High Profile Football Matches in Europe Are Linked to Traffic Accidents in Asia

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Author contributions
K. C. Yam formulated the research idea, designed the study, analyzed the data, and drafted the manuscript. J. C. Jackson analyzed the data and drafted the manuscript. T. C. Lau coded the data and provided critical revisions to the manuscript. Q. Xin, C. Barnes, and J. K. Chong all provided critical revisions to the manuscript. K. C. Yam is the guarantor who accepts full responsibility for the conduct of the study, has access to the data, and control over the decision to publish. The corresponding authors attest that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

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Abstract

Objectives
Investigate the potential effect of watching popular football games played many time zones away on resulting traffic accidents
Design
A study based on 41,538 taxi traffic accidents in Singapore and 1,814,320 traffic accidents in Taiwan, combined with 12,788 European club football games over a seven-year period.
Setting
Singapore; Taiwan; Asia
Participants
The largest taxi company in Singapore with fine-grained traffic accident records in a three-year span and all traffic accident records in Taiwan in a six-year span.
Exposures
Days where high-profile football games were played or not.
Main Outcomes and Measures
Number of traffic accidents
Results
Regression-based and time series models suggest that days with high-profile European football matches have more traffic accidents than days with less popular European football matches. For an approximate €134.74 million increase in average market value for matches played in a given day, there would be approximately one more accident among Singapore taxi drivers, and for an approximate €7.99 million increase in average market value, there would be approximately one more accident among all drivers in Taiwan. This association cannot be explained by weather conditions, time of the year, weekend vs. weekday effects, driver demographics, or underlying temporal trends. It is also stronger for daytime traffic accidents than for nighttime traffic accidents, suggesting that the link between high profile football matches and traffic accidents cannot be attributed to celebration during or attention deficits while watching and driving. Annually, this increased rate of traffic accident may translate to approximately 371 accidents among Singapore taxi drivers and approximately 41,079 accidents in the Taiwanese public, as well as economic losses of approximately €821,448 among Singapore taxi drivers and approximately €13,994,409 to Taiwanese drivers and insurers. The total health and economic impact of this finding is likely to be much higher because GMT + 8 is the most populous time zone with 24% of the world's population.
Conclusions
We posit that watching high-profile football games in other time zones is associated with more traffic accidents. This is especially problematic in Asia, because drivers lose sleep

watching high-profile games played in Europe which occur during local times in which they typically sleep, leading to a higher prevalence of traffic accidents.

Introduction

Football is viewed by more people worldwide than any other sport (1). Although football enjoys global popularity, most high-profile games are played in Europe. The top five most-watched leagues (i.e., the English Premier League, the Spanish La Liga, the French Ligue 1, the Bundesliga, and the Italian Serie A) are all European. The Champions League—largely considered the top club competition in the world—is contested by top-division European clubs, and more than half of the past 21 World Cup tournaments have been played in Europe.

This European dominance of the football market means that fans who reside outside of the European continent must watch these games at odd local times due to differences in time zones. Asian fans are the most affected. If Manchester United, the most popular football club in 2018, is scheduled to play at 7:00 p.m. local time, fans in Beijing, Hong Kong, and Singapore will have to stay up until 3:30 a.m. to finish the game, whereas fans in Seoul and Tokyo will have to stay up until 4:30 a.m. Asian fans need to stay up just as late to watch matches played in the Americas. For example, East Asian fans had to stay up from 2:00 a.m. to 4:00 a.m. to watch the World Cup finals held in Rio de Janeiro in 2014. Despite these hardships, football viewership in Asia has been steadily increasing over the past decade (2).

Sleep deprivation is one clear outcome of staying up late to watch football games, which leads us to a novel hypothesis: on days featuring high-profile football matches in Europe, there should be more traffic accidents in other continents (most notably Asia, in which the time zone differences mean that the matches are played at typical sleep times). Given that sleep deprivation is associated with poor attention management, slower reaction times, and impaired decision making (3-6), we suggest that drivers are more likely to be involved in traffic accidents on days when high-profile football games air early in the morning. If true, this finding would have significant policy implications, since traffic accidents can result in significant economic and medical costs.

We suggest that sleep deprivation is a major reason why high-profile football matches are linked to traffic accidents, but there may be other plausible mechanisms for this relationship. High-profile football matches may, for example, include more nighttime celebration or it may lead more individuals to watch games while driving, which could lead to more traffic accidents. High-profile football matches and traffic accidents could also be rising over time due to other causes, which could account for a correlation between the variables. However, our sleep deprivation account predicts that the association between high-profile football matches and traffic accidents should hold controlling for general trends over time, and that the link may actually be stronger for daytime (rather than nighttime) accidents, since people watch games at night/early morning and feel tired the next day.

We test these hypotheses in two contexts: traffic accidents across Taiwan, and traffic accidents among taxis in Singapore. These datasets offer us unique strengths. In Taiwan, we are able to test the association between football games and traffic accidents with high scale, analyzing data on all recorded traffic accidents from 2013-2018 (N = 1,814,320 accidents) across both rural and urban regions in Taiwan. However, these data do not include information about weather at the time and location of the accident and driver demographics. Data from Singapore, although smaller in scale (N = 41,538 accidents from 2012-2014), contain fine-grained data on driver demographics as well as weather condition at the time and location of each accident. Moreover, Singapore has a climate characterized by relative uniformity in terms of rainfall, temperature, daylight hours (one-and-a-half degrees north of the equator), and generally good roadside conditions, making it a perfect test case for predictors of traffic accidents beyond these obvious factors. In both datasets, we predict that high-profile football games are associated with a higher rate of traffic accidents, and that this relationship transcends weather conditions, driver demographics, and day and month information.

Materials and Method

All data and code for our analyses are available via the Open Science Framework (OSF): https://osf.io/q9jpc/?view_only=bce492b556054785b73b43aaba5cc3e5.

Traffic Data. We retrieved separate datasets for daily accidents in Taiwan and accidents in Singapore. We retrieved Singapore data from the largest taxi company in Singapore, with a fleet size of more than 13,000 taxis. This organization accounts for over 60% market share of the taxi transport industry in Singapore. The resulting dataset contained all daily accident records from January 2012 to December 2014 (N = 41,538 accidents). The dataset also included data on detailed characteristics of the accident, including characteristics of the taxi driver involved in the accident (gender, age, education level, driving experience via number of years driving, and color of car), and weather at the time and location of the accident (wet vs. dry).

We retrieved Taiwanese data from the Taiwanese National Police Agency. This dataset contained all documented traffic accidents—not solely those involving taxis—in Taiwan between January 2013 and December 2018 (N = 1,814,320 accidents). These data did not include detailed characteristics of the accidents and the drivers associated.

Football Data. We coded all football games based on the top five European football leagues: 1) English Premier League, 2) Spanish La Liga, 3) German Bundesliga, 4) Italian Serie A, and 5) French Ligue 1. We also coded games in the knockout stage of the annual European Champion League and Europa League. We gathered all data about these teams from worldfootball.net. This source contains data on the names of football club, matching time, and matching date in either Greenwich Mean Time (GMT + 0) or British Summer Time (GMT + 1) time zone. We then converted these time zones and dates to Taiwan's and Singapore's time zone (both are GMT + 8).

The most direct measure of football match popularity is viewership ratings. However, viewership ratings in Singapore and Taiwan were not available for a majority of these matches. We therefore coded the combined team salary cap as a proxy for the game's popularity. For example, FC Barcelona had a salary cap of €1280 million in 2018, whereas Seville FC had a salary cap of €295 million in 2018, reflecting their respective popularity. We obtained all year-specific market value data from Transfer Markt (https://www.transfermarkt.com/), 2012-2018. This source provides all football players' salaries (in Euros), as well as teams' combined salary cap in every year. We then used these statistics to calculate the combined market value of a match between any two clubs. All the matches from 2012-2018 among the top five most-watched leagues – the English Premier League, the Spanish La Liga, the French Ligue 1, the German Bundesliga, and the Italian Series A – were included. We also included matches from the round of 16 or more advanced matches in both the Champions League and the Europa League. We excluded the group stage games in the Champions League and the Europa League because they are often competed by at least one (and often two) low-profile team not belonging to one of these top five football leagues. As such, group stage games are likely to be unpopular in Asia.

