Strategic Forecasting in Rank-Order Tournaments: Evidence from Horse-Racing Tipsters

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Abstract

We analyze the forecasting behavior of professional horse-racing tipsters. These tipsters participate in contests that reward the best performers at least in terms of publicity. We find that contests induce tipsters to make untruthful forecasts. In particular, tipsters react to an improvement of their rank in the contest by releasing more original forecasts. Symmetrically, tipsters react to bad performances by making more conservative forecasts. These results have implications for the efficiency of the betting markets.

1 Introduction

Rank-order tournaments are widely used to compensate agents. Since the work of Lazear and Rosen (1981), Nalebuff and Stiglitz (1983) and others, we know that rank-order tournaments can provide an efficient incentive framework for risk-neutral workers to produce more effort. While the effect of tournaments on effort is widely documented, few papers have explored the incentives in rank-order tournaments when the agents’ choice variable is risk instead of effort. This is however important in order to understand the behavior of experts such as GDP forecasters and financial analysts. Indeed, the strategic decision of

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forecasters is at least as much about risk taking (conservative versus original forecasts) than about effort. On the theoretical side, Hvide (2003) and Gilpatric (2004) develop models where agents choose both effort and risk. They find that tournaments induce risk-neutral agents to take high risk. Bronars (1987) and Acker and Duck (2001) show that leaders have incentives to take fewer risks than followers in order to secure the first ranks. On the opposite, Taylor (2003) finds that, when strategic interactions of agents are taken into account, leaders have incentives to take more risk than followers.

In this paper we analyze the effect of rank-order tournaments on the risk-taking of horse-racing tipsters. We specifically address two questions. First, do rank-order tournaments induce tipsters to make untruthful forecasts? Second, do leaders and followers in tournaments develop different strategies regarding the riskiness of their forecasts?

In order to answer these questions, we have built a unique dataset on horse racing tipsters. We have collected data from two main French horse-racing daily newspapers: Paris-Turf (PT henceforth) and Tiercé Magazine (TM). Both newspapers report every day, before each race, the tips of a set of professional and non-professional horse-racing tipsters. There are as a whole 101 tipsters: 71 professionals and 30 non-professionals (10 jockeys, 10 drivers and 10 trainers). A tip consists of an ordered list of 8 horses that are expected to be the most competitive. After each race, every tipster scores some points if his tip succeeded in predicting the outcome of the race. The more precise the tip, the more points he scores. Both newspapers rank their tipsters according to the number of points scored during the current year. At the end of the year, the top tipster is declared winner which can be a strong boost for his career. There are two distinct contests for 65 professional tipsters (TM: 35 tipsters and PT: 30 tipsters) and three other PT contests for 30 non-professional tipsters. All these contests started on January 1st 2004 and ended on December 31st 2004.

We measure the originality by the distance between a forecast and the public
information. We attribute a low level of originality to a forecast that is close to public information and vice-versa. We proxy public information by ranking -per race- each horse on his likelihood of winning the race. This likelihood is proxied by a set of 12 publicly known variables such as the form of the horse, the jockey quality etc. By doing so, we get an ordered list of horses from the most likely to win to the least likely.

We find that contestants are getting more original than usual as their rank improves and more conservative if their rank gets worse. Indeed, a successful tipster in $t$ is all the more original in $t + 1$ that the number of successful tipsters in $t$ is small and reciprocally. This means that tipsters react to the success of their previous forecast relative success of the other tipsters. Symmetrically, an unsuccessful tipster in $t$ is all the more conservative in $t + 1$ that the number of unsuccessful tipsters in $t$ is small and reciprocally. These results are clearly significant in the case of the two most prestigious contests (professional tipsters, minimum of 30 contestants). Interestingly, tipsters do not react to "absolute" success. This clearly suggests that rank-order tournaments have an effect on the behavior of these tipsters. Our results are in line with the predictions of Taylor (2003).

This first result directly implies that tipsters make more original forecast that their private information would imply. Indeed, efficient forecasting would require the forecasts to include the best horses given tipsters’ information. The fact that forecasts depends on past success shows that this is not the case. Forecasts are therefore inefficient and necessarily too risky given the information available to the tipsters. There are also indications that forecasts are excessively far from the public information. Indeed, original forecasts are less successful than conservative forecasts. This suggests that originality is not driven by precise private

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1For other empirical studies, see Knoeber and Thurman (1994) who find that broiler farmers who are bottom-ranked in tournaments do indeed take riskier actions in order to improve their rank. Busse (2001) finds that funds that are ranked above the median fund in their category increase total risk more than below-median funds. This is more in line with our results.
information\textsuperscript{2}. This result fits the prediction of Ottaviani and Sorensen (2005\textsuperscript{a}). They analyze the incentives of forecasters to deviate from public information in forecasting contests and find that in order to win the contest, forecasters release forecasts that are excessively far from public information.

