Research
Macquarie Wealth Management

MACQUARIE

AUSTRALIA

Horses Most Likely to Win

Rank	Horse	Odds*	Probability of Winning
1	(2) Almandin	11.2	9.8%
2	(5) Marmelo	8.4	9.6%
3	(6) Red Cardinal	12	9.0%
4	(3) Humidor	11	8.2%
5	(7) Johannes Vermeer	12	7.9%

Source: Macquarie Research, Tabcorp, November 2016

Most Undervalued Horses

Rank	Horse	Odds*	Relative Under-valuation
1	(9) Max Dynamite	18.4	33.7%
2	(2) Almandin	11.2	29.2%
3	(6) Red Cardinal	12	26.1%
4	(20) Wall of Fire	12.7	12.6%
5	(7) Johannes Vermeer	12	11.7%

Source: Macquarie Research, Tabcorp, November 2016
* TAB Odds as of 3pm 06/11/2017

6 November 2017
Macquarie Securities (Australia) Limited

Melbourne Cup: Quant Style

Going Max Active

Event

- As the race that stops a nation draws near, we revisit the **Macquarie Quant *H*alpha Model** from our 2016 Melbourne Cup note.
- As with Macquarie's Quant Alpha Model for equities, the Halpha model is designed to statistically capture inherent biases in the preferences of other market participants, which skew odds (or prices) away from fair valuation. It then takes advantage of these inefficiencies by betting (or trading) against the direction of the skew.
- This year, we were provided with updated data from 3,800 races (for a total of 7,200 races) by the fine folks behind the Horses for Courses dataset on Kaggle to refine our model.
- Our results show that just as in equity markets, behavioural biases in betting markets tend to be both persistent and profitable to systematically trade against.

Impact

- The updated data set confirms, out-of-sample, many of the trends we observed in our report last year. In particular, we find that punters **incorrectly crowd (i.e. over-pay for)** their bets into**:**
  - ⇒ Younger horses
  - ⇒ Both very long and very short odds
  - ⇒ Lower handicap weights
  - ⇒ Fewer days since the last run
  - ⇒ Better form ratings
- The updated *H*alpha model, which trims spurious factors, now takes a greater tilt towards horses with shorter odds than our original model. This presents a more favourable risk profile compared to last year's model.
- We tested the updated *H*alpha model by simulating $1 bets on 1,900 actual races, and achieved a net profit $551.