Analytic Plan. In total, there were 1,379 game days from 2012 to 2018 (the total coverage of our datasets, we excluded non-game days). Each of these game days featured at least one football match, but not all matches were equally high profile. For example, December 27th, 2013 featured several high-profile games, including a match between Manchester City and Liverpool FC, with games representing teams with an average market value of €742 million. In contrast, May 4th, 2012 featured lesser viewed games, including a match between Dijon FCO and AJ Auxerre, with games representing teams with an average market value of €62.7 million.

Our primary models analyzed the relationship between this market value statistic (the average market value, in millions, for football games played on day k) and number of traffic accidents on day k. Since games aired early in the morning, we predicted that accidents that same day would be higher since people would be more sleep deprived during the rest of the day. Our analyses excluded traffic accidents that occurred before the first European football match that day, to avoid conflating traffic accidents that occurred after games and traffic accidents that occurred before games. This procedure excluded 960 accidents from the Singapore dataset, and 51,131 Taiwan accidents.

We conducted three sets of analyses to test for the relationship between high-profile football matches and traffic accidents. The first set of analyses used Poisson regression models to predict the total number of accidents in a day. Using a dataset in which cases represented days, we regressed the number of traffic accidents per day on the average market value of football games from that day. We used Poisson modelling because our traffic accident variables represented count data, but results were similar using more traditional OLS modelling (SI Table S3 to S4). We first conducted this regression controlling for factors that could plausibly influence the rate of traffic accidents: weekday vs. weekend (0 = weekend; 1 = weekday) and month of year (11 dummy-coded variables contrasted against December, the month with the most rainfall in Singapore). For the Singapore dataset, we next added weather and demographic controls: weather (0 = dry; 1 = precipitation), the percentage of male vs. female drivers, the average age of drivers, the average educational level of drivers, the average driving experience of drivers (number of years driving), and the percentage of yellow cars involved in accidents, because past research suggests that the color of a vehicle is associated with accident rates (7). These models did not contain days where no football matches were played, but there were no other cases of missing data.

The second set of analyses replicated our initial models but separated "day" and "night" accidents. One possibility is that high-profile football matches are associated with traffic accidents because people celebrate during or immediately after football games or watch and check football games while they are driving, resulting in higher rates of nighttime accidents. In contrast, our sleep-deprivation account predicts that high-profile football games are associated with traffic accidents because people are tired from staying awake to watch football games early in the morning, which may result in more daytime accidents as people drive to work on the same day. Analyzing daytime and nighttime accidents separately allowed us to adjudicate between these two accounts.

Sunrise and sunset times in Singapore do not vary substantially across months. For example, the average sunrise time is 7:07am in January and 7:03am in July. For Singapore accidents, we therefore classified “day accidents” as those falling between 7:00am and 7:00pm throughout the entire year. Taiwan daylight hours vary across season. For example, the average Taiwan sunrise time is 6:40am in January but 5:08am in July. For Taiwan accidents, we therefore classified “day accidents” differently depending on sunrise and sunset data throughout the year.

The third and final set of analyses used time-series models that allowed us to rule out the possibility that average market value and number of traffic accidents were related because of an underlying temporal trend (e.g. both factors increasing linearly over time). These time-series models could also isolate whether the association between average market value and number of accidents is contemporaneous (as we predict), or is defined by a more complex lagged dynamic. Prior to this analysis, we identified a linear trend in market value within the 2013-2018 Taiwan dataset, such that market value correlated with time ($r = .40$, $p < .001$) whereas there was no linear trend in the 2012-2014 Singapore dataset ($r = < .01$, $p = .87$). To account for this trend, we prewhitened the Taiwanese cross-correlation function before estimating coefficients. We also confirmed that all time-series were stationary using augmented Dickey-Fuller root tests ($ps < .001$) before fitting our cross-correlation functions.

We also fit Granger causality models, which evaluate whether two variables are related contemporaneously or via a time-lag. We note that stationary time series still have autoregressive (AR) and moving average (MA) processes that can affect bivariate associations between time series. To ensure that our results were not driven by these processes, our supplemental materials replicate key associations using ARIMA-residualized time series that are entirely stripped of AR and MA processes.

Behavioral Study. Our analysis plan was designed to rigorously test the hypothesis that high-profile football matches predict traffic accidents in Asia. However, our analysis still relied on two key assumptions. The first assumption was that taxi drivers are a representative sample of Singaporeans, in terms of football viewing habits. One the one hand, taxi drivers demographically skew male and less educated, which may make them more likely to watch football matches than the average Singaporean. On the other hand, taxi drivers often work long shifts, and their schedule may make them less likely to watch football matches than the average Singaporean. Our second assumption was that the market value of football teams is a valid indicator of viewership. Indeed, Asian fans may be more likely to watch games involving low-budget teams if they are evenly matched, or may only watch their favorite teams regardless of market value. Although the first assumption does not apply to our Taiwan data because we included all accidents that occurred, the second assumption could affect analyses in both contexts.

To confirm that our assumptions were correct, we conducted a supplemental behavioral study involving 100 taxi drivers (Mage = 53.07, SD age = 11.71; 99 males) that we surveyed as they were waiting for customers at taxi stands, and 100 non-taxi drivers (Mage = 34.78, SD age = 14.33; 49 males) that we surveyed at two local malls as a comparison group (see SI for details).

Survey respondents all answered two key items. First, participants responded to the item: “how many nights have you stayed up late to watch a European football game in the last month” using a scale from 0 (“zero nights”) to 4 (“four or more nights”). This item allowed us to test whether taxi drivers actually stay up late to watch football games, and whether they are vastly more or less likely to do so compared to a sample of non-drivers in Singapore. Second, participants used a 1 (“very unlikely”) to 7 (“very likely”) scale to indicate how likely they would be to watch several types of football games: a football game between (a) a top team and a bottom team, (b) a bottom team and a similarly ranked bottom team, (c) a top team vs. a top team, (d) their favorite team vs. a bottom team, (e) their favorite team vs. a top team, and (f) their favorite team vs. any team. This item allowed us to confirm that individuals would be more likely to watch games if they involved top teams, even if these games involved unequal matchups.

Results

Evaluating Assumptions. Before testing our central hypothesis, we used data from our behavioral study to evaluate our key assumptions: 1) that Singapore taxi drivers watch football matches at the same rate as other Singaporeans and 2) that people are more likely to watch games involving high market value teams than games with low market value teams.

Of the 100 taxi drivers surveyed, 37 self-reported to have stayed up to watch football at least once in the past month. This was similar to the general population, of whom 35 (out of 100) stayed up late at least once. There was no significant difference between the average number of nights that taxi drivers ($M = .98$, $SE = .15$) and the general public ($M = .70$, $SE = .12$, $p = .144$) stayed up late to watch games. The lack of difference was even more apparent when gender is controlled for ($p = .991$). In sum, this suggests that many taxi drivers do lose sleep to watch football games, and that this tendency is at least somewhat representative of the general population in Singapore.

We next examined whether individuals would be more interested in watching games involving teams with higher (vs. lower) market values. We examined this question across two repeated measures analyses of variance (ANOVAs). The first ANOVA investigated participants’ interest in games involving their favorite team. This analysis revealed a significant effect, $F(1,199) = 11.88$, $p < .001$, with group means suggesting that participants were more interested in watching their favorite team against a top team ($M = 3.68$, $SE = .17$), compared with a bottom team ($M = 3.05$, $SE = .16$) or any team ($M = 3.24$, $SE = .16$). The next analysis investigated participants’ interest in games not involving their favorite team. This analysis also revealed a significant effect, $F(1,199) = 97.14$, $p < .001$, with group means suggesting that participants were more interested in watching two top teams ($M = 3.30$, $SE = .09$), compared with a top team against bottom team ($M = 2.09$, $SE = .11$) and that they were least interested in watching two bottom teams ($M = 1.75$, $SE = .09$). Each of these analyses suggested that participants were indeed more interested in watching games involving teams with high market values, rather than watching equally matched bottom teams.

