Traffic Accidents as a Risk of Watching Football (Soccer) at Home

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Author contributions
K. C. Yam formulated the research idea, designed the study, 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.

This PDF file includes:
Main Text
Figures 1 to 2
Table 1
Supplementary information

Key Points

Question
What is the effect of watching popular football games played many time zones away on Asian fans' sleep deprivation and the resulting traffic accidents?
Findings
In this study that included 41,538 traffic accidents over a three-year span, we find that the presence of high-profile football matches predicts increased number of traffic accidents on the same day. This increased rate of may translate to between 382.12 and 8,182.44 accidents per year in Singapore alone.
Meaning

Given high-profile football games' health and economic impacts on Asian fans, strategic scheduling of games and increased roadside safety on game days may be warranted.

Abstract

Importance
Because Asian fans often watch football games played in Europe during local times in which they would typically sleep, football viewership can lead Asians to be more dangerous drivers as a result of sleep deprivation on game days, with significant health and economic consequences.

Objective
To estimate the health and economic impacts of high-profile football games on traffic accidents in Asia.

Design
A longitudinal study based on 41,538 taxi traffic accident records in Singapore, combined with 5,536 European club football games over a three-year period.

Setting
Singapore; South East Asia

Participants
The largest taxi company in Singapore with all traffic accident records in a three-year span.

Exposures
Days where high-profile football games were played or not.

Main Outcomes and Measures
Number of traffic accidents and the cost of each accident.

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 a US $170 million increase in average market value for matches played in a given day, there would be approximately one more accident that same day. 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. This increased rate of traffic accident may translate to between 382.12 and 8,182.44 accidents, as well as economic losses of between US $951,014 and $20,153,349, annually in Singapore. 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 and Relevance
We posit that watching high-profile football games can be dangerous for roadside safety in Asia, because drivers lose sleep watching games played in Europe which occur during local times in which they typically sleep, which leads to 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 heavily 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 in Asia). 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. We chose traffic accidents in Singapore as the outcome of interest for a few reasons. First, traffic accidents should affect both those who stayed up late to watch the games (at-fault sleepy drivers causing accidents) and those who did not stay up late to watch the games (not-at-fault drivers being hit by sleepy drivers). Second, because 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. Finally and most importantly, traffic accidents can result in causalities and significant medical costs. Overall, if high-profile football matches played in far-removed time zones do result in more frequent traffic accidents in Asia, these findings may have significant policy implications.

To test whether there is a relationship between high-profile game days and traffic accidents in Singapore, we analyzed a dataset from the largest taxi company in Singapore with a fleet size of more than 13,000 taxis. This dataset contained all daily accident records from January 2012 to December 2014 (N = 41,538 accidents). We coded game days 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 game days in the knockout stage of the annual European Champion League and Europa Champion League. For all games, we coded the combined team salary cap as a proxy for the game's popularity, because viewership data were not available for all matches. All data and codes have been anonymized and are available via Open Science Framework: https://osf.io/q9jpc/?view_only=bce492b556054785b73b43aaba5cc3e5.

In total, there were 591 game days from 2012 to 2014. Each of these games 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 US $841 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 US $71 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. Of the 41,538 total accidents, we excluded 960 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.

Results

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 S2). We first conducted this regression controlling for factors that could plausibly influence the rate of traffic accidents: weather (0 = dry; 1 = precipitation), 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). We next added demographic controls: 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 taxi is associated with accident rates (8).

As predicted, market value and traffic accidents had a significant association in these models (estimate = .0002, ∆incidence = 1.00, $z = 3.75$, $p < .001$, Table 1, initial model). This association replicated with a similar effect size when controlling for demographic covariates (estimate = .0002, ∆incidence = 1.00, $z = 3.43$, $p < .001$, Table 1, demographics model). Each model predicted that, for a US $170 million increase in average market value for matches played in a given day (roughly the difference between Barcelona FC and Seville FC), there would be approximately one more accident that same day. The average market value coefficient did not significantly interact with weather ($p = .84$), weekday ($p = .55$), or any demographic information (ps > .17), suggesting that the association between average market value and traffic accidents is generalizable. These interaction models are fully summarized in the supplementary information (SI Tables S3-9).