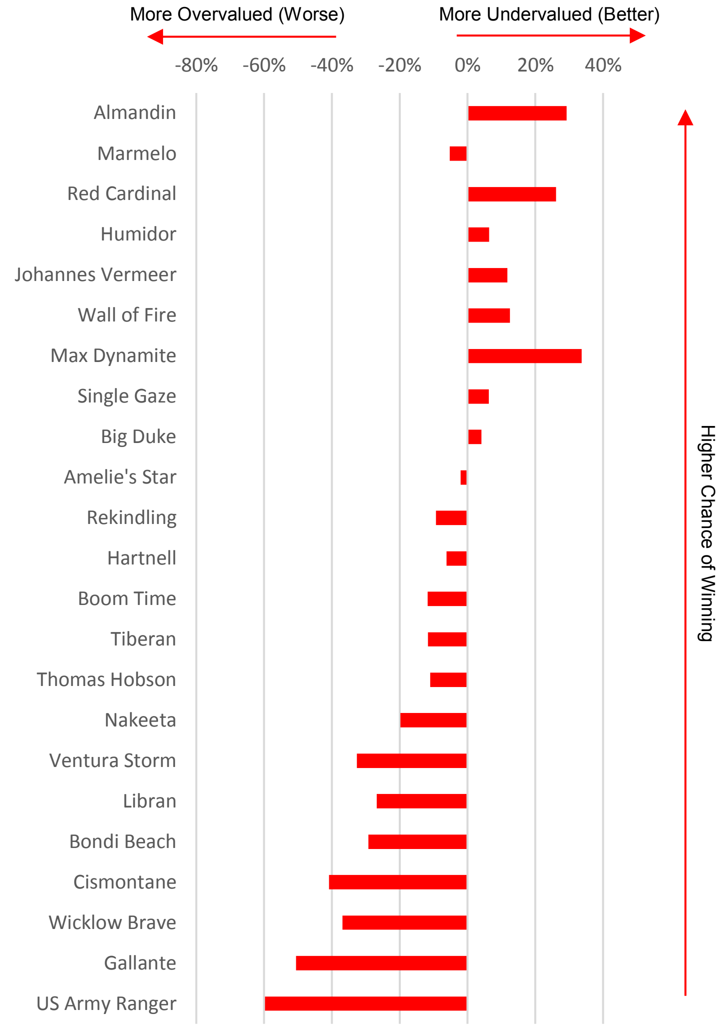
Strategy

- For punters who are out for gold and glory, we use the unbiased odds calculated by our updated *H*alpha model to pick horses with the highest likelihood of winning. Our top three are **Almandin**, **Marmelo** and **Red Cardinal.**
- However, for value investors out for a bargain, the most undervalued horse is **Max Dynamite**. In addition, **Almandin** and **Red Cardinal** are also cheap, despite the short odds. 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! Please use your own good judgement when betting, and happy punting!

Predicted Finishing Order for the 2017 Melbourne Cup

Figure 1: Predicted Finishing Order

Rank	Horse	Jockey	Odds (3pm 06/11/2017)	Form Rating	Age	Handicap	Barrier	*Halpha**	Probability of Winning
1	(2) Almandin	L. Dettori	11.2	94	8	56.5	14	29.2%	9.8%
2	(5) Marmelo	J. Bowman	8.4	94	5	55	16	-5.2%	9.6%
3	(6) Red Cardinal	K McEvoy	12	87	6	55	24	26.1%	9.0%
4	(3) Humidor	B. Shinn	11	100	5	56	13	6.3%	8.2%
5	(7) Johannes Vermeer	B. Melham	12	95	5	54.5	3	11.7%	7.9%
6	(20) Wall of Fire	C. Williams	12.7	94	5	53	15	12.6%	7.6%
7	(9) Max Dynamite	Z. Purton	18.4	78	8	54	2	33.7%	6.2%
8	(19) Single Gaze	Ms K O'Hara	16.7	91	5	53	11	6.3%	5.4%
9	(13) Big Duke	B. Avdulla	18.3	93	6	53.5	5	4.1%	4.8%
10	(23) Amelie's Star	D. Yendall	20.5	93	6	51	10	-2.0%	4.1%
11	(22) Rekindling	C. Brown	19.6	91	4	51.5	4	-9.3%	3.9%
12	(1) Hartnell	D. Lane	23.4	93	7	57.5	12	-6.1%	3.4%
13	(15) Boom Time	C. Parish	24.4	91	6	53	9	-11.8%	3.1%
14	(4) Tiberan	O. Peslier	26.1	86	6	55.5	23	-11.7%	2.9%
15	(21) Thomas Hobson	J. Moreira	26.8	95	8	52	21	-11.0%	2.8%
16	(18) Nakeeta	G. Schofield	34.5	85	7	53	19	-19.8%	2.0%
17	(10) Ventura Storm	G. Boss	29.2	96	5	54	6	-32.6%	2.0%
18	(17) Libran	D. Dunn	33	93	7	53	7	-26.7%	1.9%
19	(8) Bondi Beach	M. Walker	38.2	86	6	54	1	-29.2%	1.6%
20	(24) Cismontane	B. Mertens	34.4	93	5	50	17	-40.9%	1.5%
21	(12) Wicklow Brave	S. Baster	53.8	91	9	54	8	-36.9%	1.0%
22	(16) Gallante	M. Dee	63	90	7	53	18	-50.5%	0.7%
23	(14) US Army Ranger	J. P. Spencer	57.9	89	5	53.5	22	-59.7%	0.6%



Source: Macquarie Research, Tabcorp, November 2017

* 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)

Going Max Active

As the Melbourne Cup rolls around again for 2017, we turn our attention back to that most worthy and intellectually satisfying of pursuits: Figuring out how to take a good punt at the races. Despite the lacklustre performance of the Macquarie Quant *H*alpha Model at the 2016 Melbourne Cup, we believe that fundamental approach behind the model – to pick undervalued horses rather than those with the greatest absolute probability of winning – remains the rational objective for the fiscally minded punter. Our model does this by identifying factors that other punters systematically over-value. For example, punters tend to over-value the form of a horse. Hence, while horses with good form are indeed more likely to win, the odds offered on these are typically too short to justify them as a systematically profitable bet.