This paper also has implications for the efficiency of betting markets. Numerous studies have shown the existence of a clear favorites-longshots bias in the horse races betting markets: Favorites win more frequently than their odds indicate, while longshots win less frequently.\textsuperscript{3} We believe that our results explain at least partially the favorites-longshots bias. Indeed, if the contest induces professional tipsters to produce excessively original forecasts, we could expect bettors to bet excessively on longshots as long as they follow the advices of tipsters. This could explain why the odds do not match the probability of winning.

Note that Snyder (1978) already provided hints of untruthful reporting among horse-racing tipsters. He observes that tipsters’ odds diverge more from unbiased predictions than the betting markets odds. Tipsters odds imply indeed an even greater favorite-longshot bias. This can be seen as the result of exaggeration among professional handicappers competing for the best record.

Section 2 presents the dataset and some stylized facts. Section 3 presents the main results. Section 4 concludes.

2 The Data

2.1 Sources

The data have been collected from two main French horse-racing daily newspapers: Paris-Turf and Tiercé Magazine. Both newspapers publish tips the day

\textsuperscript{2}For other evidence of untruthful reporting among experts, see Zitzewitz (2001), Bernhardt, Campello and Kutsoati (2005) and Chen and Jiang (2005).

\textsuperscript{3}See Thaler and Ziemba (1998) and Ottaviani and Sorensen (2005\textsuperscript{b}) among others.
before each race. More precisely, they report the tips of not-less than 101 experts. Each of them tips an ordered list of 8 horses that they expect to be the most competitive during the race.

Tipsters are of two types: professional (i.e. full-time) and non-professional (i.e. part-time). The latter category is made of three types: trainers, drivers and jockeys. 6 tipsters (1 part-time and 5 full-time) enjoy a high level of reputation in the field of Pari-Mutuel Betting (Omar Sharif for instance). A particularity is that their performances are not accounted for, given that these Superstars do not participate in any contest, contrary to “normal” tipsters who get points for each of their tips given their relevance, i.e. ability to predict the race outcome. They score some points if the top 3 (tiercé), top 4 (quarté) or top 5 (quinté) finishers are among the 8 horses they tipped. The number of points they score also depends on whether the race was easy to predict or not, and they get a special bonus when they succeed in predicting a tiercé, a quarté or a quinté in the exact order. At the end of the year, the tipster having scored the most points is declared the contest’s winner. The dataset contains as a whole 95 different tipsters involved in 5 distinct annual contests/championships (January 1st, 2004 till December 31st, 2004) plus 6 Star tipsters:

This original dataset allows to address several interesting issues related to the experts’ strategic behavior. In particular, we are interested in analysing their risk-taking strategy, the extent to which tipsters depart from the consensus, in what circumstances they tend to herd or anti-herd.

In order to analyse the tipsters’ strategic forecasting behavior, we need a "consensus forecast" or "public information". To proxy this public information, we rank -per race- each registered horse (between 15 and 20 horses) on the basis of their likelihood of winning the race from a set of 12 dummy variables: whether or not the horse is suited to the track, whether or not he is on form, whether or not his jockey/driver performs well, etc. We assume that these information
are common knowledge among all the experts even if they are published in $t-1$ along with the tips for race $t$. In details, we compute a sum of these 12 dummies (consensus forecast) and rank horses according to this statistics. This proxy is then used to estimate how original a forecast is by calculating how distant from the consensus forecast it is.

### 2.2 Descriptive Statistics

There are as a whole 25,563 different tips as follows:
Table 1: Risk-Taking statistics

<table>
<thead>
<tr>
<th>Contest</th>
<th>Tipsters</th>
<th>Races</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Part-time tipsters</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drivers</td>
<td>10</td>
<td>142</td>
<td>0.71</td>
<td>9.71</td>
<td>3.92</td>
<td>1.47</td>
</tr>
<tr>
<td>Jockeys</td>
<td>10</td>
<td>39</td>
<td>1.29</td>
<td>8.57</td>
<td>3.78</td>
<td>1.25</td>
</tr>
<tr>
<td>Trainers</td>
<td>10</td>
<td>126</td>
<td>0.86</td>
<td>9.00</td>
<td>4.21</td>
<td>1.37</td>
</tr>
<tr>
<td>Full-time tipsters</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paris-Turf</td>
<td>35</td>
<td>330</td>
<td>0.00</td>
<td>9.38</td>
<td>3.81</td>
<td>1.19</td>
</tr>
<tr>
<td>Tiercé-Mag.</td>
<td>30</td>
<td>299</td>
<td>0.50</td>
<td>9.13</td>
<td>3.83</td>
<td>1.21</td>
</tr>
<tr>
<td>Stars</td>
<td>6</td>
<td>329</td>
<td>0.63</td>
<td>8.63</td>
<td>3.84</td>
<td>1.24</td>
</tr>
<tr>
<td>Total</td>
<td>101</td>
<td>-</td>
<td>9.71</td>
<td>3.84</td>
<td>1.23</td>
<td></td>
</tr>
</tbody>
</table>