Table 1.

Poisson Regression Predictors of Taxi Driver Accident Incidence

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Initial Model	590				
Intercept		3.56 (.03)	35.24	129.85	< .001

Average Market Value		.0002 (.00004)	1.00	3.75	< .001
Weather		.29 (.05)	1.34	5.88	< .001
Weekday		-.10 (.02)	.90	-6.19	< .001
Demographics Model	582				
Intercept		3.33 (.25)	27.80	13.27	< .001
Average Market Value		.0002 (.00004)	1.00	3.43	< .001
Weather		.27 (.05)	1.31	5.34	< .001
Weekday		-.09 (.02)	.91	-5.82	< .001
Percent Male		.29 (.23)	1.33	1.27	.20
Average Age		.0006 (.003)	1.00	.20	.84
Percent Yellow		-.06 (.09)	.94	-.73	.47
Average Education		-.01 (.02)	.99	-.63	.53
Average Experience		-.008 (.005)	.99	-1.82	.07

Market value is in millions of US dollars. “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 incidence rate of 1.00016 for market value translates to 1 additional accident for every $170 million in average market value for football matches (the average market value per game day is $333.86 million). Month-of-year effects are reported in the SI.

The second set of analyses replicated our initial models but separated accidents into “day accidents,” namely those occurring between 7:00 a.m. local time (average sunrise time in Singapore) and 7:00 p.m. local time (average sunset time in Singapore), and “night accidents,” namely those occurring outside of those times. One possibility is that high-profile football matches are associated with traffic accidents because people celebrate during/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.

Consistent with a sleep-deprivation account, average market value of football games predicted daytime accidents, estimate = .0003, SE = .00005, Δincidence = 1.00, $z = 5.02$, $p < .001$, but not nighttime accidents, estimate = -.00009, SE = .00008, Δincidence = .99, $z = -1.08$, $p = .28$. These associations, displayed in Figure 1 and SI Tables S10-11, support our sleep deprivation-account of high-profile football matches and traffic accidents.

Figure 1.

The relationship between average market value of football games and number of daytime traffic accidents (in gold) and nighttime traffic accidents (in blue). Values have been residualized to control for covariates, and then linearly transformed to be positive for display purposes. Average market value of football games was significantly associated with daytime traffic accidents but not nighttime traffic accidents.

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) or autocorrelated residuals. 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. After checking that both time-series were stationary using augmented Dickey-Fulley root tests ($ps < .001$), we ran cross-correlations analyses, which probe for the relationship between variables at a variety of lags. We next fit Granger causality models, which evaluate whether two variables are related contemporaneously or via a time-lag.

The output from our cross-correlation function are displayed in Figure 2. Our cross-correlations showed a significant contemporaneous relationship, $r = .11$, with no other correlations exceeding this magnitude in the expected direction, $rs < .10$ (see SI Table S12). 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. Results using vectoral auto-regression (VAR) and Granger causality tests mirrored these cross-correlation results. A Granger test of causality that we extracted from a VAR model with a lagged threshold of 4—recommended by AIC fit statistics—estimated that average market value had a significant contemporaneous association with number of traffic accidents, $= 4.40$, $p = .03$, but no lagged association, $F(4,1140) = 1.50$, $p = .20$.

Figure 2.

Left: The time series of total accidents and average market value of football games. Each vector has been linearly transformed so they can be viewed together on the same scale (the Y-scale has been removed since the numbers have been transformed for visalualization purposes). Market value does not have values for days when European football games were not played.

Right: The results of our cross-correlation analysis involving average market value of football games and number of daily traffic accidents. 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.

Discussion

Our longitudinal analysis of traffic accidents in Singapore supports our hypothesis that days with high-profile European football matches also have higher-than-average rates of traffic accidents. 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 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. 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 or because of autocorrelation in our longitudinal data.