In sum, our behavioral study supported our key assumptions. Singapore taxi drivers do watch football games late at night, and there is no difference in viewing habits compared to typical Singaporeans. In addition, games involving teams with large market values attract more interest than games involving teams with less market value.

Do High Profile Matches Predict Total Traffic Accident Rates? Our hypothesis was that days with higher profile football matches (via team market value), would also feature more traffic accidents. As predicted, market value and traffic accidents had a significant association in Taiwan (estimate = .0002, ∆incidence = 1.00, z = 19.40, p < .001, Table 1, Taiwan model 1) and Singapore (estimate = .0002, ∆incidence = 1.00, z = 3.75, p < .001, Table 1, Singapore Model 1). The Singapore association replicated with a similar effect size when controlling for demographic covariates (estimate = .0002, ∆incidence = 1.00, z = 3.43, p < .001, Table 1, Singapore Model 2).

In Taiwan, incidence rates predicted that there would be an additional accident for every €7.99 million increase in market value for matches played in a given day. In the Singapore dataset, which was considerable smaller, models predicted that there would be an additional accident for every €134.74 (Singapore Model 1) to 145.68 (Singapore Model 2) million increase in average market value. In the Singapore data, we also tested for all possible interaction effects between average market value and demographic, weekday, and weather data. In the Taiwan data, we tested for the interaction effect between average market value and weekday. None were statistically significant (see Tables S5 to S12). The supplemental information also contains more information about the functional form of these models, examining linear as well as quadratic effects. The overall linear trends remain significant in both the Taiwan and Singapore data when quadratic effects were controlled for (Tables S17 to S18; see also S19-20).

Table 1.
Poisson Regression Predictors of Accident Incidence Rates in Taiwan and Singapore

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Taiwan Model	1066				
Intercept		6.74 (.004)	841.98	1533.27	< .001
Average Market Value		.0002 (.000008)	1.00015	19.40	< .001
Weekday		-.003 (.003)	.99	-1.28	.20
Singapore Model 1	590				
Intercept		3.56 (.03)	35.29	129.81	< .001
Average Market Value		.0002 (.00006)	1.00021	3.63	< .001
Weather		.29 (.05)	1.34	5.87	< .001
Weekday		-.10 (.02)	.91	-6.17	< .001
Singapore Model 2	582				
Intercept		3.32 (.03)	27.71	13.25	< .001
Average Market Value		.0002 (.00006)	1.00020	3.31	< .001
Weather		.27 (.05)	1.31	5.33	< .001
Weekday		-.09 (.02)	.91	-5.80	< .001
Percent Male		.29 (.23)	1.33	1.28	.20

Average Age	.0006 (.003)	1.00058	.21	.83
Percent Yellow	-.06 (.09)	.94	-.73	.47
Average Education	-.01 (.02)	.99	-.60	.55
Average Experience	-.008 (.005)	.99	-1.81	.07

Market value is in millions of Euros. “DF” refers to model degrees of freedom. Incidence change is the expected change in predicted accident incidence for every unit-increase in the predictor. The Taiwan incidence rate of 1.0001487 translates to 1 additional accident for every €7.99 million in average market value, whereas the Singapore incidence rate of 1.0002103 for market value translates to 1 additional accident for every €134.74 million in average market value for football matches (the average market value per game day is €297.25 million). Month-of-year effects are reported in the SI Tables S1-2.

Do High Profile Matches Predict Daytime Accidents? We hypothesized that the link between average market value and traffic accident rate would be stronger for daytime than nighttime accidents. Consistent with this sleep-deprivation account, the Taiwanese dataset revealed a stronger link between market value and daytime (estimate = .0002, SE = .000009, Δincidence = 1.00, z = 20.17, $p < .001$) vs. nighttime (estimate = .00005, SE = .00002, Δincidence = 1.00, z = 3.16, p = .002) accidents. Moreover, 95% confidence intervals of the estimates revealed that the daytime effect [.00016, .00019] was significantly stronger than the nighttime, [.000020, .000087] effect. The Singapore dataset showed an even stronger pattern. The average market value predicted daytime accidents (estimate = .0004, SE = .00007, Δincidence = 1.00, z = 4.92, $p < .001$) but not nighttime accidents (estimate = -.0001, SE = .0001, Δincidence = .99, z = -1.12, p = .26). These associations, displayed in Figure 1 and SI Tables S13-16, suggests that high-profile football matches are linked to accidents because of sleep deprivation rather than nighttime celebration or viewing games while driving.

Figure 1.

The relationship between average market value of football games and number of daytime traffic accidents and nighttime traffic accidents. Values have been residualized to control for covariates, and then linearly transformed to be positive for display purposes.

Time Series Analysis of Football Matches and Traffic Accidents. The output from our cross-correlation function are displayed in Figure 2. The contemporaneous relationship between market value and traffic accident rate was significant and positive in both Taiwan, r = .10, and Singapore, r = .11, with no other correlations reaching the same magnitude in either sample (rs < .10; see Tables S21-22). This suggests that our effects were not driven by increases in traffic volume the day before high-profile football games, which could have plausibly biased our regression analyses.

Figure 2.

The results of our cross-correlation analysis involving average market value of football games and number of daily traffic accidents in Taiwan (left) and Singapore (right). Each bar in this plot represents a correlation at a different lag. Negative lags indicate that accidents preceded high-market-value football games. Positive lags indicate that accidents followed high-market-value games. The dashed blue bar represents significance at alpha = .05.

Results using vectoral auto-regression (VAR) and Granger causality tests mirrored these cross-correlation results. In the Taiwanese data, a Granger test of causality extracted from a VAR model with a lagged threshold of 5—recommended by AIC fit statistics—estimated that average market value had a significant contemporaneous association with number of traffic accidents, = 11.61, $p < .001$, with a smaller lagged association, $F(5,2102) = 3.18$, $p = .01$.

In the Singapore data, a Granger test of causality extracted from a VAR model with a lagged threshold of 4—again recommended by AIC fit statistics—estimated that average market value had a significant contemporaneous association with number of traffic accidents, = 4.68, $p = .03$, with a null lagged association, $F(4,1156) = 1.81$, $p = .12$. These tests suggest that the relationship between high profile football matches and traffic accidents is better characterized by same-day effects than by multi-day lagged effects, consistent with our account.

Discussion

Our analysis of traffic accidents in Taiwan and Singapore supports our hypothesis that days with high-profile European football matches also have higher-than-average rates of traffic accidents in Asia. Our account of these findings is that people in East Asia stay awake until the early hours of the morning to watch high-profile football games. Our data were correlational, which means that we cannot make causal claims. However, our models show that the association between high profile football matches and traffic accidents holds across two geographically and culturally diverse regions (Singapore and Taiwan), and also when controlling for weather, weekday vs. weekend effects, month of year, and driver demographics, making it unlikely that this association is confounded by an unmodeled covariate or regionally differences. Moreover, our time-series models rule out the possibility that high-profile football matches and traffic accidents are linked only because of an underlying temporal trend from extraneous variables.

There are limitations in this work, which could spark future research. First, the consequences of traffic accidents can range from minor injuries to multiple deaths, but unfortunately we do not have data on the severity of the accidents reported which limits our ability to discern the total medical impact of these findings. Second, although our results from both data sets provide convergent support to our sleep deprivation explanation of these effects, future research could conduct primary survey studies and directly assess drivers who were in accidents and survey their football viewing habits and sleep hours prior to their accidents. Finally, we do not distinguish sleep disruption arises from staying up at midnight vs. 3am. Although crucial recovery, maintenance, and growth activities occur during both Rapid Eye Movement (REM) and non-REM sleep (8-9), future research could explore whether disruptions to REM vs. non-REM sleep, as a result of watching football games, are more detrimental for traffic accidents.

Our model estimates allow us to calculate the potential monetary impact of football matches on East Asian drivers. Based on our incidence rates, €134.74 million in football games' market value translates to one extra daily automobile accident among Singapore taxi drivers in our dataset, whereas €7.99 million translates to one extra daily automobile accident among all Taiwanese drivers. Given these figures, we estimate that football games may be responsible for at least 371.53 accidents per year among Singapore taxi drivers (the figure is likely much larger across all Singapore drivers) and approximately 41,079.50 accidents per year among the Taiwanese general public (see SI for the impact analyses). Furthermore, insurance data (10-11) indicate that the average Singapore insurance claim was €2,129 and the average Taiwan insurance claim was €2,044. The economic impacts of our findings thus total at least €821,448 annually among Singapore taxi companies, and €13,994,409.50 for Taiwanese drivers and insurance companies.

