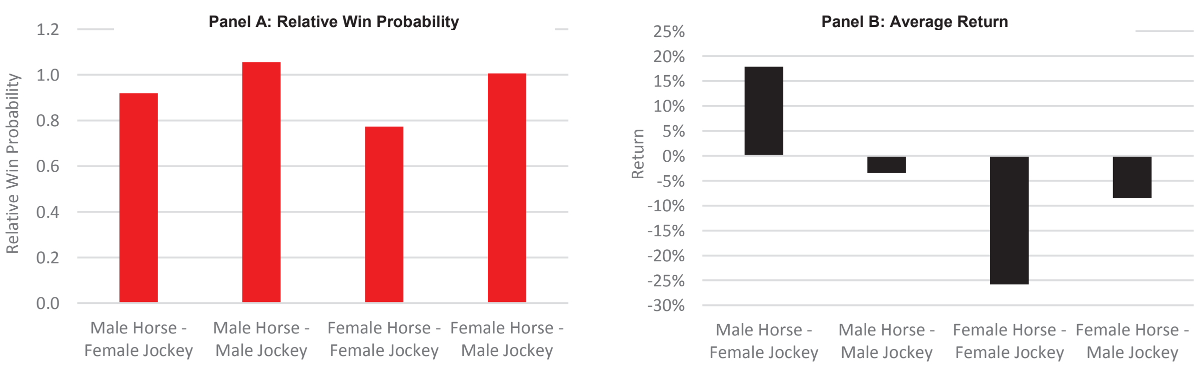
Sex of the Horse/Sex of the Jockey

The sex of the horse appears to explain a very small proportion of the variation in performance among race-horses. On average, male horses are 2.8% more likely to win than the average horse, while female horses 4.8% less likely to win. The asymmetry between the two numbers is explained by the fact that there are more participating male horses than female horses. Female jockeys also seem to be disadvantaged in their allocation of horses. A horse ridden by a male jockey will win about 3.6% more than on average, while one ridden by a female jockey wins 14.3% less.

There is, however, one quirky exception. Of the 39,801 race participants we examined, 127 of them were female jockeys riding unneutered male horses (i.e. a male horse that was not classified as a gelding). Not very many, but in this group, the relative win probability is a massive 1.7 – that is, they are 70% more likely to win a race than the average horse in the race. Not only that, the expected return on this horse/rider combination was +211%. In comparison, male jockeys on unneutered male horses have a win probability of 1.4 and an expected return of +1.9% per race. Now, we could speculate about some kind of pheromone interaction between horse and rider, but really, the sample size is pretty small and our statistical confidence (at this stage) is low. Still, something to keep an eye on for future races.

We also observe some unexpected results when we examine the market valuation of male and female horses and jockeys. It turns out that male horses ridden by female riders are massively undervalued by the market. The average return on this combination is +17.9% per race. We call this: the *Prince of Penzance effect*. The relative win probabilities (Figure 8, Panel A) show that it's not actually because female jockeys on male horses are actually faster. For whatever reason, punters just don't believe that they'll race as well as they do. The opposite is true for female jockeys on female horses. On average, the female jockey/female horse combination wins only about 0.77x as often as the average horse, but the bet is hugely crowded. The expected loss from a bet on this combination is roughly five times greater than a random pick.

Figure 8 – Sex of the Rider/Sex of the Horse



Source: Macquarie Research, Kaggle, October 2016

Building the Macquarie Quant *H*alpha

The quant team at Macquarie is dedicated to helping our clients make profitable equity investments. In the spirit of this, we've put our investor hats on and devised a completely new approach to picking horses in the Melbourne Cup. Rather than maximising the chances of picking the winner, the aim of this model is to pick the most undervalued horse; that is, the horse with the highest expected returns. Since the purpose of this model is maximise returns rather than hit rate, readers should note that direct application of this model will predict the winner far less frequently than relying on just the odds. The model depends on the fact that when it does pick the winner, the payoff should more than compensate for its low hit-rate.

At its core, the Macquarie Quant *H*alpha Model is based on a simple premise – that betting markets for horse racing are not perfectly efficient. Punters predictably overvalue factors that they believe will make a difference to race outcomes, and hence crowd their bets into favoured horses. The *H*alpha model identifies horses whose odds are too long for their expected probability of winning, and backs these.

The Quant *H*alpha Model is multifactor Ordinary-Least-Squares (OLS) regression model fitted on the observed returns of the horse. We use a simple rule to calculate these observed returns: If a horse won the race, the return is its odds minus one (i.e. the profit). Otherwise, the return is negative one.