Given that our models suggest that an extra US $170 million in football games' market value translates to one extra daily automobile accident, we estimate that football games may be responsible for as many as 386.12 accidents per year among taxi drivers, and may be responsible for as many as 8,182.44 accidents among all drivers in Singapore (taxis represent less than 5% of the total number of active vehicles in Singapore). Furthermore, data from General Insurance Association of Singapore (7) indicate that the average insurance claim for a traffic accident was S$3,355 in 2018 (i.e., population estimate), which equates to approximately US $2,463. The economic impacts of our findings thus total at least US $951,014, and may be up to $20,153,349, annually (SI Supplementary Texts).

Importantly, even the upper bound of these estimates are likely 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 represents 0.32% of the population in this particular time zone. Given that this is 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, even adjusting the start time of a high-profile game played in Europe from 7pm to 6pm local time can save Asian fans an hour of sleep and potentially reduce traffic accident rate. Another implication is to schedule more high-profile games in Saturday or Sunday mornings, when fans can sleep in immediately after watching the games. Finally, increased roadside safety in Asia on high-profile game days (e.g., more traffic patrols) could potentially reduce these economic impacts and could potentially save numerous lives each year.

Materials and Methods

Football clubs and games data: The paper uses data from worldfootball.net, 2011/2012 – 2014/2015. Information about these data includes 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 Singapore's time zone (GMT + 8).

Market values data are from Transfer Markt (https://www.transfermarkt.com/), 2011/2012 – 2014/2015. This source provides all football players' salaries (in Euros), as well as teams' combined salary cap. We then used these statistics to calculate the combined market value of a given match between any two clubs. Finally, we converted this dollar value from Euros to USD. Information about these data includes market values of football clubs 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. We also coded for the Champions League and the Europa League given their popularity.

All the matches from 2011/2012 – 2014/2015 among the top 5 leagues are included, while the round of 16 or more advanced matches in both the Champions League and the Europa League are included. 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 5 football leagues. As such, viewership to group stage games are likely very low.

Singapore taxi accident data: We obtained our traffic accident data from a large taxi company in Singapore. This organization has an over 60% market share of the taxi transport industry in Singapore. We obtained all taxi traffic accident records from this organization from January 1st 2012 to December 31st 2014. Each accident is accompanied by details such as the driver's age, gender, roadside condition (wet vs. no), date, time of the day, etc.

All of our data and codes can be found on OSF:
https://osf.io/q9jpc/?view_only=bce492b556054785b73b43aaba5cc3e5

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Supplementary Information for

Traffic Accidents as a Risk of Watching Football at Home

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This PDF file includes:

Supplementary text
Tables S1 to S12
Full Poisson Models. Table 1 in our main text contained results from a Poisson regression model, 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

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Initial Model	590				
Intercept		3.56 (.03)	35.24	129.85	< .001
Average Market Value		.0002 (.00004)	1.00	3.75	< .001
Weather		.29 (.05)	1.34	5.88	< .001
Weekday		-.10 (.02)	.90	-6.19	< .001
January		-.04 (.03)	.96	-1.33	.19
February		-.05 (.03)	.95	-1.74	.08
March		-.04 (.03)	.96	-1.43	.15
April		.002 (.03)	1.00	.06	.96
May		-.01 (.03)	.99	-.30	.77
June		.02 (.10)	1.02	.20	.84
August		-.05 (.03)	.95	-1.53	.13
September		.08 (.03)	1.08	2.58	.01
October		.04 (.03)	1.04	1.26	.21
November		.19 (.03)	1.02	.60	.55
Demographics Model	582				
Intercept		3.33 (.25)	27.80	13.27	< .001
Average Market Value		.0002 (.00004)	1.00	3.43	< .001
Weather		.27 (.05)	1.31	5.34	< .001
Weekday		-.09 (.02)	.91	-5.82	< .001
Percent Male		.29 (.23)	1.33	1.27	.20
Average Age		.0006 (.003)	1.00	.20	.84
Percent Yellow		-.06 (.09)	.94	-.73	.47
Average Education		-.01 (.02)	.99	-.63	.53
Average Experience		-.008 (.005)	.99	-1.82	.07
January		-0002 (.06)	.99	-.003	.99
February		-.01 (.06)	.99	-.22	.82
March		-.006 (.08)	1.01	.09	.93
April		.04 (.07)	1.04	.58	.56