As with our standard Macquarie Quant Alpha Model, the *H*alpha model is designed to statistically capture inherent biases in the preferences of other market participants. These biases skew both betting odds and stock prices away from fair valuation. Quantitative models such as the Quant *H*alpha Model (and our regular Alpha Model) then takes advantage of these inefficiencies by betting (or trading) against the direction of the skew.

In order to improve the confidence and robustness of the *H*alpha model, this year, we have a (not-so-secret) secret weapon: More data. Thanks to Luke Byrne and Jared Pohl, the fine folks behind Kaggle's Horses for Courses dataset, we have been provided access to data for an additional 3,700 horse races from 2017 to complement the existing dataset of 3,400 races from 2016. The expanded data sample both allows a larger training set to construct the *H*alpha model, and enables us to partition out-of-sample validation and test sets.

While inventing strategies for horse-racing betting markets is mostly just for a bit of fun, the quantitative processes we apply here (i.e. identifying the forecast parameters and detecting pricing inefficiencies) largely reflect those used to address more sophisticated cash equity markets. In comparison to the latter, betting markets provide a cleaner prediction environment based on behavioural biases with less interference from macroeconomic cycles and idiosyncratic news-flow. As such, the *H*alpha model provides a useful didactic tool for exploring underlying concepts behind quantitative equities models.

The Macquarie *H*alpha Model

The Macquarie *H*alpha Model is a multifactor strategy that identifies characteristics about race participants that the betting market systematically under- or over-values. The model involves a number of stages:

1. Setting up the Prediction Problem

We set up the relevant prediction problem for which the solution maximises returns for punters. Contrary to conventional wisdom, this is not necessarily identifying the race participant who is most likely to win – after all, odds already largely reflect and price-in these probabilities, and a systematic strategy consistently betting on the favourite does not lead to an empirically profitable outcome.

If we frame this scenario as an analogy to the cash equities space, it is often not in an investor's best interest to merely identify the stock with the highest expected future EPS. The most profitable outcome arises when these future EPS flows can be acquired at the cheapest price. This is essentially what the *H*alpha model attempts to do in the betting space: Given each horse has some intrinsic probability of winning (and therefore an expected payoff), the model identifies where the expected payoff can be acquired most cheaply.

In the context of horse racing, we use the realised return of each race participant as the forecast variable, assuming a $1 bet. Hence, the return for a winning horse is the odds of that horse (e.g. say $6) minus the original $1 punted (i.e. a $5 return). The return for a losing horse is -$1, reflecting total loss of the initial amount bet. The quantitative model is then set up to maximise expected future return.

2. Data Normalisation

The raw data reports the specific characteristics of each race participant, such as age, form, handicap, as well as the odds associated with each participant. From these, we select a number of factors that we believe may unduly influence the offered odds:

- Age
- Form Rating

- Last Five Race Results
- Days Since Last Run
- Handicap Weight
- Barrier
- Odds

One issue with the raw data as they are presented however, is that the range in variation for any one of these factors can differ substantially across races. For example, all participates in one race may be younger horses, while all participants of another race may be older horses. When the data is pooled across races (which we need to do for panel-style analysis), information about the relativity of the data within each race becomes lost and the signal becomes more difficult to extract.

This is analogous to time-series effects in equity markets, where all stocks may be relatively cheap during one part of the market cycle, while at another point in the cycle, they may all be relatively expensive. The solution in quantitative equity models is to explicitly measure only the cross-sectional effect of a signal through, for example, an information coefficient or a long/short returns spread. In horse-racing data, however, such cross-sectional metrics tend to by highly noisy due to the extremely low breadth of each race (most races field less than 10 participants) and the extreme skewness of realised returns (one horse wins everything and all other horses lose everything).