* A 8-horse tip corresponding exactly to the consensus forecast Top 8 horses is given a 0 here.

In the matter of Risk-taking, part-time tipsters are slightly more original than full-time tipsters even if their tips vary more on average (see Table 1). The fact that their reputation and revenues don’t depend on their forecasting activity may explain why they behave more freely and why they forecast more originally. One may also interpret this difference from the number of tipsters involved in the contest: the smaller the contest is, the more original the forecasts are. A big contest seems to provide more incentives to tipsters who take less risk to win.

From Table 2, we learn that full-time tipsters score more frequently than part-time tipsters. Surprisingly, the six Superstars are not the more efficient than the other tipsters (average frequency of success of 31%). The best tipsters are thus those involved in the two main contests (PT and TM). We see here
that tips are more frequently successful when the tipster is a full-time one, when it is involved in a contest and when this contest is a large and prestigious one.

Table 2: Frequency of Success

<table>
<thead>
<tr>
<th>Contest</th>
<th>Contestants</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Part-time tipsters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drivers</td>
<td>10</td>
<td>28</td>
</tr>
<tr>
<td>Jockeys</td>
<td>10</td>
<td>18</td>
</tr>
<tr>
<td>Trainers</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Full-time tipsters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paris-Turf</td>
<td>35</td>
<td>33</td>
</tr>
<tr>
<td>Tiercé-Mag.</td>
<td>30</td>
<td>32</td>
</tr>
<tr>
<td>Stars</td>
<td>6</td>
<td>31</td>
</tr>
<tr>
<td>Total</td>
<td>101</td>
<td>29</td>
</tr>
</tbody>
</table>

With the following figures, we see how Originality varies with the average ranking computed -contest by contest- over the whole contest. Top-ranked tipsters tend to be less original than middle-ranked tipsters and bottom-ranked tipsters. Note also an interesting quadratic shape for PT.

This positive relationship between Originality and Ranking is confirmed by a simple OLS regression between the two variables (see Table 3 - Model 0). Note (figure 2) that the standard deviation of the rank tends to decrease during the contest. The rank does not vary much during the second half of the contest.
Figure 2:
3 Results

3.1 Fixed-Effects Regressions

In this section, Originality (O) is regressed against several measures of Success using a series of fixed-effect analyses\(^4\). Letting \( i = 1, \ldots, I \) index the tipsters, \( t = 1, \ldots, T \) index the races (and thus time), the basic model is:

\[
O_{it} = \alpha + \beta Rk_{it-1} + \epsilon_{it1} \tag{1}
\]

With \( Rk_{it-1} \), the relative rank of individual \( i \) in period \( t - 1 \) and contest \( c \). By relative rank we mean the absolute rank divided by the number of tipsters involved in the contest (either 35, 30 or 10). Strangely, \( \beta \) is non-significant in Model (2), a model in which unobservable individual heterogeneity is controlled

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\(^4\)The Hausman test rejects systematically the random-effects specifications.

\(^5\)Index \( c \) is dropped here and in what follows for convenience.
for (see Table 3). It is likely the indication that the rank captures this individual heterogeneity and perhaps the talent of tipsters.

We use thereafter the other available and continuous measure of *Success* instead of *Rk*$_{it-1}$: the number of points the tipster gets after each successful race. In Model (2), *Success* is either cumulative (*S*$_{it-1}$) or not (*s*$_{it-1}$). *S*$_{it-1}$ is proxied by the total number of points (*P*$_{it}$) a tipster accumulates, race by race, given the relevance of its successive tips up to period *t* − 1: $S_{it-1} = \sum_{t=0}^{t-1} P_{it}$. *s*$_{it-1}$ is a dummy variable which takes the value 1 when the previous tip is successful, otherwise 0. Model (2) has the following structure:

$$O_{it} = \alpha + \beta S_{it-1} + \gamma s_{it-1} + \delta T + \epsilon_{it2}$$

(2)

PT and TM have different assessment systems. PT has also adopted a particular system for its three part-time tipsters contests (Jockeys, Drivers and Trainers). As a whole, we have three distinct assessment systems (PT full-time, PT part-time and TM). We take this aspect into account by interacting the continuous variable *S*$_{it-1}$ with the following dummies: PT, TM, Part-time (Jockeys + Drivers + Trainers) and Stars. Finally, to introduce the 6 Star-tipsters in the analysis, we have simulated for each of them a series of points randomly using a standard normal distribution.

