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The Relationship Between Unexpected Outcomes and Lottery Gambling Rates in a Large Canadian Metropolitan Area

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Abstract: The purchase of lottery tickets is widespread in Canada, yet little research has directly examined when and why individuals engage in lottery gambling. By leveraging a large urban dataset of lottery sales in Toronto, Canada, and using a simple computational framework popular in psychology, we examined whether city residents gamble more when local outcomes are better than expected; for example, wins by local sports teams or amounts of sunshine based on recent weather history. We found that unexpectedly sunny days predict increased rates of fixed-prize lottery gambling. The number of local sports team wins also predicted increased purchase rates of fixed-prize lottery, but unexpected positive outcomes in sports did not. Our results extend previous findings examining the linkage between sunshine and gambling in metropolitan areas beyond the US, but do not fully replicate the previously observed relationships between unexpected sports outcomes and gambling in US cities. These results suggest that the observed malleability of lottery gambling in response to incidental events in the gambler's environment may vary considerably across geographies.

Keywords: prediction error, gambling, lottery, big data, mood

Introduction

Purchasing lottery tickets is the most popular form of legal gambling in Canada, with 65% of Canadians reporting that they purchase lottery tickets at least weekly (Planinac et al., 2011). Further, a large proportion of gamblers participate in lottery gambling at least occasionally (i.e., more than 45% purchased tickets once a month or more) (Short et al., 2015). Considered a leisure activity by many, lottery gambling is thus pervasive—for example, in the fiscal year 2018–2019, the lottery generated $3.7 billion of proceeds in Ontario alone (Ontario Lottery and Gaming Corporation, 2019).

The lotteries offered by the Ontario Lottery and Gaming Corporation (OLG), can be classified into two categories: those with fixed prizes (e.g., 'Daily Keno', 'Pick-2', 'Pick-4') and those with progressive prizes (e.g., 'Lottario', 'Lotto 6/49', 'Lotto Max'). The odds of winning the jackpot for the progressive-prize lotteries range from 1 in 4,000,000 to 1 in 33,000,000; for example, 'Lotto 6/49' costs $3 per draw and the odds for the top prize (beginning at $3,000,000) are 1 in 13,983,816. The odds for the top prize in fixed-prize lotteries vary considerably depending on the format of the lottery. For example, 'Pick-4' costs $1 per ticket and the odds for the top prize of $5,000 are 1 in 10,000. Despite the better odds of winning, fixed-prize lotteries incur a net loss for gamblers (in terms of expected value), and when individuals decide to wager money on a highly unlikely outcome, they are thought to be engaging in a type of risk-seeking behaviour (Rogers, 1998).

In this study, we aim to understand what influences people's day-to-day participation in fixed-prize gambling in a large metropolitan area in Canada. Within the sphere of gambling research, there is a growing interest in examining the relationship between gambling practices and the external environment of lottery gamblers (Bedford, 2021; Casey, 2008; Nicoll, 2019). Here we seek to expand this line of inquiry and elucidate the relationship between environmental factors and willingness to participate in gambling.

In the psychology literature, it has been demonstrated that unpredictable events in daily life drive variations in mood states (Clark & Watson, 1988; Kuppens et al., 2010), and these affective state changes in turn are believed to influence an individual's attitude towards risk-taking (Ashby et al., 1999; Isen & Patrick,

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1983). At the same time, a body of work reveals how the effect of positive or negative outcomes upon an individual's mood state is nuanced: an outcome exerts a stronger effect when it is unexpected rather than expected, and this manifests in both affective experience (Mellers et al., 1997; Shepperd & McNulty, 2002) and momentary happiness (Rutledge et al., 2014). It thus appears that the difference between expected and true outcomes—so-called 'prediction errors'—drive many important behavioural phenomena inside and outside the lab.

Recently, we employed a 'big data' approach to understand how lottery gambling in New York City's 8.5 million residents varies over time as a function of unexpected outcomes in the external environment unrelated to lottery gambling (Otto et al., 2016). As professional sports events and weather are a source of continually occurring events known to exert striking effects on mood states (Cunningham, 1979; Edmans et al., 2007), we reasoned prediction errors from these sources would alter risk attitudes via mood shifts that would be evident in per-capita lottery ticket purchasing rates. Using a simple computational model to calculate prediction errors stemming from local professional sports teams and local sunshine that spanned an entire year, we were able to quantify the extent to which 1) the city's professional sports teams had performed better or worse than expectations based on recent performance, and 2) the extent to which the day's sunshine was greater or less than expectations informed by recent sunshine levels. We found that positive, unexpected local outcomes stemming from sports and weather—but importantly, not *absolute* outcomes in either domain—predicted increases in day-to-day lottery gambling behaviour (Otto et al., 2016).

Further, a recent follow-up study demonstrated that the predictive relationships between sports- and sunshine-based prediction errors and lottery gambling rates are observable in other metropolitan regions in the United States—in this case, the Chicago metropolitan statistical area (Otto & Eichstaedt, 2018). This work complements a growing body of work suggesting that these deviations from short-term expectations exert a larger impact on positive mood states than outcomes themselves (Eldar et al., 2016; Rutledge et al., 2014; Villano et al., 2020; Vinckier et al., 2018) and these mood states in turn have well-documented effects on risk attitudes (Bassi et al., 2013; Isen & Patrick, 1983; Schulreich et al., 2014). At the same time, these large-scale real-world datasets further demonstrate the malleability of individuals' gambling propensities, opening the door to further examine possible linkages between events (unexpected or otherwise) in the gambler's environment and their attitudes toward lottery gambling.