May	.02 (.06)	1.01	.25	.80
June	.05 (.13)	1.05	.38	.70
August	-.04 (.05)	.96	-.80	.43
September	.08 (.04)	1.09	1.92	.05
October	.05 (.05)	1.06	1.07	.28
November	.03 (.04)	1.03	.68	.50

Note. Market value is in millions of US dollars. “DF” refers to model degrees of freedom. Incidence change is the expected change in predicted accident incidence for every unit-increase in the predictor. July is not displayed because no games were played in July.

Gaussian Models. Table S2 displays the parameters of a Gaussian regression model, rather than the Poisson model that we used for our count data. Results were largely identical across the Gaussian and Poisson models.

Table S2

Variable	Model DF	b (SE)		t	p
Initial Model	577				
Intercept		35.35 (1.31)		27.03	< .001
Average Market Value		.006 (.002)	.12	2.81	.005
Weather		10.73 (2.42)	.18	4.34	< .001
Weekday		-3.57 (.77)	-.19	-4.67	< .001
January		-1.36 (1.39)	-.05	-.98	.33
February		-1.78 (1.37)	-.06	-1.30	.19
March		-1.44 (1.33)	-.05	-1.10	.28
April		.05 (1.29)	.002	.04	.97
May		-.35 (1.46)	-.01	-.24	.81
June		.96 (5.68)	.007	-.17	.87
August		-1.83 (1.60)	-.06	-1.15	.87
September		2.91 (1.51)	.10	1.93	.06
October		1.45 (1.55)	.05	.93	.35
November		.66 (1.50)	.02	.44	.66
Demographics Model	564				
Intercept		26.87 (11.72)		2.29	.02
Average Market Value		.005 (.002)	.11	2.56	.01
Weather		9.88 (2.47)	.17	4.01	< .001
Weekday		-3.40 (.78)	-.18	-4.39	< .001
Percent Male		10.20 (10.47)	.04	.97	.33
Average Age		.02 (.13)	.02	.15	.88
Percent Yellow		-2.11 (4.02)	-.02	-.53	.60
Average Education		-.51 (1.05)	-.04	-.48	.63
Average Experience		-.29 (.21)	-.14	-1.36	.17
January		.004 (3.01)	.0001	.001	.99
February		-.49 (2.99)	-.02	-.16	.87
March		.18 (3.38)	.01	.05	.96
April		1.39 (3.26)	.06	.43	.67
May		.48 (2.75)	.02	.18	.86
June		1.85 (6.11)	.01	.30	.76

August	-1.35 (2.30)	-.04	-.59	.56
September	3.02 (2.08)	.10	1.45	.15
October	1.93 (2.42)	.06	.80	.43
November	.93 (1.82)	.03	.51	.61

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

Interaction models. Tables S3-S9 include the interaction of market average with each other substantive predictor in our model. 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.

Table S3

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Demographics Model	564				
Intercept		3.33 (.25)	27.79	13.27	<.001
Average Market Value		.00016 (.00005)	1.00	3.08	0.002
Weather		.29 (.12)	1.34	2.49	.01
Weekday		-.09 (.02)	.91	-5.82	<.001
Percent Male		.29 (.22)	1.33	1.27	.20
Average Age		.0005 (.003)	1.00	.19	.85
Percent Yellow		-.06 (.09)	.94	-.71	.48
Average Education		-.01 (.02)	.99	-.63	.53
Average Experience		-.008 (.005)	.99	-1.8	.07
January		.0006 (.06)	1.00	.009	.99
February		-.01 (.06)	.98	-.20	.84
March		.007 (.07)	1.01	.10	.92
April		.04 (.07)	1.04	.59	.55
May		.02 (.06)	1.02	.27	.78
June		.05 (.13)	1.05	.39	.70
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	.68	.50
Market Value * Weather		-.00006 (.0003)	1.00	-.20	.84