We do note, however, that these economic impacts should be interpreted with caution because there are other obvious economic benefits associated with football viewership in Asia such as revenues for restaurants and bars in extended hours. We thus encourage future researchers to account for all potential costs and benefits associated with European football games. Nevertheless, these estimates are also probably conservative because our account suggests that cities within the GMT + 8 time zone are likely to be affected similarly. To put this into perspective, Singapore and Taiwan combined represent less than 1.73% of the population in this particular time zone.

Our analysis has revealed an association between high-profile football matches and traffic accidents in the most populous time zone in the world, with over 1.7 billion people (~24% of the world's population). These findings have significant policy implications for traffic regulation and televised sports in Asia. Although dramatically adjusting all the start time of European football matches is impractical, we suggest that one policy implication is that football governing societies/leagues can consider scheduling high-profile games more strategically. For example, scheduling more high-profile games in Saturday or Sunday early mornings (local Asia time zones) when fans can sleep in immediately after watching the games can considerably reduce sleep deprivation and the resultant traffic accidents. Finally, increased roadside safety in Asia on high-profile game days (e.g., more traffic patrols) as well as banning all video-based devices for drivers could potentially reduce these economic impacts and injuries related to traffic accidents.

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Supplementary Information for

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This Supplemental Materials include:

Supplementary text
Tables S1 to S22

Supplemental Material Table of Contents

1. More Information about Behavioral Survey

A research assistant (RA) recruited 100 taxi drivers at two different taxi stands at various time of the day. The RA approached drivers when they were waiting for customers. The same RA also approached and recruited 100 random Singaporeans in two local malls at various time of the day. All survey participants were compensated with SGD 5 (~€ 3.2) and the survey took no more than 2 minutes. Below are the questions used in the survey (demographic questions are not shown).

Have you stayed up late to watch a European football game in the last month?

Never -------- Once -------- Twice -------- Thrice -------- Four nights or more

How likely would you watch a European football game played between…?

A top team vs. a bottom team

(Not at all) 1 -------- 2 -------- 3 -------- 4 -------- 5 -------- 6 -------- 7 (Very likely)
A bottom team vs. a similarly ranked bottom team

(Not at all) 1 -------- 2 -------- 3 -------- 4 -------- 5 -------- 6 -------- 7 (Very likely)
A top team vs. a top team

(Not at all) 1 -------- 2 -------- 3 -------- 4 -------- 5 -------- 6 -------- 7 (Very likely)
Your favorite team vs. a bottom team

(Not at all) 1 -------- 2 -------- 3 -------- 4 -------- 5 -------- 6 -------- 7 (Very likely)
Your favorite team vs. a top team

(Not at all) 1 -------- 2 -------- 3 -------- 4 -------- 5 -------- 6 -------- 7 (Very likely)
Your favorite team vs. any team

(Not at all) 1 -------- 2 -------- 3 -------- 4 -------- 5 -------- 6 -------- 7 (Very likely)

Full Poisson Model for Taiwan Accidents

Table 1 in our main text contained results from a Poisson regression model for the Taiwan data, but omitted coefficients associated with month of the year to save space. Table S1 presents the full set of coefficients from these models, including coefficients for month of the year.

Table S1. Full Poisson Model for Taiwan Accidents

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	1066				
Intercept		6.74 (.004)	841.98	1533.27	<.001
Average Market Value		.0001 (.000007)	1.00015	19.40	<.001
Weekday		-.003 (.002)	.99	-1.28	.20
January		.08 (.004)	.92	-19.64	<.001
February		-.09 (.005)	.84	-38.37	<.001

March	-.05 (.005)	.88	-28.63	<.001
April	-.09 (.004)	.84	-40.43	<.001
May	-.06 (.005)	.87	-29.85	<.001
June	-.06 (.02)	.87	-6.75	.004
August	-.14 (.005)	.80	-43.34	<.001
September	-.06 (.005)	.87	-30.43	<.001
October	-.04 (.005)	.88	-26.47	<.001
November	-.01 (.005)	.91	-19.24	<.001

- Full Poisson Model for Singapore Accidents

Table 1 in our main text contained results from a Poisson regression model for the Singapore data, but omitted coefficients associated with month of the year to save space. Table S2 presents the full set of coefficients from these models, including coefficients for month of the year.

Table S2. Full Poisson Model for Singapore Accidents

Variable	DF	Estimate (SE)	Δ Incidence	z	p
Model 1	590				
Intercept		3.56 (.03)	35.29	129.81	<.001
Average Market Value		-.0002 (.00006)	1.00021	3.63	<.001
Weather		.29 (.05)	1.34	5.87	<.001
Weekday		-.10 (.02)	.91	-6.17	<.001
January		-.04 (.03)	.96	-1.33	.18
February		-.05 (.03)	.95	-1.75	.08
March		-.04 (.03)	.96	-1.44	.15
April		.002 (.03)	1.00	.07	.95
May		-.009 (.03)	.99	-.29	.77
June		.03 (.12)	1.03	.22	.83
August		-.05 (.03)	.95	-1.53	.13
September		.08 (.03)	1.08	2.57	.01
October		.04 (.03)	1.04	1.25	.21
November		.02 (.03)	1.02	.59	.56
Model 2					
Intercept		3.32 (.03)	27.71	13.25	<.001
Average Market Value		.0002 (.00006)	1.00019	3.31	<.001
Weather		.03 (.05)	1.31	5.33	<.001
Weekday		-.09 (.02)	.91	-5.80	<.001
Percent Male		-.29 (.25)	1.33	1.28	.20
Average Age		.0006 (.003)	1.001	.21	.83
Percent Yellow		-.06 (.09)	.94	-.73	.46
Average Education		-.01 (.02)	.99	-.60	.55
Average Experience		-.008 (.005)	.99	-1.81	.07
January		-.0002 (.06)	.99	-.004	1.00
February		-.01 (.06)	.99	-.23	.82
March		.006 (.07)	1.01	.09	.93
April		.04 (.07)	1.04	.59	.56
May		.02 (.06)	1.02	.26	.79

June	-.05 (.12)	1.05	.4	.69
August	-.04 (.05)	.96	-.79	.43
September	.08 (.04)	1.09	1.93	.05
October	.05 (.05)	1.06	1.07	.28
November	.03 (.04)	1.03	.67	.50

Full Gaussian Model for Taiwan Accidents

We used Poisson regression for all analyses pertaining to the Taiwan data reported in the main texts. Below, we reported Gaussian regression results with Ordinary Least Squares (OLS) estimation. Results across the Poisson and Gaussian are largely identical.

Table S3. Full Gaussian Model for Taiwan Accidents

Variable	DF	Estimate (SE)		z	p
Model 1054					
Intercept		845.15 (15.68)		53.91	<.001
Average Market Value		.12 (.03)	.13	4.41	<.001
Weekday		-2.48 (8.78)	-.01	-.28	.78
January		-69.51 (14.94)	-.17	-4.65	<.001
February		-137.89 (15.48)	-.32	-8.91	<.001
March		-110.78 (16.45)	-.24	-6.74	<.001
April		-139.10 (14.87)	-.35	-9.36	<.001
May		-115.27 (16.45)	-.24	-7.01	<.001
June		-117.27 (72.17)	-.05	-1.63	.10
August		-176.11 (17.48)	-.34	-10.08	<.001
September		-117.74 (16.49)	-.25	-7.14	<.001
October		-103.27 (16.58)	-.22	-6.23	<.001
November		-80.04 (17.48)	-.16	-4.58	<.001

Full Gaussian Model for Singapore Accidents

We used Poisson regression for all analyses pertaining to the Singapore data reported in the main texts. Below, we reported Gaussian (OLS) regression results. Results across the Poisson and Gaussian are largely identical.