We address this problem by range-normalising the factors across each race, using the following transformation:

$$R(F_{i,r}) = \frac{F_{i,r} - min(F_r)}{max(F_r) - min(F_r)}$$

$R(F_{i,r})$	Range-normalised value of $F_{i,r}$
$F_{i,r}$	Value of Factor for participant i in race r
$min(F_r)$	Minimum value of Factor F in race r
$max(F_r)$	Maximum value of Factor F in race r

The range-normalisation process removes inter-race variation in the range of factor values; similar to how cross-sectional mean-variance normalisation controls for time-series effects in quantitative equity models. We then partition the data into three sub-sets:

- **Training Set** – 3,412 races (June 2016 – September 2016): The Training Set is used to derive the initial regression coefficients. This is essentially the full data set used in our report last year.
- **Validation Set** – 1,855 races (April 2017 – May 2017): The Validation Set provides an out-of-sample check of whether (a) the factor loadings remain persistent and (b) returns to the strategy continue to be positive. Prediction performance in the Validation Set also helps inform the investment strategy in the Test Set (e.g. what proportion of horses to bet on per race).
- **Test Set** – 1,898 races (June 2017 – August 2017): The Test Set is used to derive the final out-of-sample returns to the strategy. By separating the Test Set from the Validation Set, we gain substantially greater confidence that the strategy has not generated positive out-of-sample returns purely by chance.

3. Panel Regression Analysis

In the final step, we apply the following multivariate regression specification to detect factors that have had significant predictive power on realised returns:

$$\begin{aligned} Observed\ Return = \alpha + \beta_1 R(Age) + \beta_2 R(Form) + \beta_3 R(Past5Results) + \\ \beta_4 R(DaysSinceLastRace) + \beta_5 R(Handicap) + \\ \beta_6 R(Barrier) + \beta_7 R\left(\frac{1}{Odds}\right) + \beta_8 R\left(\frac{1}{Odds}\right)^2 + \varepsilon \end{aligned} \quad \text{Equation (1)}$$

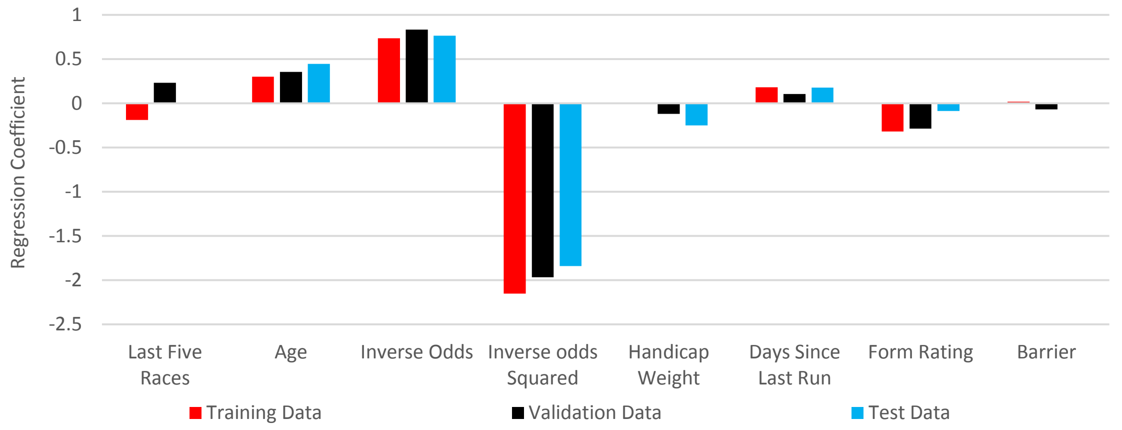
Note that the odds are inverted to give a relative implied probability of winning, which has a far less skewed distribution than the raw odds themselves (and hence, less sensitive to outliers). Further, we've introduced a quadratic specification to the way odds are incorporated into the regression function to more accurately reflect the non-linear relationship between odds and ex-post returns observed in the training data. The panel format of this analysis shares similarities with the stock-level performance measurement techniques we explored in our Factor Discovery report.

