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The shape of gambling risk-curves for frequency, expenditure, and proportion of income in Australia.

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Abstract

**Background and aim:** Examining risk-curves is important to understanding the degree to which indices of gambling consumption are associated with gambling-related harm. Risk-curves have largely been described as J-shaped, suggesting that at low levels of consumption harm remains constant but then increases sharply at a certain threshold. Alternative methods in recent work, however, have described risk-curves as linear and r-shaped, indicating that risk of harm increases as consumption increases, at all levels of consumption. The aim of the current study is to estimate the shape of gambling risk-curves using competing methods.

**Design:** Systematic comparison of gambling risk-curves using categorical (via plots) and continuous (via bootstrapped regression analyses) operationalisations of gambling consumption.

**Setting and participants:** Data were 2,873 gamblers (1,417 women) from the fourth Social and Economic Impact Study of Gambling in Tasmania.

**Measurements:** Gambling-related harm was assessed using the Problem Gambling Severity Index (PGSI) and Short Gambling Harm Screen (SGHS). Gambling consumption was assessed as annual frequency, expenditure, and expenditure as a proportion of income.

**Findings:** Categorical gambling consumption data plotted with equal magnitudes evidenced J-shaped risk-curves. When the magnitude of gambling categories was rescaled to the midpoints, risk-curves no longer appeared J-shaped. Additionally, bootstrapped regression analyses using the continuous gambling consumption data did not provide evidence for J-shaped risk-curves.
Conclusions: Gambling risk-curves in Tasmania appear not to be J-shaped, but rather suggest that risk of gambling-related harm increases with even small increases in gambling consumption.

Key words: risk-curves, gambling, gambling harm, gambling limits

1 Introduction

Examining risk (dose-response) curves is an important step in understanding the degree to which indices of gambling consumption are associated with gambling-related harm. Currie and colleagues (1) were the first to examine the relationship between indices of gambling consumption and risk of gambling-related harm. Based on results from a large Canadian sample (n = 19,012), using categorical measurements of gambling frequency (e.g., 1-5 times/years), expenditure (e.g., $0-$50), and expenditure as a proportion of income (e.g., midpoint 0.04%) they describe the risk-curves as J-shaped. A J-shaped risk-curve suggests that the chances of experiencing gambling-related harm (e.g., endorsement of ≥ 2 negative consequence on the Problem Gambling Severity Index [PGSI]) is low and remains constant at low levels of gambling consumption, but then increases sharply when a certain threshold of gambling consumption is reached. The J-shape risk-curve has been identified in subsequent research using similar methodologies (2,3), with some results even suggesting that low-level gamblers may experience less harm than very low-level gamblers, although the degree of protection is likely relatively small (3).

Recently, however, Markham, Young, and Doran (4) questioned the shape of these risk-curves. Based on secondary analysis of data from four nationally representative cross-
sectional surveys of adults in Australia (n=10,632), Canada (n=3,120), Finland (n=4,484), and Norway (n=5,235), they argue that the J-shape of previously identified risk-curves (1,2) is an artefact of the categorical data (4). Specifically, of concern was that risk-curves were visualised by treating ordered-categorical gambling consumption data as though categories were of equal magnitude. Recoding of Currie and colleagues (1,2) expenditure data using category mid-points and dropping the final open-ended bracket was suggestive of a linear relationship. Moreover, subsequent bootstrapped linear regression analyses estimating the shape of gambling expenditure risk-curves and multiple continuous measures of problem gambling severity (PGSI, South Oaks Gambling Screen, and NORC diagnostic screen) found that risk-curves were either linear or r-shaped. R-shaped curves suggest no low-risk region of the curve with risk of harm increasing rapidly as gambling expenditure increases. Linear relationships also suggest no low-risk region of the curve and imply a linear increase in risk of harm as gambling expenditure increases.

While both Currie’s and Markham’s methodological approaches share some similarities, there are key differences which make comparisons difficult. First, while both methods attempt to deal with the presence of outliers (predominately in gambling consumption) Currie et al. (1–3) categorise data, whereas Markham et al. (4) employ bootstrapping. Second, to date, Markham et al.’s approach has not been extended to other indices of gambling consumption, such as gambling frequency or gambling expenditure as a proportion of income. Third, the two methodologies operationalise harm differently. While both studies employed measures of problem gambling severity to measure gambling-related harm, Currie et al. (1–3) derived risk-curves using the proportion of individuals experiencing...
harm, whereas Markham et al. (4) employed total scores. While it has been argued that the PGSI is a viable instrument to measure gambling-related harm because it emphasises negative consequences over behavioural symptoms (5), the examination of risk-curve shape could be enhanced by using recently developed validated measures of harm attributable to gambling, such as the Short Gambling Harms Screen (SGHS) (6).