Table S4

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Demographics Model	564				
Intercept		3.34 (.25)	28.27	13.25	<.001
Average Market Value		.00007 (.0002)	1.00	.44	.66
Weather		.27 (.05)	1.31	5.35	<.001
Weekday		-.12 (.05)	.89	-2.51	.01
Percent Male		.29 (.23)	1.34	1.30	.19
Average Age		.00053 (.0028)	1.00	.19	.85

Percent Yellow		-.06 (.09)	.94	-.71	.48
Average Education		-.01 (.02)	.99	-.61	.54
Average Experience		-.008 (.005)	.99	-1.78	.08
January		-.002 (.06)	1.00	-.03	.98
February		-.02 (.06)	.98	-.26	.79
March		.005 (.07)	1.00	.06	.95
April		.04 (.07)	1.04	.55	.58
May		.01 (.06)	1.01	.22	.82
June		.07 (.13)	1.07	.53	.60
August		-.04 (.05)	.96	-.82	.42
September		.08 (.04)	1.09	1.91	.06
October		.05 (.05)	1.05	1.06	.29
November		.03 (.04)	1.03	.68	.50
Market Value * Weekday		.00009 (.0002)	1.00	.59	.55

Table S5

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Demographics Model	564				
Intercept		3.78 (.57)	44.02	6.6	<.001
Average Market Value		-.001 (.002)	1.00	-.80	.42
Weather		.27 (.05)	1.31	5.4	<.001
Weekday		-.09 (.02)	.91	-5.8	<.001
Percent Male		-.17 (.56)	.84	-.31	.76
Average Age		.0004 (.003)	1.00	.15	.88
Percent Yellow		-.06 (.09)	.94	-.74	.46
Average Education		-.01 (.02)	.99	-.66	.51
Average Experience		-.008 (.005)	.99	-1.84	.07
January		.005 (.06)	1.01	.08	.94
February		-.008 (.06)	.99	-.13	.90
March		.01 (.07)	1.01	.17	.87
April		.04 (.07)	1.05	.64	.52
May		.02 (.06)	1.02	.35	.72
June		.04 (.13)	1.05	.36	.72
August		-.04 (.05)	.96	-.73	.47
September		.09 (.04)	1.09	1.98	.05
October		.06 (.05)	1.06	1.16	.25
November		.03 (.04)	1.03	.72	.47
Market Value * Male		.002 (.002)	1.00	.89	.37

Table S6

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Demographics Model	564				
Intercept		3.45 (.27)	31.54	12.91	<.001
Average Market Value		-.0002 (.0003)	1.00	-.81	.42
Weather		.27 (.05)	1.31	5.38	<.001
Weekday		-.10 (.02)	.91	-5.91	<.001

Percent Male		.30 (.23)	1.35	1.33	.18
Average Age		-.002 (.003)	1.00	-.59	.55
Percent Yellow		-.06 (.09)	.94	-.68	.50
Average Education		-.01 (.02)	.99	-.64	.52
Average Experience		-.008 (.005)	.99	-1.8	.07
January		.01 (.06)	1.01	.16	.87
February		-.004 (.06)	1.00	-.06	.95
March		.02 (.07)	1.02	.24	.81
April		.05 (.07)	1.05	.70	.49
May		.02 (.06)	1.02	.42	.68
June		.06 (.13)	1.06	.47	.64
August		-.03 (.05)	.97	-.67	.50
September		.09 (.04)	1.09	1.97	.05
October		.06 (.05)	1.06	1.19	.23
November		.02 (.04)	1.02	.65	.52
Market Value * Age		.000007 (.000005)	1.00	1.36	.17