Table S4. Full Gaussian Model for Singapore Accidents

Variable	DF	Estimate (SE)		z	p
Model 1	577				
Intercept		35.39 (1.31)		27.04	<.001
Average Market Value		.007 (.003)	.11	2.72	<.001
Weather		10.71 (2.42)	.18	4.42	<.001
Weekday		-3.57 (.77)	-.19	-4.66	<.001
January		-1.37 (1.39)	-.05	-.98	.33
February		-1.78 (1.37)	-.07	-1.30	.19
March		-1.45 (1.33)	-.06	-1.09	.28
April		.06 (1.28)	.002	.04	.97
May		-.34 (1.46)	-.01	-.23	.82

June		1.01 (5.69)	.01	.18	.86
August		-1.83 (1.60)	-.06	-1.15	.25
September		2.90 (1.51)	.10	1.92	.055
October		1.44 (1.55)	.04	.93	.36
November		.65 (1.50)	.02	.43	.67
Model 2	564				
Intercept		26.76 (11.73)		2.28	.023
Average Market Value		.007 (.003)	.11	2.47	.014
Weather		9.86 (2.47)	.17	4.00	<.001
Weekday		-3.39 (.78)	-.18	-4.37	<.001
Percent Male		10.27 (10.47)	.04	.98	.33
Average Age		.02 (.13)	.02	.15	.89
Percent Yellow		-2.13 (4.02)	-.02	-.53	.60
Average Education		-.48 (1.05)	-.03	-.46	.65
Average Experience		-.29 (.21)	-.14	-1.35	.18
January		.0009 (3.01)	.00004	0.00	1.00
February		-.49 (3.00)	-.02	-.16	.87
March		.18 (3.38)	.01	.05	.96
April		1.41 (3.26)	.06	.43	.67
May		.50 (2.75)	.02	.18	.86
June		1.92 (6.11)	.01	.31	.76
August		-1.34 (2.30)	-.04	-.58	.56
September		3.02 (2.08)	.10	1.45	.15
October		1.93 (2.42)	.07	.80	.43
November		.92 (1.82)	.03	.51	.61

Note. Month effects are contrasted against December. “July” is not displayed because no games were played in July.

Interaction Model for Taiwan Accidents

Tables S5 include the interaction of market average with the weekday vs. weekend control in the Taiwan data. All coefficients are derived from Poisson models. As with any model, main effects are estimated where interaction terms are “0,” so they must be interpreted with caution.

Table S5. Interaction Between Market Value and Weekday for Taiwan Accidents

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	1066				
Intercept		6.74 (.0002)	844.16	1057.50	< .001
Average Market Value		.0001 (.00002)	1.00014	8.51	< .001
Weekday		-.007 (.006)	.99	-1.02	.31
January		-.08 (.004)	.92	-19.63	< .001
February		-.17 (.004)	.84	-38.37	< .001
March		-.13 (.005)	.88	-28.64	< .001
April		-.17 (.004)	.84	-40.43	< .001
May		-.14 (.005)	.87	-29.85	< .001
June		-.14 (.02)	.87	-6.70	< .001
August		-.22 (.005)	.80	-43.34	< .001

Variable	DF	Estimate (SE)	∆ Incidence	z	p
September		-.14 .005)	.87	-30.37	< .001
October		-.12 (.005)	.88	-26.44	< .001
November		-.09 (.005)	.91	-19.23	< .001
Market Value * Weekday		.00001 (.00002)	1.00	.56	.58

Interaction Models for Singapore Accidents

Tables S6-S12 include the interaction of market average with each other substantive predictor in our model in the Singapore data. As we summarize in the main text, none of these interactions reach significance. For the sake of parsimony, we present models containing all our covariates rather than an “initial” model and a “demographics” model. As with our primary models, results involving interactions substantively unchanged (i.e. the interactions remain null) when excluding demographic information. All coefficients are derived from Poisson models. As with any model, main effects are estimated where interaction terms are “0,” so they must be interpreted with caution.

Table S6. Interaction Between Market Value and Weather for Singapore Accidents

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	582				
Intercept		3.32 (.25)	27.70	13.25	<.001
Average Market Value		-.0002 (.00007)	1.00020	3.00	.003
Weather		.03 (.01)	1.35	2.51	.01
Weekday		-.09 (.02)	.91	-5.80	<.001
Percent Male		.29 (.22)	1.33	1.28	.20
Average Age		.0005 (.003)	1.00	.19	.85
Percent Yellow		-.06 (.09)	.94	-.71	.48
Average Education		-.01 (.02)	.99	-.61	.55
Average Experience		-.008 (.005)	.99	-1.80	.07
January		.0007 (.06)	1.001	.01	.99
February		-.01 (.06)	.99	-.20	.84
March		.007 (.07)	1.01	.11	.92
April		.04 (.07)	.94	.60	.55
May		.02 (.06)	1.02	.29	.77
June		.05 (.13)	1.05	.41	.68
August		-.04 (.05)	.96	-.76	.45
September		.08 (.04)	1.09	1.94	.05
October		.06 (.05)	1.06	1.09	.28
November		.03 (.04)	1.03	.68	.50
Market Value * Weather		-.0001 (.0004)	.99	-.24	.81

Table S7. Interaction Between Market Value and Weekday for Singapore Accidents

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	582				
Intercept		3.34 (.52)	28.19	13.23	<.001
Average Market Value		.00008 (.0002)	1.000079	.39	.69
Weather		.27 (.05)	.89	5.34	<.001
Weekday		-.12 (.05)	1.31	-2.48	.01
Percent Male		.30 (.23)	1.34	1.31	.19
Average Age		.0006 (.003)	1.001	.20	.84

Percent Yellow		-.06 (.09)	.94	-.71	.48
Average Education		-.01 (.02)	.99	-.59	.56
Average Experience		-.008 (.005)	.99	-1.77	.08
January		-.002 (.06)	.99	-.03	.98
February		-.02 (.06)	.98	-.26	.79
March		.004 (.07)	1.00	.06	.95
April		.04 (.07)	1.04	.56	.58
May		.01 (.06)	1.01	.23	.82
June		.07 (.13)	1.07	.55	.58
August		-.04 (.05)	.96	-.81	.42
September		.08 (.04)	1.09	1.91	.06
October		.05 (.05)	1.06	1.06	.29
November		.03 (.04)	1.03	.67	.50
Market Value * Weekday		.0001 (.0002)	1.0001	.59	.55

Table S8. Interaction Between Market Value and Gender for Singapore Accidents

Variable	DF	Estimate (SE)	Δ Incidence	z	p
Model	582				
Intercept		3.82 (.57)	45.45	6.69	<.001
Average Market Value		-.002 (.002)	.99	-.87	.38
Weather		.27 (.05)	1.31	5.36	<.001
Weekday		-.09 (.02)	.91	-5.80	<.001
Percent Male		-.21 (.56)	.81	-.37	.71
Average Age		.0004 (.003)	1.0004	.15	.88
Percent Yellow		-.06 (.09)	.94	-.74	.46
Average Education		-.01 (.02)	.99	-.64	.52
Average Experience		-.008 (.005)	.99	-1.83	.07
January		.005 (.06)	1.005	.08	.93
February		-.008 (.06)	.99	-.12	.90
March		.01 (.07)	1.01	.17	.87
April		.04 (.07)	1.05	.65	.51
May		.02 (.06)	1.02	.37	.71
June		.05 (.12)	1.05	.37	.71
August		-.04 (.05)	.97	-.72	.47
September		.09 (.04)	1.09	1.98	.05
October		.06 (.05)	1.06	1.16	.24
November		.03 (.04)	1.03	.72	.48
Market Value * Male		.002 (.002)	1.002	.96	.34

Table S9. Interaction Between Market Value and Age for Singapore Accidents

Variable	DF	Estimate (SE)	Δ Incidence	z	p
Model	582				
Intercept		3.46 (.27)	31.72	12.89	<.001
Average Market Value		-.0003 (.0004)	.99	-.89	.37
Weather		.27 (.05)	1.31	5.37	<.001
Weekday		-.10 (.02)	.91	-5.90	<.001
Percent Male		.03 (.23)	1.35	1.34	.18
Average Age		-.002 (.003)	.99	-.63	.53