Considering the ongoing debates, there remains a need to further explore the shape of gambling risk-curves to inform the dose-response relationships between gambling consumption and gambling-related harm, with the aim of informing low-risk gambling guideline development. The current study therefore aims to estimate the shape of gambling risk-curves and compare: (1) categorical and continuous operationalisations of gambling consumption indices; (2) multiple gambling consumption indices (gambling frequency, expenditure, and expenditure as a proportion of income); and (3) binary and continuous operationalisations of the problem gambling severity (PGSI) and gambling harm (SGHS).

### 2 Methods

#### 2.1 Participants

Data were from the fourth Social and Economic Impact Study (SEIS) of Gambling in Tasmania (7). Data was collected via Computer Assisted Telephone Interviews (CATI) with 5,000 residents of Tasmania aged 18 years and over from 13 June to 7 August 2017. The average interview duration was 15 minutes. Further details regarding data collection are presented in the original report (7). Of the total sample, the current study utilised those who...
The shape of gambling risk-curves reported past-year gambling participation (n=2,873, 1,417 women). This project was approved by the Deakin University Human Research Ethics Committee (2017-145).

2.2 Measures

Measures of gambling-related harm and consumption are described in Table 1.

**INSERT TABLE 1 HERE**

2.3 Statistical analysis

All analyses were conducted in Stata 15 (11). Analyses were not preregistered. Missing data were removed via pairwise deletion, due to the low level of missing amongst exposure (gambling consumption) and outcome (harms) variables (range <1% to 5%), with exception of expenditure as a proportion of income (19%).

*Categorical methodology.* For the categorical approach to gambling consumption, each gambling consumption variable was categorised into 6 equal percentile-groups representing increasing levels of behaviour. A series of plots were then conducted to examine risk-curve shape: 1) PGSI and SGHS scores (i.e., mean scores for continuous harm outcomes; mean proportion endorsing harm for binary harm outcomes) for which each level of gambling consumption was plotted with equal magnitude on the x-axis; 2) plots repeated whereby the categorical measures of gambling consumption are rescaled to the midpoint, in order to capture differences in magnitude between gambling consumption categories; and 3) to further examine risk-curve shape at the lower ends of gambling consumption, plots were repeated using the rescaled categories and a reduced range where the highest category of gambling consumption was dropped. Risk-curve shape was determined via visual inspection.
**Continuous methodology.** Based on the approach described by Markham et al. (4) linear (for continuous outcomes) and logistic (for binary outcomes) regression analyses were used, whereby each outcome was regressed onto continuously measured gambling consumption variables. To aid in the interpretation of risk-curve shape, all continuous exposures and harm outcomes were standardised (z-scores). Both linear and quadratic terms of gambling consumption were included in the regression models. To reduce the impact of outliers, regressions were estimated using 1,000 bootstrapped samples. The shape of the risk-curve was inferred by interpreting the direction of estimated regression coefficients. Specifically, the linear coefficient infers the direction of the linear shape, a positive quadratic term implies an upward inflection (e.g., a J-shape or U-shape), and a negative quadratic term implies a downward inflection (e.g., r-shape or inverted U-shape). Plots of the bootstrapped regression line are presented for visual aid.

3 Results

3.1 Categorical methodology

Based on 6 equal percentile-groups categorical variables were operationalised (midpoint in square brackets) as: Frequency (times per year) = 0-3 [1.5], 4-8 [6.0], 9-22 [5.5], 23-52 [37.5], 53-65 [59.0], 66-1479 [772]; Expenditure (expenditure per year) = 0-35 [17.5], 36-104 [70.0], 105-260 [182.5], 262-557 [409.5], 560-1248 [904.0], 1250-48340 [24795]; Expenditure as a proportion of income (% of median disposable income) = 0-0.1 [0.04], 0.1-0.3 [0.2], 0.3-0.7 [0.5], 0.7-1.7 [1.2], 1.7-4.0 [2.9], 4.1-100 [52.0].
Figure 1 presents the shape of gambling risk-curves using categorical measurements of gambling consumptions, illustrated using the continuous and binary PGSI outcome (full scale). Risk-curves using the negative consequences items of the PGSI and SGHS showed similar patterns of results and are presented in the Supplementary Material (Figure S1, S2).

When categories of gambling consumption were plotted with equal magnitude, all gambling risk-curves appeared J-shaped, whereby increases in gambling harm appeared notably only for the final category (i.e., largest amount of consumption). When gambling consumption categories were re-scaled using the midpoint (to capture differences in magnitude in gambling consumption) the increases in gambling harm observed at the final category, now, appeared much more gradual and no longer J-shaped. When the final category was removed from the plots entirely, the patterns of harm outcomes at lower levels of consumption now appeared r-shaped. Results were similar across all exposure-outcome risk-curves.

3.2 Continuous methodology

Table 2 presents the results of the bootstrapped linear and logistic regression analyses (using continuous gambling consumption indices). Results for all models included positive linear terms (continuous outcomes: \( b \) range=0.22 to 0.50; binary outcomes: \( b \) range=0.72 to 1.32) and negative quadratic terms (continuous outcomes: \( b \) range=-0.01 to -0.03; binary outcomes: \( b \) range=-0.03 to -0.06), suggesting that the shape of risk-curves was not J-shaped.
The shape of gambling risk-curves

Figure 2 visualises the estimated shape of the risk-curves. Patterns were largely consistent across outcome measures and continuous and binary operationalisations.