On the basis of this line of work, an open question remains concerning the extent to which the predictive relationship between unexpected positive outcomes and lottery gambling rates generalizes to populations outside of the United States (Kaizeler & Faustino, 2008). Interestingly, Toronto, as the largest urban area in Canada with a population of 2.7 million (Statistics Canada, 2017), is similar in size to the US cities studied previously (New York City and Chicago). Toronto also has similar marked day-to-day fluctuations in rates of lottery purchase that mirror the pattern previously observed in US cities. Toronto also similarly hosts several professional sporting teams (i.e., 3 major professional teams) as well as sunshine levels that exhibit comparable levels of intrinsic variability. Finally, as the structures of fixed-prize lottery games are, by and large, similar across the United States and Canada, this study may help identify factors affecting gambling that are sensitive to cultural or regional differences. One such difference is the pervasiveness of professional sports: New York City has 13 major league teams, across the National Football League (NFL), Major League Baseball (MLB), National Basketball Association (NBA), National Hockey League (NHL), Major League Soccer (MLS), National Women's Soccer League (NWSL), and Women's National Basketball Association (WNBA); whereas Toronto only has four teams across the NHL, NBA, MLB, and MLS. Taking this as an indicator of how much influence sports outcomes exert on residents' psychological states, we might expect that the influence of sports on local residents' lottery gambling behaviour might be attenuated in Toronto.

Accordingly, here we aimed to leverage the well-characterized relationship between mood states and risk attitudes established in the previous US-based studies to examine which mood-influencing events in the external environment predict when residents of a large Canadian metropolitan area (the Toronto Metropolitan Area) are more likely to participate in lottery gambling. Our hypothesis is that both sports and sunshine-based prediction errors will have a significant and positive relationship with lottery gambling. Critically, we were able to assess how rates of fixed-prize lottery gambling in Toronto respond to these kinds of prediction errors over the course of two years (2014 and 2015), at the same time controlling for the influence of cyclical variables such as seasonal and day-of-week effects. This rich dataset allows us to examine these day-to-day changes in gambling behaviour across nearly 100 diverse neighborhoods. Again, to ensure that fluctuations in lottery consumption are not driven by changes in jackpot value—as in the case of jackpot-based gambles where prize values change over time—we only considered fixed-prize lottery tickets administered by the Ontario Lottery and Gaming Commission (e.g., 'Daily Keno', 'Megadice Lotto', 'Pick-2'). In turn, the expected values of the gambles considered do not vary as a function of time or the number of winning participants. Thus, we believe that the day-to-day variations in lottery ticket purchases would reflect factors extrinsic to the lotteries themselves, possibly reflecting changes in the gamblers' underlying risk attitudes (Conlisk, 1993; Rogers, 1998).

Method

Toronto Lottery Data

Via an Access to Information Act request, we acquired fixed-prize lottery purchase data by forward sortation area (FSA) for the years 2014 and 2015 in Toronto from the Ontario Lottery and Gaming Corporation (OLG). FSAs are defined as geographic regions where all postal codes share the same three starting characters, roughly correspond to city neighborhoods, and are associated with well-defined geographical boundaries in the Greater Toronto Area (Varga et al., 2013). Further, the 2011 census provides rich FSA-level demographic information. We requested aggregated daily sales data in the City of Toronto for all fixed-prize lottery tickets available (i.e., 'Daily Keno', 'Living the Life Lottery', 'Megadice Lotto', 'NHL Lotto', 'Pick-2', 'Pick-4', 'Poker Lotto', and 'Wheel of Fortune'). This includes all the FSAs beginning with 'M'; 100 FSAs in total (see Fig. 1A).

We sought to analyze the effect of prediction errors at a per-capita level in the city and on the individual FSA level. One possible confounding factor is FSAs that are mostly comprised of commercial or industrial real estate. To ensure that our analysis only covered residential zones, we only included FSAs with 1000 or more adult residents, according to the *2011 National Household Survey* (Statistics Canada, 2013), which left 95 FSAs for analysis.

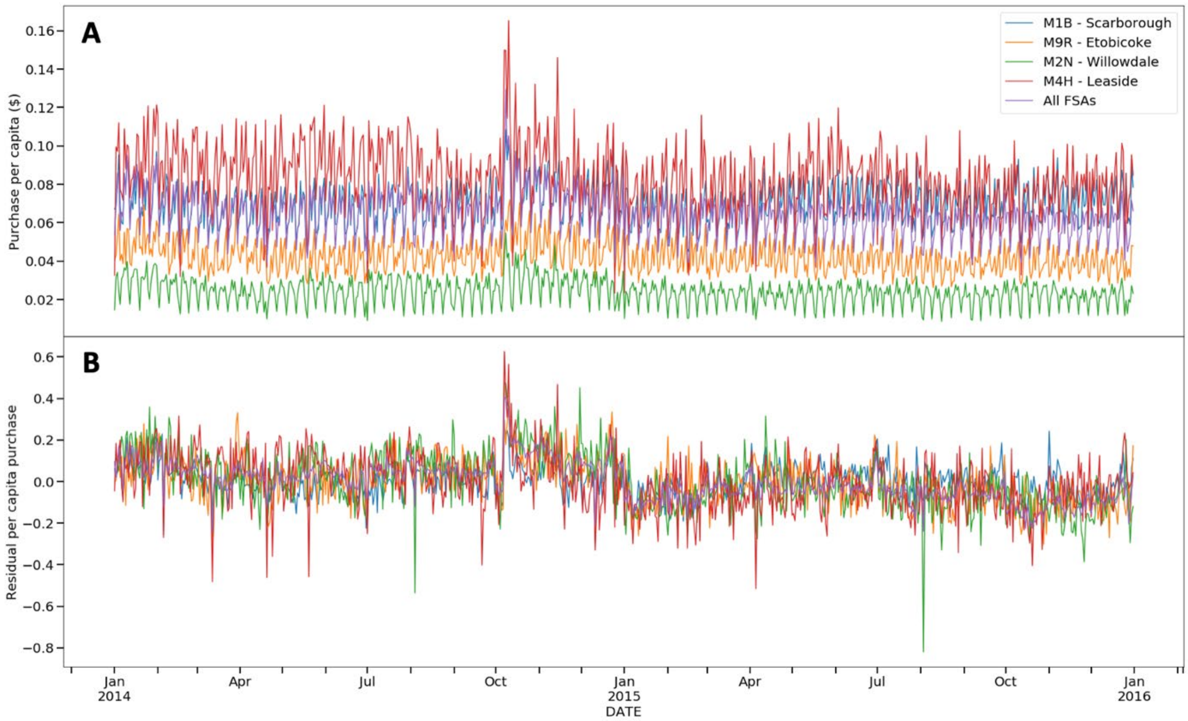

Fig. 1. Timecourse of daily-lottery purchases in Toronto fluctuate heavily every day in the years 2014 and 2015. (A) The composite per-capita purchases of daily-lottery tickets, in 4 different forward sortation areas (FSAs) and averaged over all FSAs, shows strong weekly cyclical effects. (B) After controlling for a number of cyclical and non-cyclical nuisance variables (Methods), we still observe variations in purchase rates correlated at the FSA level in the city-wide average.