An initial prediction model is derived by trimming non-significant factors when the regression framework is applied to the Training Set. This model is applied to the Validation Set to verify whether the model holds out-of-sample. We then re-train the model with the trimmed parameters on the union of Training and Validation Sets to derive a final model that is tested on the Test Set.

Factor Persistence

The efficacy of the *H*alpha model is contingent on the assumption that historical trends (i.e. biases in bettor preferences) are persistent through time. In order to demonstrate that this assumption, by-and-large, empirically holds true, we run the regression specification presented in the prior section on each of the three data subsets separately. The magnitude of the regression coefficients are reported in graphical format in Figure 2.

Figure 2 – Model Coefficients across Training, Validation, and Test Data



Source: Macquarie Research, Kaggle, November 2017

The results show a considerable degree of consistency in both the direction and magnitude of most regression coefficients across Training, Validation, and Test datasets. In particular, we note strong persistent trends for the following factors:

- **Inverse Odds** – Inverse Odds and the square of Inverse Odds appear to be significantly positive and negative predictors of expected betting returns respectively. The negative coefficient to the square of Inverse Odds indicates a concave relationship between expected returns and the odds-implied probability of a horse winning – horses with either very long or very short odds are both overvalued and have odds that are too short for systematic betting on these horses to be profitable. This observation is consistent with standard assumptions of risk aversion, as well as Amos Tversky and Daniel Kahneman's Prospect Theory (1979)[1] at the long end (i.e. preference for lottery-like payoffs). The positive coefficient on the Inverse Odds themselves suggest that over-valuation is more extreme for horses with very long odds – it is still relatively more profitable (or less unprofitable, rather) to bet on favourites, even at much lower odds, than long shots.
- **Age** – The positive regression coefficient for age indicates that punters place a significant premium on younger horses. In fact, as we showed in our previous report, while younger horses are indeed more likely to win than their older peers, the effect is not as strong as punters believe. This results in the odds for younger horses being shorter than their unbiased win probabilities would dictate.
- **Days since Last Race** – There appears to be a mild over-preference for horses that have raced more recently, compared to those that have sat out for a longer period of time. Again, the effect is milder than punters price in, resulting in superior "value" betting on horses with a longer rest period.
- **Form** – As with age, horses with better form are more likely to win overall (see last year's note for more detailed analysis). However, punters exhibit overconfidence in this information, and so bid down the odds more than the actual magnitude of the advantage.

The overall trend across the last three factors is that "good" traits are frequently overvalued – that is, the benefit that they imbue on a horse is lesser than punters price into their odds, and hence taking the counter-consensus view results in greater expected returns.

[1] Kahneman, D., Tversky, A. (1979), "Prospect Theory: An Analysis of Decision under Risk", Econometrica, 46:2, 263-291

Model Validation and Back-testing

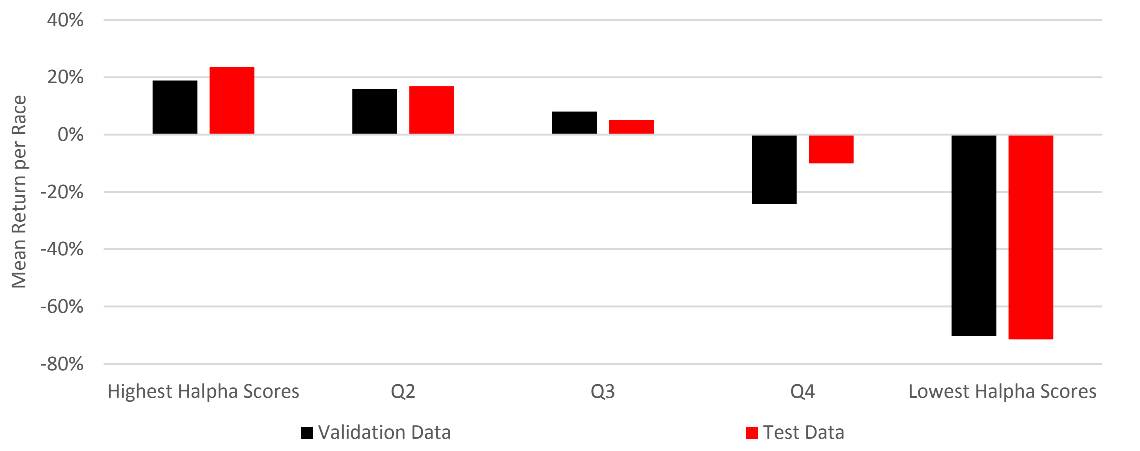
The model derived from the Training Set is a trimmed form of Equation (1):