Percent Yellow		-.06 (.08)	.94	-.68	.50
Average Education		-.01 (.02)	.99	-.62	.54
Average Experience		-.008 (.005)	.99	-1.79	.07
January		.01 (.06)	1.01	.17	.87
February		-.004 (.06)	.99	-.06	.95
March		.02 (.07)	1.02	.24	.81
April		.05 (.07)	1.05	.71	.48
May		.03 (.06)	1.02	.43	.67
June		.06 (.13)	1.06	.49	.63
August		-.03 (.05)	.97	-.66	.51
September		.09 (.04)	1.09	1.97	.05
October		.06 (.05)	1.06	1.19	.23
November		.02 (.04)	1.03	.64	.52
Market Value * Age		.000009 (.000006)	1.000009	1.42	.15

Table S10. Interaction Between Market Value and Car Color for Singapore Accidents

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	582				
Intercept		3.37 (.25)	29.02	13.21	<.001
Average Market Value		.00004 (.0002)	1.00004	.23	.82
Weather		-.094 (.02)	1.31	-5.81	<.001
Weekday		.28 (.22)	.91	1.25	.21
Percent Male		.27 (.05)	1.32	5.23	<.001
Average Age		.0006 (.003)	1.0006	.23	.82
Percent Yellow		-.25 (.21)	.78	-1.20	.23
Average Education		-.01 (.02)	.99	-.62	.54
Average Experience		-.008 (.005)	.99	-1.80	.07
January		-.002 (.06)	.99	-.03	.98
February		-.01 (.06)	.99	-.23	.82
March		.003 (.07)	1.003	.05	.96
April		.04 (.07)	1.04	.59	.56
May		.01 (.06)	1.01	.21	.83
June		.05 (.12)	1.05	.40	.69
August		-.04 (.05)	.96	-.79	.43
September		.08 (.04)	1.09	1.92	.05
October		.05 (.05)	1.05	1.04	.30
November		.02 (.04)	1.03	.65	.52
Market Value * Color		.0007 (.0008)	1.0007	.99	.32

Table S11. Interaction Between Market Value and Education for Singapore Accidents

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	582				
Intercept		3.31 (.25)	27.49	13.15	<.001
Average Market Value		2.33 (.0001)	1.00024	1.63	.10
Weather		.27 (.05)	1.31	5.33	<.001
Weekday		-.09 (.02)	.91	-5.81	<.001
Percent Male		.30 (.23)	1.34	1.30	.19
Average Age		.0005 (.003)	1.0005	.17	.87

Percent Yellow		-.06 (.09)	.94	-.71	.48
Average Education		-.006 (.03)	.99	-.18	.86
Average Experience		-.008 (.005)	.99	-1.81	.07
January		.002 (.06)	1.002	.03	.97
February		-.01 (.06)	.99	-.19	.85
March		.008 (.07)	1.008	.11	.91
April		.04 (.07)	1.04	.61	.54
May		.02 (.06)	1.02	.29	.78
June		.05 (.13)	1.05	.42	.68
August		-.04 (.05)	.96	-.77	.44
September		.08 (.04)	1.09	1.93	.05
October		.06 (.05)	1.06	1.09	.28
November		.03 (.04)	1.03	.67	.50
Market Value * Education		-.00003 (.0001)	.99	-.30	.77

Table S12. Interaction Between Market Value and Driver Experience for Singapore Accidents

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	582				
Intercept		3.40 (.25)	29.75	13.39	<.001
Average Market Value		-.00008 (.0002)	.99	-.52	.60
Weather		.27 (.05)	1.31	5.38	<.001
Weekday		-.10 (.02)	.91	-5.92	<.001
Percent Male		.30 (.22)	1.35	1.33	.18
Average Age		.0002 (.003)	1.0002	.06	.95
Percent Yellow		-.06 (.08)	.94	-.67	.50
Average Education		-.01 (.02)	.99	-.61	.54
Average Experience		-.02 (.006)	.98	-2.66	.008
January		.02 (.06)	1.02	.25	.80
February		.0005 (.06)	1.0005	.008	.99
March		.02 (.07)	1.02	.33	.75
April		.05 (.07)	1.05	.77	.44
May		.03 (.06)	1.03	.52	.60
June		.07 (.13)	1.07	.57	.58
August		-.03 (.05)	.97	.61	.54
September		.09 (.04)	1.09	1.98	.05
October		.06 (.05)	1.06	1.21	.22
November		.02 (.04)	1.02	.61	.54
Market Value * Experience		.00003 (.00002)	1.00003	1.98	.05

- Full Daytime vs. Nighttime Models for Taiwan

Tables S13 and S14 show the full summaries of the day-time and night-time models reported in the main text in the Taiwan data. For the sake of parsimony, we present models containing all our covariates rather than an “initial” model and a “demographics” model. As with our primary models, results involving interactions substantively unchanged (i.e. the interactions remain null) when excluding demographic information. All coefficients are derived from Poisson models.

Table S13. Daytime Accidents in Taiwan

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	1066				
Intercept		6.46 (.005)	639.29	1301.16	<.001
Average Market Value		.0002 (.000009)	1.00017	20.17	<.001
Weekday		.007 (.003)	1.007	2.56	.01
January		-.08 (.005)	.92	-17.36	<.001
February		-.02 (.005)	.85	-33.42	<.001
March		-.11 (.005)	.90	-20.82	<.001
April		-.15 (.005)	.86	-30.46	<.001
May		-.03 (.005)	.97	-5.71	<.001
June		-.02 (.02)	.98	-.88	<.001
August		-.11 (.006)	.90	-19.48	.38
September		-.11 (.005)	.90	-20.94	<.001
October		-.12 (.006)	.89	-22.39	<.001
November		-.09 (.006)	.92	-15.88	<.001

Table S14. Nighttime Accidents in Taiwan

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	1066				
Intercept		5.32 (.009)	204.51	563.61	<.001
Average Market Value		.00005 (.00002)	1.00005	3.16	.002
Weekday		-.04 (.006)	.96	-7.85	<.001
January		-.08 (.009)	.92	-9.21	<.001
February		-.18 (.009)	.84	-18.93	<.001
March		-.22 (.01)	.80	-21.85	<.001
April		-.27 (.009)	.77	-28.85	<.001
May		-.64 (.01)	.53	-55.01	<.001
June		-.72 (.06)	.49	-12.29	<.001
August		-.74 (.01)	.48	-56.74	<.001
September		-.26 (.01)	.77	-25.47	<.001
October		-.14 (.01)	.87	-14.28	<.001
November		-.12 (.01)	.89	-11.16	<.001

Full Daytime vs. Nighttime Models for Singapore

Tables S15 and S16 show the full summaries of the day-time and night-time models reported in the main text in the Singapore data. For the sake of parsimony, we present models containing all our covariates rather than an "initial" model and a "demographics" model. As with our primary models, results involving interactions substantively unchanged (i.e. the interactions remain null) when excluding demographic information. All coefficients are derived from Poisson models.

Table S15. Daytime Accidents in Singapore

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	582				
Intercept		3.28 (.30)	26.43	11.08	<.001
Average Market Value		.0004 (.00007)	1.00035	4.92	<.001

Weather		.17 (.06)	1.18	2.61	.009
Weekday		-.10 (.02)	.90	-5.02	<.001
Percent Male		-.03 (.28)	.98	-.09	.93
Average Age		-.004 (.003)	.99	-1.23	.22
Percent Yellow		-.05 (.11)	.95	-.48	.63
Average Experience		.003 (.006)	1.002	.53	.59
January		.05 (.08)	1.05	.66	.51
February		.07 (.08)	1.07	.84	.40
March		.08 (.09)	1.09	.95	.34
April		.12 (.08)	1.12	1.39	.16
May		.08 (.07)	1.08	1.14	.25
June		.07 (.16)	1.07	.43	.66
August		.02 (.06)	1.02	.38	.70
September		.12 (.05)	1.12	2.25	.02
October		.13 (.06)	1.14	2.07	.04
November		.03 (.05)	1.03	.68	.50

Table S16. Nighttime Accidents in Singapore

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	582				
Intercept		1.44 (.41)	4.24	3.54	<.001
Average Market Value		-.0001 (.0001)	.99	-1.12	.26
Weather		.46 (.08)	1.58	5.48	<.001
Weekday		-.08 (.03)	.92	-3.01	.003
Percent Male		.87 (.38)	2.39	2.26	.002
Average Age		.01 (.004)	1.01	2.25	.02
Percent Yellow		-.10 (.14)	1.01	-.68	.50
Average Experience		-.03 (.008)	.97	-3.68	<.001
January		-.07 (.11)	.93	-.71	.48
February		-.14 (.11)	.87	-1.35	.18
March		-.11 (.12)	.90	-.91	.36
April		-.07 (.11)	.93	-.62	.54
May		-.07 (.09)	.93	-.79	.43
June		.05 (.21)	1.05	.25	.81
August		-.12 (.08)	.89	-1.54	.12
September		.05 (.07)	1.05	.76	.45
October		-.06 (.08)	.94	-.76	.45
November		.02 (.06)	1.02	.37	.71

Full Models for Taiwan Accidents Incorporating Non-Linearity

Table S17 and shows the full summaries of results reported in the main text in the Taiwan data when the quadratic form of average market value is controlled for. All coefficients are derived from Poisson models.