Demographic Data

We computed the number of adult residents per FSA from population data acquired from the *2011 National Household Survey* (Statistics Canada, 2013).

Sunshine Data

We used satellite-derived estimates of Direct Normal Irradiance (DNI), a measure of solar irradiance in units of W/m^2 on a surface normal to the sun, obtained from Clean Power Research (www.SolarAnywhere.com), following our previous analyses of sunshine data (Otto & Eichstaedt, 2018; Otto et al., 2016). Intuitively, larger DNI values are indicative of sunnier days (i.e., absence of cloud cover). For each day in 2014 and 2015, we calculated the mean DNI between sunrise and sunset to use as our daily estimate of solar irradiance. A daily exponentially weighted average was calculated with the equation (Fig. 2A; Otto & Eichstaedt, 2018; Otto et al., 2016):

$$\overline{DNI}(t+1) = \overline{DNI}(t) + \alpha[DNI(t) - \overline{DNI}(t)]$$

In accordance with previous work employing the same prediction error computation, the recency parameter, α, was set to a value of 0.1 (Otto & Eichstaedt, 2018; Otto et al., 2016). The prediction error for a given day was calculated as the difference between expected and observed DNI, computed as $DNI(t)$ minus $\overline{DNI}(t)$ (Fig. 2B).

Sports Outcomes

The sports outcomes (wins, losses, and ties) of regular and post-season games played by the Toronto teams in the National Basketball Association (NBA), National Hockey League (NHL), and Major League Baseball (MLB)—identified as the three most popular teams in Canada by fan base size (Elevent, 2020)—were obtained from the ESPN website (www.espn.com) for the years 2014 and 2015. To calculate prediction error from sports team results, we calculated an exponentially weighted average (Otto & Eichstaedt, 2018; Otto et al., 2016) in order to estimate the probability of winning for each team P_{win}, adjusting this estimate after each game based on the deviation between outcome and previous prediction (Fig. 3A):

$$P_{win}(t+1) = P_{win}(t + \alpha[O(t) - P_{win}(t)]$$

In this equation, t is the day of the year, $O(t)$ is the outcome (win = 1, loss = 0, tie = 0.5) on that day, and α is a recency parameter (i.e., learning rate) that makes recent outcomes more influential than those in earlier days. Similar to the analysis of sunshine, α, was set to a value of 0.1 (Otto & Eichstaedt, 2018; Otto et al., 2016). On days where a team did not play, P_{win} was carried forward from the previous day, which parallels the trial-based learning algorithms used in experimental literature (Rutledge et al., 2014). In this model, the prediction error for a team on a given day is simply the difference between that day's expected outcome $P_{win}(t)$ (previous day's moving average) and the outcome, $O(t)$ (Fig. 3B):

$$PE(t) = O(t) - P_{win}(t)$$

Each day, the prediction errors from teams that played on that day were summed to compute a 'city-wide' sports prediction error, which represents how much better or worse the city's teams performed compared with recent expectations (Fig. 3C; Otto & Eichstaedt, 2018; Otto et al., 2016).

Nuisance Variables

As in the Otto et al. (2016) and Otto and Eichstaedt (2018) studies, we specified several 'dummy' variables to control for year, day-of-week effects, month-of-year effects, statutory holidays, common paycheque cycles, severe weather events, and in accordance with prior work (Evans & Moore, 2011) for statutory holidays (New Year's Day, Family Day, Good Friday, Victoria Day, Canada Day, Labour Day, Thanksgiving, Christmas Day, and Boxing Day). Common paycheque receipt days—1st and 15th of each month—were separately dummy-coded (if these fell on the weekends, the immediately preceding weekday was used).