$$ObsObserved\ Return = \alpha + \beta_1 R(Age) + \beta_2 R(Form) + \beta_3 R(Past5Results) + \beta_4 R(DaysSinceLastRace) + \beta_5 R\left(\frac{1}{Odds}\right) + \beta_6 R\left(\frac{1}{Odds}\right)^2 + \varepsilon \qquad \text{Equation (2)}$$

Notably, Barrier number and the Handicap were trimmed from the regression specification as they were found to have no significant effect on realised returns in the training set. We then run two tests of quintile performance based on our out-of-sample Validation and Test datasets. The test procedure is as follows:

1. We refit the model described in Equation (2) to the Training Set to derive model weights.
2. The trained model is then applied to the Validation Set to produce *H*alpha forecasts for each race participant in this sample.
3. The participants in each race are partitioned into quintiles by their *H*alpha score. The mean return for each quintile across all races in the Validation Set is then computed. This is presented as the black bars in Figure 3 below.
4. We refit the model in Equation (2) on the union of the Training Set and Validation Set, to derive updated model weights.
5. Steps 2 and 3 are then repeated on the Test Set. Mean returns to *H*alpha quintiles for the Test Set are presented as the red bars in Figure 3 below.

Figure 3 – Quintile Performance of *H*alpha Scores

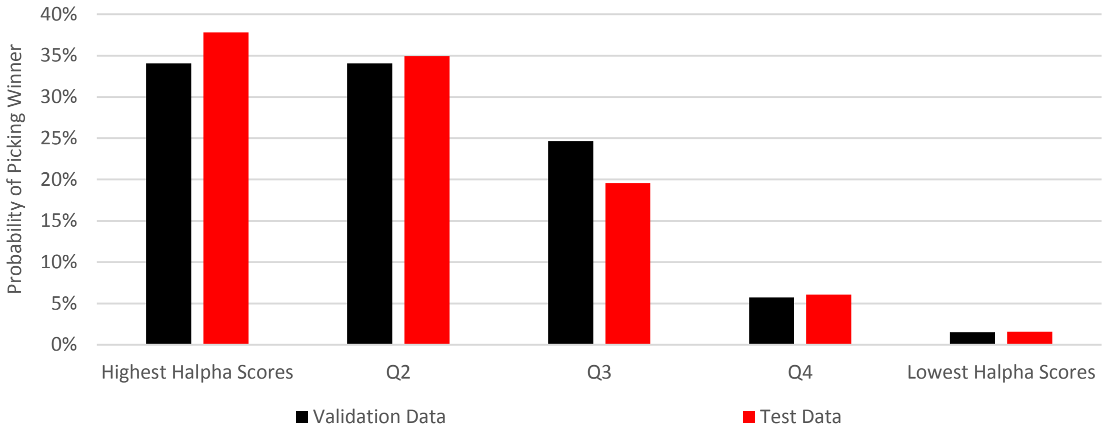


Source: Macquarie Research, Kaggle, November 2017

The results show that realised out-of-sample returns to the *H*alpha model are consistently positive and economically significant in the top two quintiles, while the reverse holds true in the bottom two quintiles. In particular, race participants identified as being in the bottom quintile by *H*alpha score earn extremely negative returns – in excess of -50% per race – and provide a strong indicator of which horses to avoid betting on.