The final specification of the model is as follows:

$$Observed\ Return = \alpha + \beta_1\left(\frac{Odds}{n}\right) + \beta_2\left(\frac{n}{Odds}\right) + \beta_3 Form + \beta_4 Past5Results + \beta_5 Age + \beta_6 Handicap + \beta_7 Barrier + \beta_8 MHFJ + \beta_9 MHMJ + \beta_{10} FHFJ + \beta_{11} FHMJ + \varepsilon$$

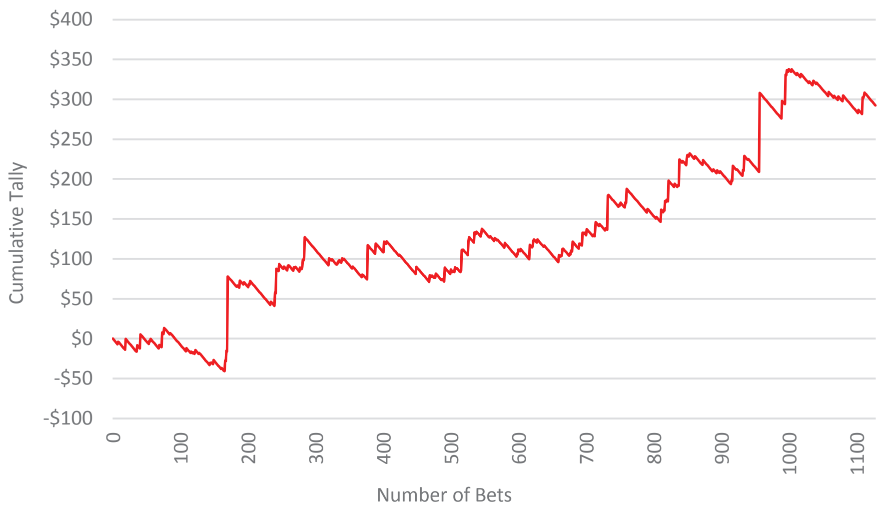
We scale the odds and the inverse of the odds by the number of horses each race (n) so they are commensurate with the expected return. Each of the other dependent variables are range normalised within the individual race.

The beta coefficients from the fitted model are then applied to data in the test model to test the model's efficacy.

Back-testing the Model

As a simple back-test of the Macquarie Quant *H*alpha Model, we trained the model on 70% of the data and then used it to bet $1 on the most under-valued horse in each of the remaining 30% of races. The results are presented in Figure 9: After 1,100 races, the strategy had made a profit of $292. As we pointed out earlier, the hit-rate for this model is not particularly high. However, the magnitude of the returns when it does pick a winner more than compensate for this.

Figure 9 – Simple Backtest ($1 Bets)