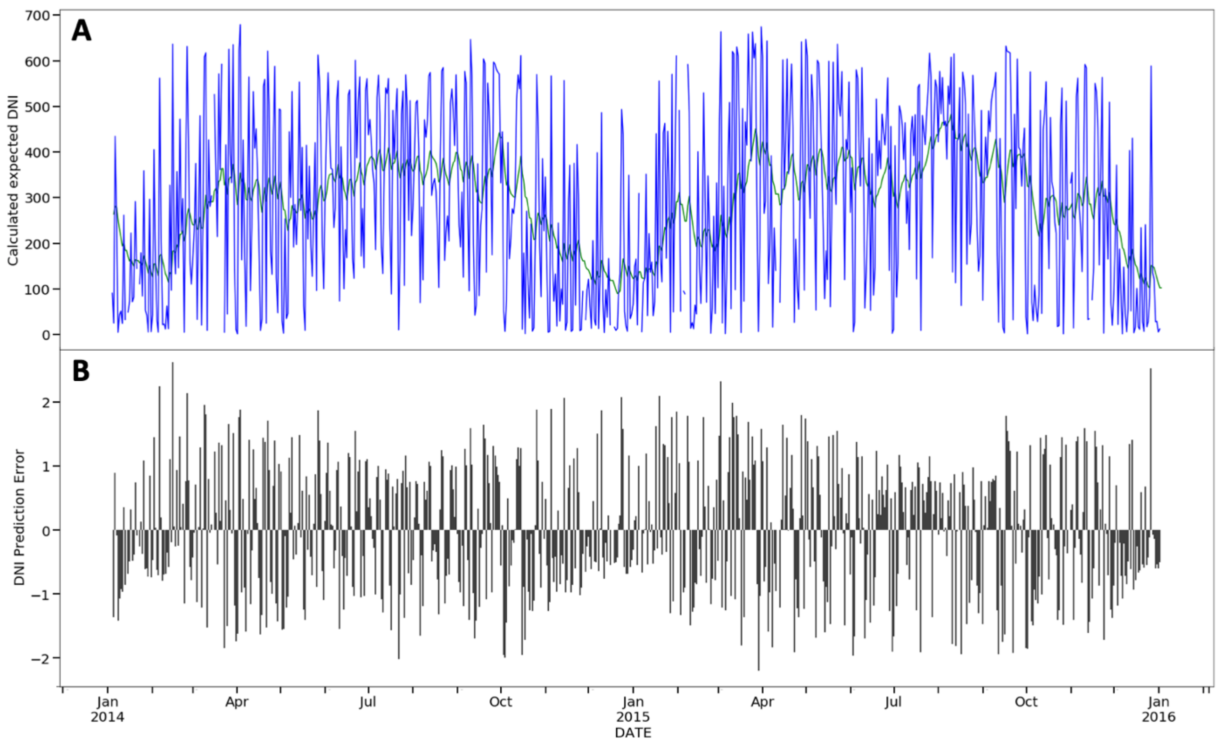

Fig. 2. Direct Normal Irradiance (DNI) varies throughout the year. (A) The cyclical nature of irradiance in Toronto varies from season to season. As expected, it is high during the summer months and low during the winter months. However, day-to-day variation still exists which contributes to prediction errors. (B) Prediction error from solar irradiance is computed as the divergence between the calculated expected DNI and the observed DNI.

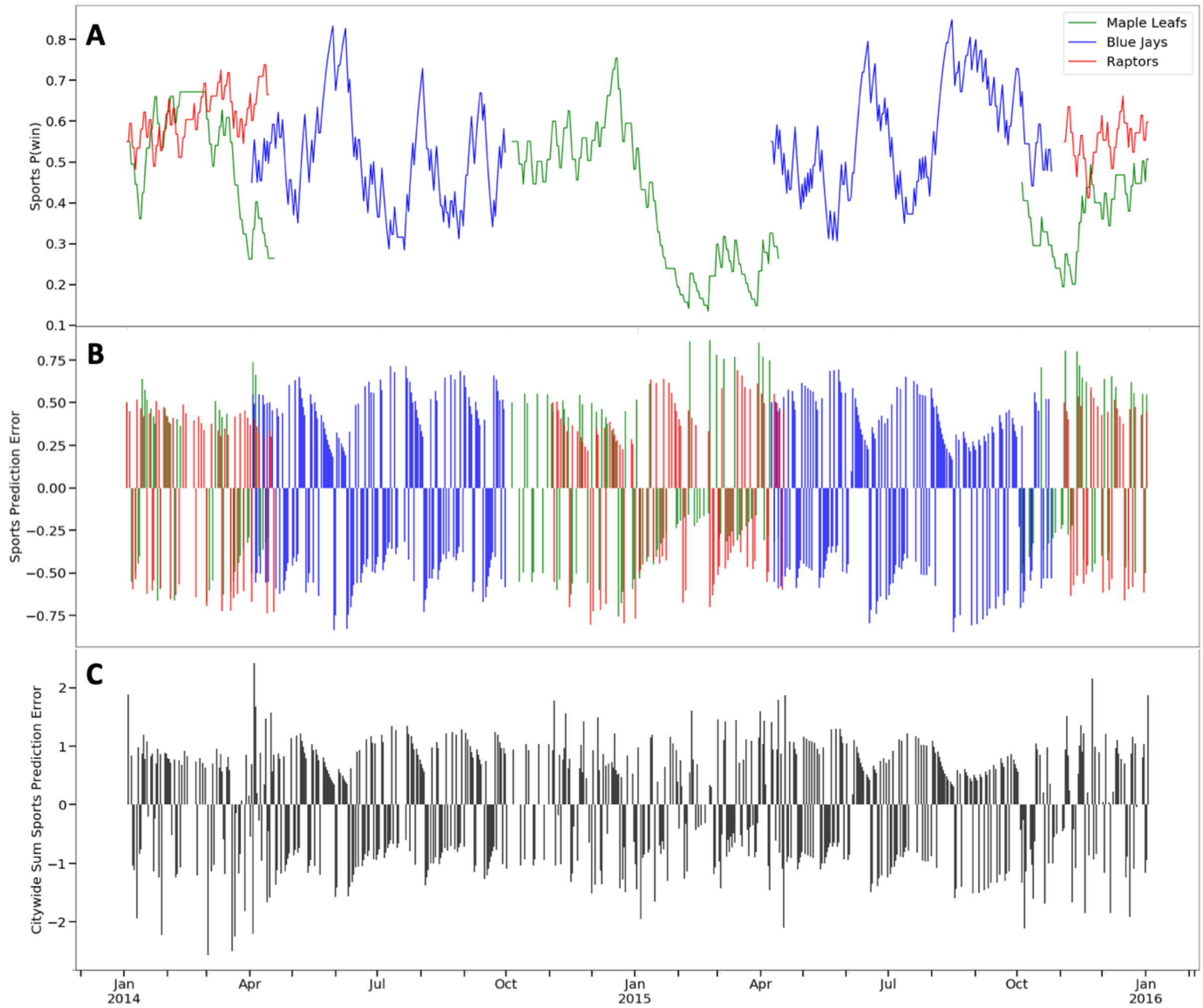

Fig. 3. Calculation of sports-based prediction errors. (A) The exponentially weighted estimates of winning probabilities, *P(win)*, for each of the three teams. The estimate is updated after every game based on their predicted probability of winning. (B) The prediction error associated with winning calculated as the difference between the outcome and the modelled *P(win)*. (C) City-wide sports-based prediction error calculated by summing each team's prediction error for each day, which mirrors a composite deviation from expectation among teams.