The updated *H*alpha model also exhibits more desirable risk characteristics compared the previous model. Specifically, it now takes a much stronger tilt towards horses with shorter odds, resulting in those with high *H*alpha scores to also be more likely to win. Figure 4 below presents the probabilities of each *H*alpha quintile picking the race winner, and shows that in the Test dataset, there is almost a ~70% probability that the winning horse comes from the top two fifth of *H*alpha scores (Figure 4). On the other hand, the combined probability of picking a winner in the bottom 40% of horses by *H*alpha score (i.e. quintiles 4 and 5) is less than 10%.

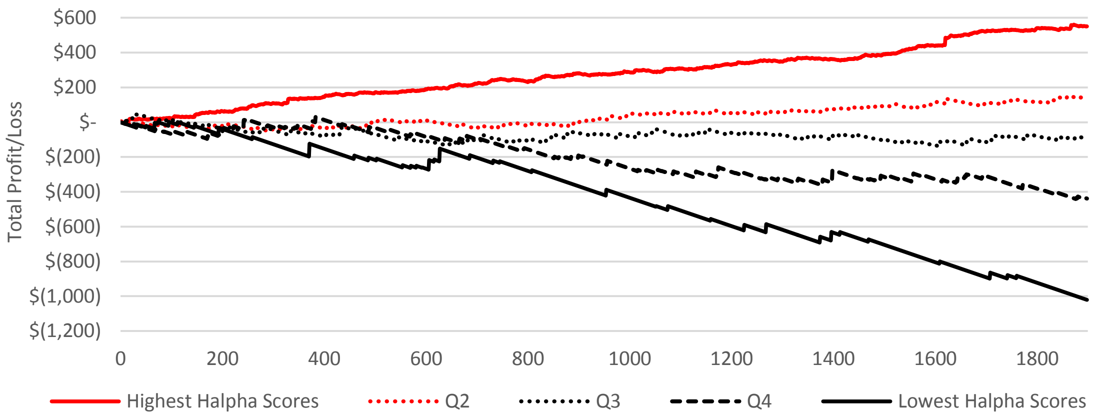
Figure 4 – Win Probabilities across *H*alpha Quintiles



Source: Macquarie Research, Kaggle, November 2017

Finally, we simulate the payoff of systematically betting across each of the *H*alpha quintiles in the Test data. For each race, we evenly spread a $1 bet across all the horses each quintile, and track the profit and loss of the strategy across the five groups. Cumulative P&L is reported in Figure 5, and show consistent profitability in the top *H*alpha quintile. Conversely, losses are large and significant in the bottom quintiles, with payoffs being infrequent but lumpy due to the relatively longer odds in these horses.

Figure 5 – Simulated Betting across *H*alpha Quintiles ($1 Bets)



Source: Macquarie Research, Kaggle, November 2017

Melbourne Cup 2017 Predictions

We form predictions for the 2017 Melbourne Cup by training the *H*alpha Model in Equation (2), on the union of the Training, Validation, and Test data sets, as well as data from prior Melbourne Cup races dating back to 2007. The model produces *H*alpha forecasts for runners in this year's Melbourne Cup, which can be interpreted as a relative measure of whether that runner is over- or under-valued. This year, the most undervalued horse is **Max Dynamite**, followed by **Almandin** and **Red Cardinal**. In addition, we use the *H*alpha forecast to modify the win probabilities of the race participants to correct for preference biases among other punters. While **Marmelo** is currently the race favourite, the correction actually drops it back below **Almandin** into 2nd preference. **Red Cardinal** brings up number 3 ahead of **Humidor** and **Johannes Vermeer**.

Concluding Remarks

As with investors in cash equity markets, punters in horse racing markets also exhibit preference biases that distort the odds away from “true” underlying probabilities of a horse winning. Quantitative methods such as the Macquarie Quant Alpha Model (for equity markets) and the *H*alpha Model (for horse-racing markets) use statistical analysis to detect these distortions, and make bets against the incorrect assumptions of other market participants.

Despite the depth of our analysis, however, we’d like to stress that we know very little about horses, and this report is not meant to be taken seriously. Past performance may not be indicative of future performance. Happy punting!

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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