Model (2) exhibits a positive and significant relationship between *Originality* and cumulative success for PT and TM and a negative one for Part-time tipsters (significant at the 5% level). Forecasters are getting more and more original as they go up in the ranking. Top-ranked tipsters appear to be more original than middle-ranked and bottom-ranked tipsters. Hopefully, the 6 Stars get a non-significant coefficient. We also get a significant and negative effect for Time, meaning that tipsters are more original on average at the beginning of the contest and that this originality tends to decrease over the contest.
it is surprisingly non-significant. This is probably due to the fact that
the effect of the last outcome (success or failure) is not captured correctly when
Success is expressed in absolute terms, i.e. when one doesn’t control for other
tipsters’ successes or failures. Our intuition here is that the reaction to the
last outcome is more likely relative than absolute. Indeed, one may wonder
how does tipster $i$ react to other tipsters’ outcomes. We test this intuition by
introducing two variables, one for the relative success ($Rs_{it-1}$) and another one
for the relative failure ($Rf_{it-1}$) of tipster $i$ at period $t - 1$:

$$Rs_{it-1} = \sum_{j \neq i} \frac{s_{jt-1}}{N - 1} \quad \text{if } s_{it-1} = 1$$
$$Rf_{it-1} = \sum_{j \neq i} \frac{s_{jt-1}}{N - 1} \quad \text{if } s_{it-1} = 0$$

$Rs_{it-1}$, and $Rf_{it-1}$ are proportions defined on an interval $[0,1]$. When $Rs_{it-1}$
$= 0$, tipster $i$ is the only successful tipster among the $N$ tipsters\(^6\) involved in the
contest at period $t - 1$. $Rs_{it-1} = 1$ means that everybody is successful in $t - 1$.
$Rf_{it-1} = 0$ means that nobody has won in period $t - 1$. $Rf_{it-1} = 1$ means that
tipster $i$ is the only loser among the $N$ tipsters involved in the contest at period
$t - 1$. Hence, a value of $Rs_{it-1}$ ($Rf_{it-1}$) close to 1 (0) may be interpreted as a
"banal" success (failure) given that a lot of (a few) contestants have a successful
outcome. These variables replace $s_{it-1}$ in Model (3):

$$O_{it} = \alpha + \beta S_{it-1} + \gamma S Rs_{it-1} + \gamma F Rf_{it-1} + \delta T + \epsilon_{it3} \quad (3)$$

Model (3) shows that tipsters react significantly to relative success as ex-
pected (negative sign). A strong relative success ($Rs_{it-1}$ close to 0) is proved to
boost originality of tipster $i$ at period $t$. Interestingly, we also get that tipsters
are less original in $t$ when they lose in $t - 1$ and that the outcome of the race
was relatively easy to predict ($Rf_{it-1}$ close to 1) in comparison with a "banal"
failure.

\(^6\)With $N$, the total number of successful tipsters in contest $c$. 

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In Model (4), we introduce $S_{it-1}^2$ and $T^2$, respectively the square of $S_{it-1}$ and $T$ to see whether the relationship between Originality, time and cumulative success is linear or not. The relationship appears quadratic for TM only and linear for the other contests (PT and Part-time). The introduction of these square terms does not add much to the results and even causes some damages (see for instance Part-time $S_{it-1}$) except perhaps in the case of Time. The coefficient of $T^2$ is positive and significant, indicating that tipsters tend to be more original both at the beginning and at the end of the contest than in the middle of the contest. A satisfying model seems to be one in which we keep the square for Time only (Model 5). In this model, cumulative success is non-significant for part-time tipsters. With this specification, we get that $\gamma_S$ is significantly different from $\gamma_F$ at the 5% level: $F_{stat}(1, 25444) = 3.90$. This indicates that tipsters react more in terms of originality in case of failure than in case of success in $t-1$ ($\hat{\gamma}_F > \hat{\gamma}_S$). A Wooldridge test for autocorrelation in panel data on the same model fails to reject the null hypothesis of no first-order autocorrelation: $F(1, 100) = 0.373$.