Data Analysis Approach

For each FSA, we summed the sales of lottery tickets and divided the composite by the adult population associated with the FSA to control for population differences across FSAs (Oster, 2004; Otto & Eichstaedt, 2018; Otto et al., 2016), which was then log-transformed to yield our dependent measure of log purchases per adult. For the analysis, there were 69,337 observations over the two-year period. Linear regressions were then conducted as mixed-effects models, performed using the lme4 package (Pinheiro & Bates, 2000) in the R programming language. The linear regression specification included all the dummy-coded nuisance regressors described above, with all predictor variables (both nuisance variables and variables of interest) taken as random effects over FSAs.

Results

Overall Lottery Data Characteristics

For each FSA, we aggregated the dollar sales of each ticket and divided this composite by the FSA's population, computing a composite-per-capita score of lottery gambling (Fig. 1A). Influences of the nuisance variables (day-of-week, month-of-year, etc.) were removed using the mixed-effects regression, resulting in residual timecourses of lottery gambling for each postal code (Fig. 1B). The observation that these residual timecourses of gambling correlate across neighbourhoods suggests that common causes, unexplained by cyclicality or seasonality, might influence these apparent fluctuations in city-wide gambling behaviour (mean $r = 0.39$ across all FSAs in 2014 and 2015).

Across the four regression models described below (Tables 1–4), we consistently observed cyclical effects such as day-of-week and month-of-year (i.e., seasonality) effects typically observed in lottery purchase behaviour (Otto et al., 2016). Interestingly, we also observed significant increases in lottery gambling on the first day of the month (a common paycheque receipt day), marked decreases on statutory holidays (presumably due to retailers being closed or gamblers engaging in other activities), and an overall higher rates of lottery gambling in the year 2014, relative to 2015.

Sunshine-Based Prediction Errors and Lottery Gambling

We examined if the timecourse Sunshine Prediction Errors—which quantify how each day's sunshine level deviates from recent expectations (Fig. 2B)—positively predicted day-to-day lottery gambling on the same day, finding that positive changes in sunshine (e.g., a sunny day following a prolonged period of cloudiness) predicted increased lottery gambling levels on the same day (Fig. 4A). Statistically, a mixed-effects linear regression revealed a significant predictive effect of this sunshine-based prediction error on fixed-prize lottery ticket sales ($\beta_{Irradiance\ PE} = 0.0025$, $p < 0.0001$; Table 1).

To determine whether the effect of weather on lottery purchase was due to unexpected outcomes or simply from good weather in general, we performed another mixed-effects linear regression that included both sunshine-based prediction error and daily sunshine levels as predictors (Fig. 4B). Statistically, both effects significantly predicted lottery gambling rates ($\beta_{Irradiance\ PE} = 0.0184$, $p < 0.0001$; Table 2) but, unexpectedly, overall sunshine level exerted a significant negative effect on purchase rates ($\beta_{Irradiance} = -0.0178$, $p < 0.0001$), suggesting that sunnier days were associated with lower levels of lottery gambling. Finally, we note that while Fig. 4B depicts, at the highest value of sunshine—at the DNI level of approximately 620, constituting a small minority of observations—an increase in purchasing rates relative to smaller values of sunshine, our regression results capture an overall (linear) negative relationship present in the bulk of the observations examined at lower values of sunshine.

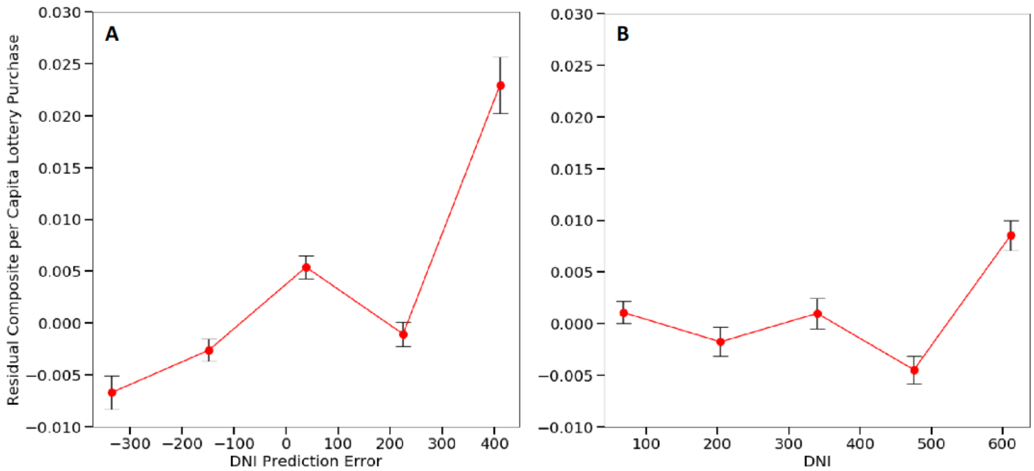

Fig. 4. Fixed-prize lottery purchases as a function of predicted and total sunshine levels. (A) Prediction errors stemming from solar irradiance are correlated with an increase in fixed-prize lottery purchases on that day. (B) High solar irradiance (DNI) is correlated to a decrease in fixed-prize lottery purchases on that day.

Sports-Based Prediction Errors and Lottery Gambling

Similarly, we examined how city-wide sports-based prediction errors (Fig. 3C)—which are positive when the city's teams perform better than expected and negative when the city's teams perform worse than expected—had predictive bearing on per capita lottery gambling rates on the following day. We found that this predictive relationship was positive, even after controlling for a number of cyclical and seasonal nuisance variables: when city-wide sports prediction errors were positive, city-wide lottery purchase rates increased the next day; when the city-wide sports prediction error was negative, city-wide lottery purchases decreased on the next day (Fig. 5A). We found that there was a statistically significant predictive effect of city-wide sports prediction error on fixed-prize lottery ticket sales on the following day (Mixed effects regression $\beta_{Citywide\ Sports\ PE} = 0.0029$, $p < 0.0001$; see Table 3 for full coefficient estimates).