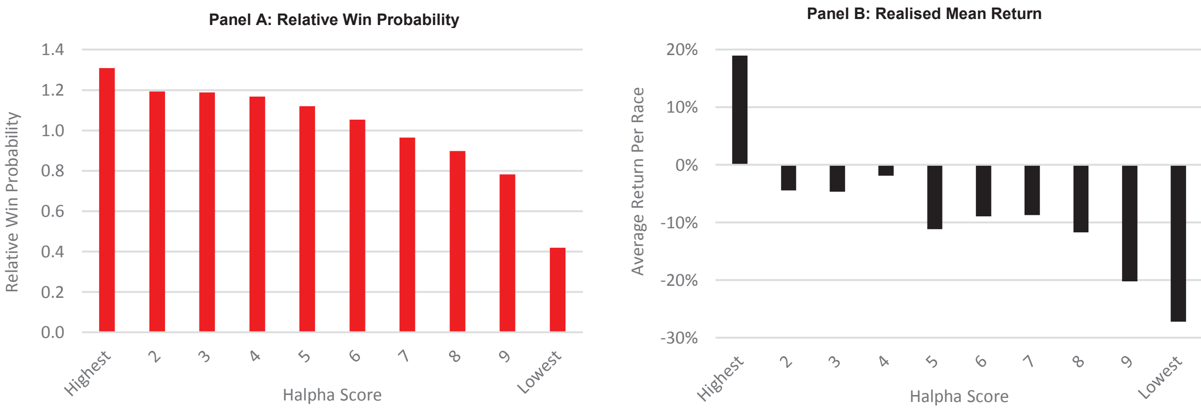


Source: Macquarie Research, Kaggle, October 2016

Cross-validation

In order to ensure a robust result, we use a cross-validation process in which we randomly assign 70% of races to a training set and the other 30% to the test set. The model was then fitted on the training set and tested out-of-sample on the test set. We repeated this 1,000 times. The results, presented in Figure 10, show that the Macquarie Quant *H*alpha Model lean towards horses that are more likely to win than the average horse (about 31% more), in part because the model specification allows it to avoid the long-shot bias where sensible. Positive returns to the *H*alpha model appear to be concentrated in the top decile – the average return to betting on the top decile horse (i.e. the most undervalued horse in a 10-horse race) is +18.9% per race, which is fairly consistent of the results from our simple backtest. This suggests that optimal deployment of the strategy is to bet on a narrow field within each race, but diversify bets across races. However, this is obviously not possible for a one-shot game like this year's Melbourne Cup, and so punters may wish to use a more precautionary but returns dilutive strategy by betting down the expected returns ladder.

Figure 10 – Cross-validation



Source: Macquarie Research, Kaggle, October 2016

Concluding Remarks

While horse-betting markets are quite removed from the equity markets that we normally deal in, we find similarities in the behavioural biases that afflict both punters and investors. Just as equity investors overvalue forecasted yield and growth (see our "Beat the Street" Quantamentals report for further details), punters also put too much emphasis on past performance and the barrier draw. Similarly, by moving away from the crowded trade, both investors and punters may benefit from improved expected returns (See our Quantamentals Report, "Stalking the Herd", for an equity markets analysis on crowding).

However, despite all our analysis, we actually know very little about horses; and even though we take our research seriously, we stress that this report is not meant to be taken seriously. Lastly, past performance is not indicative of future performance. Happy punting, and may the odds be ever in your favour!

Important disclosures:

Recommendation definitions

Macquarie - Australia/New Zealand
Outperform – return >3% in excess of benchmark return
Neutral – return within 3% of benchmark return
Underperform – return >3% below benchmark return

Benchmark return is determined by long term nominal GDP growth plus 12 month forward market dividend yield

Macquarie – Asia/Europe
Outperform – expected return >+10%
Neutral – expected return from -10% to +10%
Underperform – expected return <-10%

Macquarie – South Africa
Outperform – expected return >+10%
Neutral – expected return from -10% to +10%
Underperform – expected return <-10%

Macquarie - Canada
Outperform – return >5% in excess of benchmark return
Neutral – return within 5% of benchmark return
Underperform – return >5% below benchmark return

Macquarie - USA
Outperform (Buy) – return >5% in excess of Russell 3000 index return
Neutral (Hold) – return within 5% of Russell 3000 index return
Underperform (Sell)– return >5% below Russell 3000 index return

Volatility index definition*

This is calculated from the volatility of historical price movements.

Very high–highest risk – Stock should be expected to move up or down 60–100% in a year – investors should be aware this stock is highly speculative.

High – stock should be expected to move up or down at least 40–60% in a year – investors should be aware this stock could be speculative.

Medium – stock should be expected to move up or down at least 30–40% in a year.

Low–medium – stock should be expected to move up or down at least 25–30% in a year.

Low – stock should be expected to move up or down at least 15–25% in a year.
* Applicable to Asia/Australian/NZ/Canada stocks only

Recommendations – 12 months
Note: Quant recommendations may differ from Fundamental Analyst recommendations

Financial definitions

All "Adjusted" data items have had the following adjustments made:
Added back: goodwill amortisation, provision for catastrophe reserves, IFRS derivatives & hedging, IFRS impairments & IFRS interest expense
Excluded: non recurring items, asset revals, property revals, appraisal value uplift, preference dividends & minority interests

EPS = adjusted net profit / efpowa*
ROA = adjusted ebit / average total assets
ROA Banks/Insurance = adjusted net profit /average total assets
ROE = adjusted net profit / average shareholders funds
Gross cashflow = adjusted net profit + depreciation
*equivalent fully paid ordinary weighted average number of shares

All Reported numbers for Australian/NZ listed stocks are modelled under IFRS (International Financial Reporting Standards).

Recommendation proportions – For quarter ending 30 September 2016

	AU/NZ	Asia	RSA	USA	CA	EUR	
Outperform	47.26%	55.50%	38.46%	45.47%	59.09%	48.21%	(for US coverage by MCUSA, 8.20% of stocks followed are investment banking clients)
Neutral	38.01%	29.31%	42.86%	48.77%	37.88%	36.79%	(for US coverage by MCUSA, 8.25% of stocks followed are investment banking clients)
Underperform	14.73%	15.19%	18.68%	5.76%	3.03%	15.00%	(for US coverage by MCUSA, 8.00% of stocks followed are investment banking clients)

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