Table S17. Non-Linear Models for Taiwan Accidents

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Model	1066				
Intercept		6.78 (.003)	879.32	1981.40	<.001

Variable	Estimate (SE)	Δ Incidence	z	p
Average Market Value (Linear)	.0001 (.00001)	1.00010	10.53	<.001
Average Market Value (Quadratic)	-.0000002 (.00000002)	1.0000002	7.09	<.001
Weekday	-.004 (.003)	.99	-1.70	.09
January	-.08 (.004)	.92	-19.88	<.001
February	-.17 (.004)	.84	-38.53	<.001
March	-.13 (.005)	.88	-28.61	<.001
April	-.17 (.004)	.84	-40.30	<.001
May	-.14 (.005)	.87	-29.77	<.001
June	-.14 (02)	.87	-6.78	<.001
August	-.22 (.005)	.80	-43.31	<.001
September	-.14 (.005)	.87	-30.45	<.001
October	-.13 (.005)	.88	-26.87	<.001
November	-.09 (.005)	.91	-19.33	<.001

- Full Models for Singapore Accidents Incorporating Non-Linearity

Tables S18 and shows the full summaries of results reported in the main text in the Taiwan data when the quadratic form of average market value is controlled for. All coefficients are derived from Poisson models.

Table S18. Non-Linear Models for Singapore Accidents

Variable	DF	Estimate (SE)	Δ Incidence	z	p
Model	582				
Intercept		3.37 (.03)	28.99	13.46	<.001
Average Market Value (Linear)		.0003 (.00009)	1.00033	3.65	<.001
Average Market Value (Quadratic)		-.0000005 (.0000003)	.99	-1.95	.05
Weather		.26 (.05)	1.30	5.18	<.001
Weekday		-.09 (.02)	.91	-5.84	<.001
Percent Male		.30 (.23)	1.34	1.31	.189
Average Age		.0008 (.003)	1.00076	.27	.78
Percent Yellow		-.08 (.10)	.93	-.91	.36
Average Education		-.01 (.02)	.99	-.52	.61
Average Experience		-.008 (.005)	.99	-1.83	.07
January		-.005 (.06)	.99	-.08	.94
February		-.02 (.06)	.98	-.27	.79
March		.002 (.07)	1.002	.03	.98
April		.04 (.07)	1.04	.59	.56
May		.02 (.06)	1.02	.30	.76
June		.05 (.12)	1.02	.40	.69
August		-.04 (.05)	1.05	-.78	.43
September		.08 (.04)	1.09	1.93	.05
October		.05 (.05)	1.05	1.03	.30
November		.03 (.04)	1.03	.70	.48

- Full Model for Taiwan Accidents (top teams only)

Table S19 are replications of our first Poisson model (see Table 1) involving Taiwan accidents but only amongst matches involving one of the top ten market value teams across the “Big 5” European leagues. As predicted, average market value remains a robust predictor of traffic accident rate.

Table S19. Full Poisson Model for Taiwan Accidents Using Only Top-10 Teams

Variable	DF	Estimate (SE)	Δ Incidence	z	p
Model	1023				
Intercept		6.74 (.005)	843.01	1505.02	< .001
Average Market Value		.0001 (.000008)	1.00014	18.61	< .001
Weekday		-.01 (.003)	.99	-4.06	< .001
January		-.09 (.004)	.92	-20.37	< .001
February		-1.80 (.005)	.84	-39.56	< .001
March		-.13 (.005)	.88	-28.20	< .001
April		-.17 (.004)	.84	-40.16	< .001
May		-.14 (.005)	.87	-29.58	< .001
June		-.14 (.02)	.87	-6.69	< .001
August		-.22 (.005)	.80	-42.48	< .001
September		-.15 (.005)	.87	-30.34	< .001
October		-.13 (.005)	.88	-25.77	< .001
November		-.09 (.005)	.91	-18.73	< .001

Full Poison Model for Singapore Accidents (top teams only)

Table S20 are replications of our first Poisson model (see Table 1) involving Singapore accidents but only amongst matches involving one of the top ten market value teams across the “Big 5” European leagues.

Table S20. Full Poisson Model for Singapore Accidents Using Only Top-10 Teams

Variable	DF	Estimate (SE)	Δ Incidence	z	p
Model	553				
Intercept		3.37 (.25)	29.25	13.66	< .001
Average Market Value		.0002 (.00006)	1.00017	3.53	< .001
Weather		.30 (.05)	1.36	5.81	< .001
Weekday		-.12 (.02)	.89	-6.76	< .001
Percent Male		.09 (.23)	1.09	.38	.70
Average Age		.004 (.003)	1.004	1.25	.21
Percent Yellow		-.03 (.09)	.97	-.39	.69
Average Experience		-.009 (.005)	.99	-1.97	.049
January		-.03 (.07)	.97	-.51	.61
February		-.05 (.07)	.95	-.76	.45
March		-.06 (.07)	.94	-.84	.40
April		-.01 (.07)	.99	-.18	.85
May		-.02 (.06)	.99	-.29	.77
June		-.008 (.13)	.99	-.06	.95
August		-.04 (.05)	.96	-.85	.39
September		.08 (.04)	1.08	1.86	.06
October		.04 (.05)	1.04	.76	.45

November	.001 (.04)	1.01	.03	.98

Note. Model did not converge controlling for average driver education, so this variable has been removed from the model.

Estimating ARIMA-Residualized Traffic Accident Time Series

Many time series processes have systematic univariate processes that affect their values. For example, time series may have autoregressive (AR) processes that summarize how previous values of a time series affect future values. Time series may also have moving average (MA) processes that summarize more complex linear effects of existing values on future values of a time series. Each of these processes can summarize effects of values at time t on values at time t+1 (e.g. an AR(1) process), or can summarize effects of values at time t on values at time t+2 (e.g. an AR(2) process). An ARIMA analysis revealed that our "total accidents" time series contained several AR and MA processes. Within our Taiwan data, this included an AR(1) process (-.60, SE = .14), an AR(2) process (-.56, SE = .07), an MA(1) process (-.16, SE = .15), an MA(2) process (-.21, SE = .12), and an MA(3) process (-.56, SE = .08). Within our Singapore data, this included an AR(1) process (-.51, SE = .04). The significant AR(1) process suggests that days with frequent traffic accidents were often followed days with lower rates of traffic accidents, which is unsurprising given that frequent traffic accidents may lead people to drive with more caution the next day, or may influence the pool of drivers who drive the next day.

While we detrended our time series of traffic accidents for our primary analyses, we did not remove AR and MA processes. In one sense, it is worthwhile modeling these processes because they are meaningful elements of the time series. For example, the negative AR(1) process may mean that people are less likely to get into traffic accidents following a day with high levels of traffic accidents, and it is conceptually unclear why we should remove this process when conducting bivariate analyses. It is much more important to remove trends and check for stationarity (as we did), as these could lead to a spurious relationship between average market value and accident rate arising from both time series increasing linearly over time. Nevertheless, for the sake of robustness, we checked whether the association between average market value and total traffic accidents replicated when residualizing our time series based on our ARIMA models. For these models, we removed control variables associated with temporal elements (month and day effects) since we removed all temporal autocorrelation with our ARIMA residualizing. However, we left in all other control variables. We used OLS estimation because the residualized time series no longer represented counts, and contained negative values (which are incompatible with Poisson estimation). Follow-up models revealed that for both Taiwan, $b = .05$, $SE = .03$, $z = 2.05$, $p = .04$, and Singapore, $b = .01$, $SE = .003$, $z = 2.37$, $p = .02$, the association between average market value and traffic accidents replicated with ARIMA-residualized values of traffic accidents over time, confirming that this association was robust to removing AR and MA processes.