To ascertain whether the effect of sports on lottery gambling was attributable to prediction errors, controlling for the number of wins on the previous day, we estimated another mixed-effects linear regression, which included both sports-based prediction error on the previous day and number of wins on the previous day as predictor variables (Fig. 5B). In this regression, sports wins appeared to exert a significant and positive predictive effect on lottery purchase rates, but the predictive effect of unexpected sports wins did not emerge as significant ($\beta_{Citywide\ Sports\ PE} = 0.0010$, $p = 0.3336$; $\beta_{Citywide\ Sports\ Wins} = 0.0025$, $p = 0.0287$; Table 4), suggesting that absolute, rather than unexpected, success in local sports was a stronger determinant of lottery gambling.

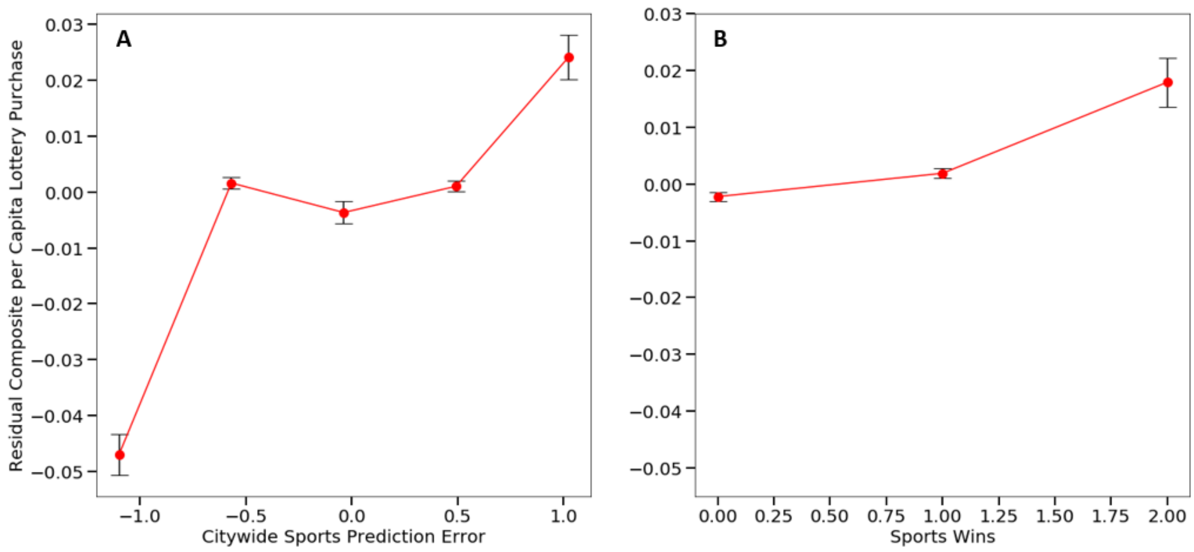

Fig. 5. Fixed-prize lottery purchases as a function of predicted and total sports wins. (A) Prediction errors from Toronto sporting events are positively associated with an increase in fixed-prize lottery purchases the day after the game. (B) City-wide sport wins are also positively associated with increases in fixed-prize lottery purchases the following day.

Discussion

In a large Canadian metropolitan area, we found evidence suggesting that the relationship between unexpected outcomes in the environment—that is, weather and sports—and fixed-prize lottery gambling might be dependent on outcome type. We observed that unexpected sunshine prediction error has a significant positive relationship with lottery purchase rates, replicating previous results (Otto & Eichstaedt, 2018; Otto et al., 2016). On a day that had the largest observed sunshine prediction error, we observed a 0.0483% increase in fixed-prize lottery purchase rates. However, we also uncovered an unexpected overall negative effect of absolute sunshine levels on lottery purchase rates—sunnier days appeared to be associated with lower levels of lottery gambling.

With respect to local sports outcomes, we did not find that unexpected sports wins (i.e., prediction errors) emerged as a significant predictor of lottery gambling behaviour, but absolute sports outcomes—that is the proportion of teams winning on the previous day—did predict lottery purchase rates. On days following the maximum observed number of sports wins (i.e., two days), we observed a 0.007% increase in fixed-lottery sales. An explanation for this phenomenon might be due to sports fans' desire to 'continue playing' or 'continue winning,' which might lead to an increased desire to participate in gambling activities. Interestingly, these sports findings dovetail well with previous work revealing how sports outcomes themselves—irrespective of expectations—drive stock market returns, presumably due to investor mood shifts (Edmans et al., 2007).

This pattern of results does not fully replicate our previous study in New York City (Otto et al., 2016), which found that only unexpected—but not absolute—sports wins predicted increased gambling rates. One potential explanation for these divergent results is the differences in sports culture. In New York City—the setting of the Otto et al. (2016) study—there are currently 13 major sports teams across seven leagues compared to four teams in four leagues in Toronto. The New York metropolitan area is also home to six different venues for their major teams (including Barclays Center, Citi Field, Madison Square Garden, and MetLife Stadium), whereas Toronto only has three (Scotiabank Arena, Rogers Centre, BMO Field). A greater number of teams and stadiums is a sign of an increased presence of sports culture in everyday life, suggesting that professional sports may exert more influence in New York City compared to Toronto. Additionally, Toronto's professional hockey team—the Maple Leafs, which constituted a large amount of the sports outcomes in question—performed generally poorly during the time period in question (see Fig. 3A), so it is possible that Toronto residents had a blunted affective response to unexpected outcomes, possibly due in part to limited interest or attention in games stemming from poor performance (Paul & Weinbach, 2013). Finally, we should note the possibility that the increases in lottery gambling observed after local sports wins in Toronto could be driven by short-term increases in disposable income resulting from sports gambling payouts. Relatedly, this sensitivity to sports outcomes might be amplified by individuals either attending 'home' sporting events or gathering with others to watch sporting events socially, who would be inclined to purchase tickets away from their homes to continue their experience of play (Reith, 2002).