Table S7

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Demographics Model	564				
Intercept		3.37 (.25)	29.03	13.22	<.001
Average Market Value		.00004 (.0001)	1.00	.32	.75
Weather		.27 (.05)	1.31	5.25	<.001
Weekday		-.09 (.02)	.91	-5.83	<.001
Percent Male		.28 (.23)	1.32	1.24	.22
Average Age		.0006 (.003)	1.00	.003	.83
Percent Yellow		-.23 (.20)	.79	-1.15	.25
Average Education		-.01 (.02)	.99	-.65	.52
Average Experience		-.008 (.005)	.99	-1.82	.07
January		-.002 (.06)	1.00	-.03	.98
February		-.01 (.06)	.99	-.23	.82
March		.004 (.07)	1.00	.05	.96
April		.04 (.07)	1.04	.58	.56
May		.01 (.06)	1.01	.21	.84
June		.05 (.13)	1.05	.38	.70
August		-.04 (.05)	.96	-.80	.43
September		.08 (.04)	1.09	1.92	.05
October		.05 (.05)	1.05	1.04	.30
November		.02 (.04)	1.03	.65	.51
Market Value * Yellow		.0005 (.0006)	1.00	.93	.35

Table S8

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Demographics Model	564				
Intercept		3.32 (.25)	27.58	13.27	< .001
Average Market Value		.0002 (.0001)	1.00	1.66	.10

Weather		.27 (.05)	1.31	5.34	<.001
Weekday		-.09 (.02)	.91	-5.83	<.001
Percent Male		.29 (.23)	1.34	1.29	.20
Average Age		.0005 (.003)	1.00	.17	.87
Percent Yellow		-.06 (.09)	.94	-.71	.48
Average Education		-.007 (.03)	.99	-.21	.84
Average Experience		-.008 (.005)	.99	-1.83	.07
January		.002 (.06)	.94	.03	.97
February		-.01 (.06)	.99	-.19	.85
March		.008 (.07)	1.01	.12	.91
April		.04 (.07)	1.04	.60	.55
May		.02 (.06)	1.02	.28	.78
June		.05 (.13)	1.05	.40	.69
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		-.00002 (.00008)	1.00	-.29	.78

Table S9

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Demographics Model	564				
Intercept		3.39 (.25)	29.68	13.39	<.001
Average Market Value		-.00004 (.0001)	1.00	-.38	.71
Weather		.27 (.05)	1.31	5.39	<.001
Weekday		-.10 (.02)	.91	-5.93	<.001
Percent Male		.30 (.23)	1.35	1.32	.19
Average Age		.0002 (.003)	1.00	.06	.95
Percent Yellow		-.06 (.09)	.94	-.67	.50
Average Education		-.01 (.02)	.99	-.63	.53
Average Experience		-.02 (.006)	.98	-2.60	.009
January		.02 (.06)	1.02	.24	.81
February		.000002 (.06)	1.00	.00	1.00
March		.03 (.07)	1.02	.32	.75
April		.05 (.07)	1.05	.75	.45
May		.03 (.06)	1.03	.50	.62
June		.07 (.13)	1.07	.55	.58
August		-.03 (.05)	.97	-.62	.54
September		.09 (.04)	1.09	1.98	.05
October		.06 (.05)	1.06	1.21	.22
November		.02 (.04)	1.02	.62	.53
Market Value * Experience		.00002 (.00001)	1.00	1.87	.06

Daytime vs. nighttime accidents full statistics. Tables S10 and S11 show the full summaries of the day-time and night-time models reported in the main text. 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 S10. Daytime Accidents

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Demographics Model	582				
Intercept		3.26 (.00005)	26.09	10.54	< .001
Average Market Value		.0003 (.00005)	1.00	5.02	< .001
Weather		.17 (.06)	1.18	2.63	.008
Weekday		-.10 (.02)	.90	-5.03	< .001
Percent Male		-.03 (.28)	.97	-.11	.91
Average Age		-.004 (.003)	.99	-1.16	.25
Percent Yellow		-.05 (.11)	.95	-.50	.62
Average Education		.005 (.03)	1.01	.18	.86
Average Experience		.003 (.006)	1.00	.55	.58
January		.05 (.08)	1.06	.68	.50
February		.07 (.08)	1.07	.90	.39
March		.09 (.09)	1.09	.97	.33
April		.12 (.08)	1.13	1.40	.16
May		.08 (.07)	1.09	1.15	.25
June		.07 (.16)	1.07	.44	.66
August		.03 (.06)	1.03	.42	.67
September		.12 (.05)	1.13	2.20	.03
October		.13 (.06)	1.14	2.08	.04
November		.03 (.05)	1.04	.71	.48