Time Series Analysis Details for Taiwan

Our Taiwan time series models used vectors representing average market value and number of accidents per day, controlling for Taiwan model covariates that we list in Table 1. We controlled for these covariates by residualizing each time series based on all covariates prior to analysis.

Before estimating our time series models, we tested the assumption in many time series analyses that data are stationary and stable, rather than characterized by an underlying trend that will eventually lead the time series to infinity or negative infinity. A common way of testing for stationarity involves an augmented Dickey-Fuller root test, which assumes the null hypothesis that a unit root is present in an autoregressive model. Both market value, $b = -.70$, $SE = .04$, $t = -17.95$, $p < .001$, and accident rates, $b = -.86$, $SE = .04$, $t = -22.41$, $p < .001$, were significant, indicating that they were not characterized by a unit root and were most likely stationary.

After confirming the stationarity of our time series, we estimated a prewhitened cross-correlation, which probed for the correlation between average market value and number of accidents at a variety of lags. Our cross-correlations showed a significant contemporaneous relationship, $r = .11$, with no other correlations exceeding this magnitude in the expected direction, $rs < .10$. The output of these cross-correlation models is displayed graphically in Figure 2, and is fully summarized in Table S12.

Table S21. CCF Estimates (Taiwan)

Lag (days)	Correlation
-10	.03
-9	.02
-8	.02
-7	.03
-6	-.02
-5	-.05
-4	.08*
-3	-.001
-2	-.03
-1	-.02
0	.10*
1	-.04
2	-.02
3	.04
4	-.04
5	-.06
6	-.01
7	-.05
8	-.04
9	.04
10	-.01

Note. Starred correlations are significant at $p < .05$.

We next conducted a vectoral auto-regression (VAR) model, which controls for different lags and makes recommendations for the appropriate lag that characterizes a bivariate association. Tests of Granger causality can also be extracted from these VAR models, which estimate the likelihood that an x-y bivariate relationship is (a) contemporaneous, with both variables rising and falling together, (b) characterized by changes in x preceding changes in y, or (c) characterized by changes in y preceding changes in x. AIC and FPE estimates from our VAR model suggested a maximum lag of 5-days, and the Granger test of causality extracted from a VAR model with a lagged threshold of 5 estimated that average market value had a significant contemporaneous association with number of traffic accidents, = 12.73, p < .001, with a much smaller lagged association, $F(5,2102) = 2.77$, $p = .02$

 Time Series Analysis Details for Singapore

Our time series models used vectors representing average market value and number of accidents per day, controlling for the demographic and non-demographic covariates that we list in Table 1 and Tables S1-2. We controlled for these covariates by residualizing each time series based on all covariates prior to analysis.

Before estimating our time series models, we tested the assumption in many time series analyses that data are stationary and stable, rather than characterized by an underlying trend that will eventually lead the time series to infinity or negative infinity. A common way of testing for stationarity involves an augmented Dickey-Fuller root test, which assumes the null hypothesis that a unit root is present in an autoregressive model. Both market value, $b = -.96$, $SE = .06$, $t = -17.34$, $p < .001$, and accident rates, $b = -1.08$, $SE = .06$, $t = -17.92$, $p < .001$, were significant, indicating that they were not characterized by a unit root and were most likely stationary.

After confirming the stationarity of our time series, we estimated a cross-correlation, which probed for the correlation between average market value and number of accidents at a variety of lags. Our cross-correlations showed a significant contemporaneous relationship, $r = .12$, with no other correlations exceeding this magnitude in the expected direction, rs < .10. The output of these cross-correlation models is displayed graphically in Figure 2, and is fully summarized in Table S12.

Table S22. CCF Estimates (Singapore)

Lag (days)	Correlation
-10	-0.01
-9	-0.06
-8	0.05
-7	0.03
-6	0.02
-5	0.003
-4	-0.02
-3	-0.11*
-2	-0.01
-1	0.003
0	0.11*
1	0.04
2	0.03
3	-0.10*
4	-0.13*
5	0.002
6	0.08*
7	0.09*
8	0.08*
9	-0.04

10 -0.11*

Note. Starred correlations are significant at $p < .05$.

We next conducted a vectoral auto-regression (VAR) model, which controls for different lags and makes recommendations for the appropriate lag that characterizes a bivariate association. Tests of Granger causality can also be extracted from these VAR models, which estimate the likelihood that an x-y bivariate relationship is (a) contemporaneous, with both variables rising and falling together, (b) characterized by changes in x preceding changes in y, or (c) characterized by changes in y preceding changes in x. AIC and FPE estimates from our VAR model suggested a maximum lag of 4-days, and the Granger causality estimates from these models found that average market value had a significant contemporaneous association with number of traffic accidents, = 5.32, $p = .02$, with a null lagged association, $F(4,1156) = 1.66$, $p = .16$.

 Taiwan Impact Analysis

The results of our Poisson regression analysis in Taiwan (Table 1, Taiwan Model) indicated an intercept incidence rate of 841.98 daily accidents per day among Taiwan drivers, and an indicate rate change of 1.00015 for average market value, in millions. This suggests that traffic accident rate is expected to be 841.98 on a day with 0 market value, and to increase by a proportion of .015% with every million-dollar increase in average market value. With these figures, we can solve for the number of millions in average market value x necessary to translate to an additional accident with the following set of equations:

(Equation 1)

(Equation 2)

(Equation 3)

(Equation 4)

With our precise model estimates, solving for x translated to an additional €7.99 in average market value for every accident among Taiwan taxi drivers. With this figure, we could next calculate the potential aggregate impact of high-profile football matches on traffic accidents among Taiwanese drivers.

In total, there were 1067 game-days, with an average market value of €307.59 million per game day. This indicates that, for an average game day, there is an expected increase of €307.59 / €7.99 = 38.50 accidents, and over the 6-year course of our dataset, there were 38.50 accidents * 1067 total game days = 41,079.50 total accidents due to high-profile football matches. This translates to 41,079.50 accidents / 6 years = 6,846.58 accidents per year. Since each accident costs an average of €2,044 according to Taiwan insurance estimates, this further translates to a potential 6,846.58 * €2,044 = €13,994,409.50 in yearly cost to Taiwanese drivers and insurance companies.

 Singapore Impact Analysis

The results of our Poisson regression analysis in Singapore (Table 1, Singapore Model 1) indicated an intercept incidence rate of 35.29 accidents per day among Singapore taxi drivers, and an indicate rate change of 1.00021 for average market value, in millions. This suggests that traffic accident rate is expected to be 35.29 on a day with 0 market value, and to increase by a proportion of .021% with every million-dollar increase in average market value. With these figures, we can solve for the number of millions in average market value x necessary to translate to an additional accident with the following set of equations:

(Equation 1)

(Equation 2)
(Equation 3)
(Equation 4)

With our precise model estimates, solving for x translated to an additional €134.74 in average market value for every accident among Singapore taxi drivers. With this figure, we could next calculate the potential aggregate impact of high-profile football matches on traffic accidents among taxi drivers in Singapore.

In total, there were 591 game-days, with an average market value of €254.11 million per game day. This indicates that, for an average game day, there is an expected increase of €254.11 / €134.74 = 1.89 accidents, and over the 3-year course of our dataset, there were 1.89 accidents * 591 total game days = 1,314.98 total accidents due to high-profile football matches. This translates to 1,114.58 accidents / 3 years = 371.53 accidents per year. Since each accident costs an average of €2,211 according to Singapore insurance estimates, this further translates to a potential 371.53 * €2,211= €821,448 in yearly cost to the taxi company that we analyzed due to traffic accidents associated with high profile football matches. This figure is likely far higher in the general Singapore population.