Similarly, the colder climate of Toronto (compared to New York City) may explain the observation here that Toronto residents purchased fewer lottery tickets on sunnier days, as on these days they may seek alternate outdoor activities (possibly further away from lottery retailers). In contrast, in New York City, we only observed that *prediction errors* stemming from sunshine—rather than sunshine levels themselves—reliably predicted lottery gambling behaviour (Otto et al., 2016).

Although our analysis demonstrated how prediction errors (or outcomes) in the environment can affect fixed-prize lottery purchases, due to the nature of the dataset, a possible limitation arises from the inability to discern purchases from residents of the FSA from purchases by non-residents (e.g., commuters). We attempted to address this problem by excluding FSAs with low populations (less than 1000 residents): this mainly targeted commercial FSAs in the downtown area of Toronto, which have inflated lottery purchase rates presumably due to commuter activity. In a recent examination of this same dataset, we found that fixed-prize lotteries are purchased more by individuals in lower-socioeconomic status (SES) than in higher-SES neighborhoods (Fu et al., 2021), suggesting that the observed purchase rates of individual FSAs likely reflects the behaviour of their residents. At the same time, SES has previously been linked to problem gambling (Orford et al., 2010; Welte et al., 2004). While the effect sizes of the sunshine- and sports-based prediction errors observed in the present study are rather subtle compared to these SES effects, the generality of the prediction error effects (particularly with respect to sunshine) across geographies is noteworthy. Moving forward, it would be beneficial to investigate the number of retailers within each FSA and its relation to lottery purchases, as previous studies have found that the density of electronic gambling machines was negatively correlated with SES (Raisamo et al., 2019). Relatedly, online lottery ticket purchasing was introduced by OLG at the beginning of 2015 (midway through the period we analyzed), but our dataset only covers in-person lottery ticket purchases. Future work could investigate the effects of introducing online lotto play and the differences between spending behaviours in online versus offline gambling.

These findings sharpen our understanding of Canadians' gambling behaviours in a large, diverse metropolitan region. Previous research has demonstrated that individuals engage in lottery gambling for reasons beyond pure financial gain: it can become embedded in everyday life, taking on a broad range of meanings that vary across cultures and contexts (e.g., Bedford, 2021; Casey, 2008; Nicoll, 2019). The present research contributes to a growing body of work aimed at deepening our understanding of the way consumption practices inform both culture and the subjective and material realities of gamblers (Casey, 2008). For example, our results suggest that the relationship between environmental factors, such as sunshine, and lottery gambling might be more complex than weather merely affecting accessibility to lottery point-of-sales. Indeed, previous work suggests more subjective motivations for lottery play such as the desire to win, curiosity, and intrinsic enjoyment of lottery play (Miyazaki et al., 1999)—this potential link to the day-to-day changes in lottery gambling rates observed here warrants further exploration.

Lottery gambling is, for the most part, seen as a relatively harmless leisure activity that, despite widespread participation, results in low rates of associated gambling-related problems (e.g., Costes et al., 2018). However, these results remain valuable in accurately understanding the external influences on gambling behaviour; specifically, the environmental factors that shape individuals' day-to-day decisions to gamble.

Authors' Note

Raw data pertaining to this study can be accessed via the Open Science Framework at https://osf.io/eh8xb.

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Table 1
Mixed-effects regression coefficients for model estimating effect of Solar Irradiance prediction errors (PEs) on log per-person lottery purchases. Predictor variables in capital letters denote nuisance variables coding for year (2014 vs. 2015), day of week, month of year, the first and fifteenth of the month, and statutory holidays.

Coefficient	*Estimate*	*Std. Error*	*p-value*
(Intercept)	-3.1232	0.0846	<0.0001*
Irradiance PE	**0.0025**	**0.0006**	**<0.0001***
YEAR_2014	0.1283	0.0110	<0.0001*
TUE	0.0652	0.0038	<0.0001*
WED	0.2945	0.0053	<0.0001*
THU	0.1084	0.0043	<0.0001*
FRI	0.2264	0.0057	<0.0001*
SAT	0.2161	0.0221	<0.0001*
SUN	-0.1982	0.0320	<0.0001*
FEB	-0.0475	0.0061	<0.0001*
MAR	-0.0682	0.0074	<0.0001*
APR	-0.0840	0.0083	<0.0001*
MAY	-0.0687	0.0095	<0.0001*
JUN	-0.0580	0.0100	<0.0001*
JUL	-0.0510	0.0087	<0.0001*
AUG	-0.1048	0.0082	<0.0001*
SEP	-0.1124	0.0087	<0.0001*
OCT	0.0007	0.0102	0.9472
NOV	-0.0417	0.0118	0.0004*
DEC	-0.0595	0.0106	<0.0001*
FIRST_OF_MONTH	0.0312	0.0042	<0.0001*
FIFTEENTH_OF_MONTH	0.0006	0.0038	0.8697
VICTORIADAY	-0.3270	0.0379	<0.0001*
LABOURDAY	-0.2759	0.0356	<0.0001*
FAMILYDAY	-0.3256	0.0376	<0.0001*
GOODFRIDAY	-0.3334	0.0343	<0.0001*
NEWYEARSDAY	-0.6054	0.0636	<0.0001*
THANKSGIVING	-0.3189	0.0410	<0.0001*
CANADADAY	-0.3924	0.0375	<0.0001*
CHRISTMASDAY	-0.6490	0.0645	<0.0001*
BOXINGDAY	-0.1809	0.0264	<0.0001*

Table 2
Mixed-effects regression coefficients for model estimating effect of Solar Irradiance PEs and Solar Irradiance on log per-person lottery purchases.