Table S11. Nighttime Accidents

Variable	DF	Estimate (SE)	∆ Incidence	z	p
Demographics Model	582				
Intercept		1.61 (.43)	4.98	3.76	< .001
Average Market Value		-.00009 (.00008)	.99	-1.08	.28
Weather		.45 (.08)	1.57	5.40	< .001
Weekday		-.08 (.03)	.92	-2.99	.003
Percent Male		.87 (.38)	2.39	2.27	.02
Average Age		.009 (.005)	1.01	1.90	.06
Percent Yellow		-.08 (.15)	.92	-.55	.58
Average Education		-.05 (.04)	.95	-1.27	.20
Average Experience		-.03 (.008)	.97	-3.84	< .001
January		-.09 (.11)	.92	-.82	.42
February		-.15 (.11)	.86	-1.44	.15
March		-.13 (.12)	.88	-1.10	.29
April		-.09 (.11)	.91	-.82	.41
May		-.99 (.10)	.91	-1.03	.31
June		.03 (.21)	1.03	.12	.90
August		-.15 (.08)	.86	-1.82	.07
September		-.02 (.07)	1.02	.32	.75
October		-.08 (.08)	.92	-.94	.35

November	-.008 (.06)	1.01	.14	.89

Time series analysis details. 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, $r = .11$, 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 S12

Lag (days)	Correlation
-30	-0.02
-29	-0.02
-28	0.04
-27	-0.01
-26	0.00
-25	0.03
-24	0.04
-23	0.04
-22	0.00
-21	0.00
-20	0.04
-19	0.05
-18	0.04
-17	-0.02
-16	-0.03
-15	-0.02
-14	0.07
-13	0.02
-12	0.02
-11	-0.03
-10	0.00
-9	-0.06
-8	0.06

-7	0.04
-6	0.02
-5	0.00
-4	-0.02
-3	-0.10*
-2	0.00
-1	0.00
0	0.11*
1	0.03
2	0.03
3	-0.09*
4	-0.13*
5	0.00
6	0.07
7	0.09*
8	0.08*
9	-0.04
10	-0.11*
11	-0.06
12	0.03
13	0.00
14	0.06
15	0.02
16	0.05
17	-0.02
18	0.07
19	0.02
20	0.07
21	0.01
22	0.07
23	0.03
24	-0.07
25	-0.04
26	0.01
27	0.04
28	0.05
29	0.02
30	-0.01

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 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, = 4.40, p = .03, but no lagged association, F(4,1140) = 1.50, p = .20.

Summary of Damage Analyses. The results from our Poisson regression indicate that $170 million USD in market value translates to an additional traffic accident in Singapore. Given Table 1's model intercept of 3.56 and average market value slope of .0001641 (rounded to .0002 in Table 1):

and

In total, there were 591 game-days, with an average market value of $333.86 million per game day. This indicates that, for an average game day, there is an expected increase of $333.86 / $170.00 = 1.96 accidents, and over the 3-year course of our dataset, there were 1.96 accidents * 591 total game days = 1,158.36 total accidents due to high-profile football matches. This translates to 1,158.36 accidents / 3 years = 386.12 accidents per year. Since each accident costs an average of $2,463, this further translates to 386.12 * $2,463 = $951,014 USD in yearly cost due to traffic accidents associated with high profile football matches.

We further more expand these analyses to all vehicles in Singapore. Taxis in Singapore represent approximately 4.67% of all active licensed vehicles. As such, our liberal estimate suggests that our findings can account for as many as 382.12 / 0.0467 = 8182.44 accidents. Since each accident costs an average of $2,463, this further translates to 8182.44 * $2,463 = $20,153,352 USD in yearly cost due to traffic accidents associated with high profile football matches.