These results suggest that there is a clear and strong tournament effect at least in the case of PT and TM main contests. Contestants are getting more and more original as their reputation in the contest goes up. Tips also appear more original both at the beginning and at the end of the contest.

We have shown that tipsters make too risky forecasts. However, these results do not tell whether forecasts are on average excessively close or far from the consensus forecast. The answer to that question maybe lies in link between originality and success. We have sorted the forecasts of each individual tipster from the most conservative forecasts to the most original ones. Then we have divide this sorted list into five quantiles. For every tipster, the first quantile includes thus the most conservative forecasts and the fifth quantile includes the most original forecasts. We then look at the rates of successful forecasts in each quantile and average these rates across tipsters. The following table shows the results.
There is a very strong relationship between originality and success. The higher is originality of a forecast, the lower is the probability that it is correct. This suggests that deviation from the public information is unlikely to be justified by precise private signals. Tipsters seem to deviate excessively from the consensus. The reason for making original forecasts is clearly that a successful original forecasts is strongly rewarded.

4 Conclusion

TBW

References


Table 3: OLS and Fixed-Effects Regressions for the relationship between Originality and Success (Dep. Var.: Oit*1000)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Notation</th>
<th>OLS (0)</th>
<th>OLS (1)</th>
<th>Fixed-Effects Regressions (2)</th>
<th>Fixed-Effects Regressions (3)</th>
<th>Fixed-Effects Regressions (4)</th>
<th>Fixed-Effects Regressions (5)</th>
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</thead>
<tbody>
<tr>
<td>Rank</td>
<td>Rk_{it-1}</td>
<td>202.452</td>
<td>-41.523</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(7.53)**</td>
<td>(0.84)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td>T</td>
<td>-155.645</td>
<td>-156.999</td>
<td>-516.699</td>
<td>(5.35)**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.21)*</td>
<td>(2.23)*</td>
<td>(2.47)*</td>
<td>(5.35)**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time²</td>
<td>T²</td>
<td>329.673</td>
<td>530.393</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>(2.00)*</td>
<td>(4.89)**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Last outcome</td>
<td>s_{it-1}</td>
<td>-18.025</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absolute</td>
<td></td>
<td>(1.05)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative &amp; Success</td>
<td>Rs_{it-1}*s_{it-1}</td>
<td>-58.306</td>
<td>-69.370</td>
<td>-69.225</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.12)*</td>
<td>(2.51)*</td>
<td>(2.51)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative &amp; Failure</td>
<td>Rs_{it-1}(1-s_{it-1})</td>
<td>-139.502</td>
<td>-151.996</td>
<td>-152.440</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumulative Success</td>
<td>s_{it-1}</td>
<td>0.021</td>
<td>0.021</td>
<td>-0.024</td>
<td>0.025</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TM</td>
<td></td>
<td>(3.13)**</td>
<td>(3.09)**</td>
<td>(1.24)</td>
<td>(3.70)**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TM²</td>
<td></td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>PT</td>
<td></td>
<td>0.070</td>
<td>0.070</td>
<td>0.063</td>
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</tr>
<tr>
<td>PT²</td>
<td></td>
<td>(3.03)**</td>
<td>(3.02)**</td>
<td>(1.00)</td>
<td>(3.64)**</td>
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</tr>
<tr>
<td>Part-time</td>
<td></td>
<td>-0.025</td>
<td>-0.025</td>
<td>-0.027</td>
<td>-0.018</td>
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</tr>
<tr>
<td>Part-time²</td>
<td></td>
<td>(1.98)*</td>
<td>(1.99)*</td>
<td>(0.95)</td>
<td>(1.46)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stars (simulated)</td>
<td></td>
<td>-0.002</td>
<td>-0.002</td>
<td>-0.023</td>
<td>-0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stars² (simulated)</td>
<td></td>
<td>(0.34)</td>
<td>(0.35)</td>
<td>(0.95)</td>
<td>(0.37)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td>3,737.212</td>
<td>3,864.071</td>
<td>3,827.618</td>
<td>3,850.873</td>
<td>3,961.996</td>
<td>3,951.535</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(234.35)**</td>
<td>(143.88)**</td>
<td>(220.56)**</td>
<td>(204.45)**</td>
<td>(139.21)**</td>
<td>(141.58)**</td>
</tr>
<tr>
<td>Observations</td>
<td></td>
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<tr>
<td>R-squared</td>
<td></td>
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<td>0.0022</td>
<td>0.0010</td>
<td>0.0007</td>
<td>0.0000</td>
<td>0.0003</td>
</tr>
</tbody>
</table>

Absolute value of t statistics in parentheses
* significant at 5%; ** significant at 1%