Coefficient	*Estimate*	*Std. Error*	*p-value*
(Intercept)	-3.1312	0.0846	<0.0001*
Irradiance PE	**0.0184**	**0.0028**	**<0.0001***
Irradiance	**-0.0178**	**0.0030**	**<0.0001***
YEAR_2014	0.1257	0.0110	<0.0001*
TUE	0.0652	0.0038	<0.0001*
WED	0.2942	0.0053	<0.0001*
THU	0.1084	0.0043	<0.0001*
FRI	0.2266	0.0057	<0.0001*
SAT	0.2162	0.0215	<0.0001*
SUN	-0.1983	0.0310	<0.0001*
FEB	-0.0457	0.0061	<0.0001*
MAR	-0.0566	0.0076	<0.0001*
APR	-0.0716	0.0086	<0.0001*
MAY	-0.0567	0.0097	<0.0001*
JUN	-0.0446	0.0102	<0.0001*
JUL	-0.0347	0.0091	0.0001*
AUG	-0.0868	0.0087	<0.0001*
SEP	-0.0969	0.0091	<0.0001*
OCT	0.0090	0.0103	<0.0001*
NOV	-0.0373	0.0118	<0.0001*
DEC	-0.0636	0.0106	<0.0001*
FIRST_OF_MONTH	0.0328	0.0042	<0.0001*
FIFTEENTH_OF_MONTH	-0.0008	0.0038	0.8418
VICTORIADAY	-0.3286	0.0370	<0.0001*
LABOURDAY	-0.2739	0.0348	<0.0001*
FAMILYDAY	-0.3255	0.0365	<0.0001*
GOODFRIDAY	-0.3325	0.0335	<0.0001*
NEWYEARSDAY	-0.6138	0.0617	<0.0001*
THANKSGIVING	-0.3149	0.0399	<0.0001*
CANADADAY	-0.3972	0.0364	<0.0001*
CHRISTMASDAY	-0.6520	0.0630	<0.0001*
BOXINGDAY	-0.1807	0.0261	<0.0001*

Table 3
Mixed-effects regression coefficients for model estimating effect of City-wide (Sum) Sports PEs on log per-person lottery purchases.

Coefficient	*Estimate*	*Std. Error*	*p-value*
(Intercept)	-3.1078	0.0847	<0.0001*
Citywide Sports PE	**0.0029**	**0.0007**	**<0.0001***
YEAR_2014	0.1180	0.0109	<0.0001*
TUE	0.0649	0.0040	<0.0001*
WED	0.2877	0.0052	<0.0001*
THU	0.1046	0.0044	<0.0001*
FRI	0.2243	0.0058	<0.0001*
SAT	0.2121	0.0221	<0.0001*
SUN	-0.1938	0.0322	<0.0001*
FEB	-0.0539	0.0054	<0.0001*
MAR	-0.0830	0.0072	<0.0001*
APR	-0.0885	0.0080	<0.0001*
MAY	-0.0781	0.0093	<0.0001*
JUN	-0.0671	0.0098	<0.0001*
JUL	-0.0606	0.0088	<0.0001*
AUG	-0.1127	0.0079	<0.0001*
SEP	-0.1225	0.0084	<0.0001*
OCT	-0.0418	0.0105	<0.0001*
NOV	-0.0471	0.0114	<0.0001*
DEC	-0.0631	0.0103	<0.0001*
FIRST_OF_MONTH	0.0402	0.0044	<0.0001*
FIFTEENTH_OF_MONTH	-0.0051	0.0042	0.224203
VICTORIADAY	-0.3255	0.0382	<0.0001*
LABOURDAY	-0.2840	0.0360	<0.0001*
GOODFRIDAY	-0.3878	0.0371	<0.0001*
NEWYEARSDAY	-0.6293	0.0632	<0.0001*
THANKSGIVING	-0.2904	0.0405	<0.0001*
CANADADAY	-0.2531	0.0363	<0.0001*

Table 4
Mixed-effects regression coefficients for model estimating effect of City-wide (Sum) Sports PEs and City-wide Sports Wins on log per-person lottery purchases.

Coefficient	*Estimate*	*Std. Error*	*p-value*
(Intercept)	-3.1221	0.0850	<0.0001*
Citywide Sports PE	**0.0010**	**0.0011**	**0.3336**
Citywide Sports Wins (z-scored)	**0.0025**	**0.0011**	**0.0287***
YEAR_2014	0.1274	0.0111	<0.0001*
TUE	0.0641	0.0038	<0.0001*
WED	0.2875	0.0051	<0.0001*
THU	0.1072	0.0041	<0.0001*
FRI	0.2271	0.0057	<0.0001*
SAT	0.2150	0.0221	<0.0001*
SUN	-0.1968	0.0321	<0.0001*
FEB	-0.0445	0.0063	<0.0001*
MAR	-0.0741	0.0073	<0.0001*
APR	-0.0840	0.0082	<0.0001*
MAY	-0.0687	0.0096	<0.0001*
JUN	-0.0578	0.0101	<0.0001*
JUL	-0.0499	0.0088	<0.0001*
AUG	-0.1048	0.0083	<0.0001*
SEP	-0.1120	0.0088	<0.0001*
OCT	0.0000	0.0102	0.9982
NOV	-0.0447	0.0119	<0.0001*
DEC	-0.0565	0.0107	<0.0001*
FIRST_OF_MONTH	0.0311	0.0042	<0.0001*
FIFTEENTH_OF_MONTH	0.0026	0.0038	0.4891
VICTORIADAY	-0.3247	0.0378	<0.0001*
LABOURDAY	-0.2806	0.0353	<0.0001*
FAMILYDAY	-0.3232	0.0379	<0.0001*
GOODFRIDAY	-0.3351	0.0346	<0.0001*
NEWYEARSDAY	-0.6118	0.0635	<0.0001*
THANKSGIVING	-0.3232	0.0413	<0.0001*
CANADADAY	-0.3881	0.0377	<0.0001*
CHRISTMASDAY	-0.6535	0.0642	<0.0001*
BOXINGDAY	-0.1809	0.0262	<0.0001*