**Discussion**

The current study sought to extend investigations into the shape of gambling risk-curves by comparing the relationship between gambling consumption indices and gambling harm using varied methods. Gambling consumption was examined via various indices both categorically and continuously. Similarly, gambling harm was examined using binary and continuous operationalisations of both the PGSI and SGHS. Overall, findings did not suggest that gambling risk-curves were J-shaped. Findings were robust across varied operationalisations of gambling consumption and gambling-related harm. These findings support suggestions that the previously identified J-shaped risk-curves (1) may be an artefact of erroneously representing categorical brackets of gambling consumptions as having equal magnitude (4).

When plotted as having equal magnitudes, categorical gambling consumption displayed J-shaped risk-curves, suggesting that, at a certain point, levels of harm increase drastically. However, when data were plotted using the mid-points of each of the gambling consumption categories, the J-shape was no longer apparent. Specifically, the final category of gambling consumption (i.e., with the highest level of gambling consumptions) appeared to drive much of the original J-shaped curve. When this category was more appropriately scaled
The shape of gambling risk-curves

along the x-axis, the added distance from the lower categories highlighted differences in the magnitude of gambling consumption indices and no longer supported a J-shaped risk-curve. To observe the pattern of harm at the lower categories of gambling consumption, the final category of gambling consumption was removed from the plots. Even at low levels of gambling consumption, there appeared to be increases in harm, as gambling consumption indices increased.

Moreover, bootstrapped linear (for continuous harm outcomes) and logistic (for binary harm outcomes) regressions did not identify any J-shapes. Specifically, all models identified risk-curves marked by positive linear terms and negative quadratic terms. The impact of outliers in these analyses is reduced using bootstrapping. Together these findings support previous suggestions that the J-shaped risk-curves presented throughout the literature are likely to be the product of misrepresenting the relevant magnitude of categorical data points (4).

There are, however, some limitations to note. First, the data used in the current study rely upon self-report gambling consumption that may have resulted in some underestimation of behaviour (12), however, the rank order of responses is likely to be consistent (2,13). Second, the risk-curves are based on cross-sectional data, which makes the temporal sequence of exposure (gambling consumption) and outcome (harms) unclear. Given associations between gambling consumption and subsequent gambling harm (9), it is possible that similar risk-curves would be observed prospectively, however, further research is needed to explore this. Third, the current study does not examine the shape of risk-curves for specific gambling activities. Previous literature has identified variation in the relationship between
gambling consumption and harm across gambling activities (3,4,14,15). Additionally, it has been noted that individual factors, such as past problem gambling, may present with additional vulnerability (16). As such, further research examining risk-curves across gambling types and vulnerable populations remains necessary. Finally, the current study utilises data from only one jurisdiction and the relationships between gambling consumption indices and harms may differ in other contexts. While previous work has found similar gambling risk-curve shapes across multiple western countries (4), there exists a need to examine risk-curves in other socio-cultural environments.

Despite these limitations, this systematic comparison of gambling risk-curves suggests that they are not J-shaped, which provides some support for the argument that gambling at any levels appears to carry some level of risk and that risk increases rapidly with even small increases in gambling consumption (9). These findings have implications for the development of low-risk limits, whereby limits may need to be based on tolerable levels of absolute risk (4,17,18), as opposed to at an amount of consumption at which risk rapidly increases thereafter. The amount of tolerable risk from gambling (19), however, can be somewhat arbitrary and needs to be defined before absolute risk methods can be employed (17,18). Future work, including qualitative interviews with the general population and vested public health groups, is needed to define and examine potential acceptable levels of absolute risk.
References


Table 1. Summary of problem gambling severity, gambling harm, and gambling consumption measures

### Measures of gambling-related harm

<table>
<thead>
<tr>
<th>Measure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Problem gambling severity</strong></td>
<td>9-item Problem Gambling Severity Index (PGSI) (8). The PGSI was scored using all 9 items and using just the 7 negative consequences items (3, 9). Binary variables were also derived to indicate the endorsement of 2 or more items.</td>
</tr>
<tr>
<td><strong>Gambling harm</strong></td>
<td>10-item Short Gambling Harm Screen (SGHS) (6). The SGHS was scored using all 10 items. Binary variables were also derived to indicate the endorsement of 2 or more items.</td>
</tr>
</tbody>
</table>

### Gambling consumption indices

<table>
<thead>
<tr>
<th>Measure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gambling frequency</strong></td>
<td>Assessed as ‘In the last 12 months, how many times per week, per month or per year have you played/bet on [gambling activity]?’ for different modalities (e.g., venue, telephone, racetrack, off-course venue, internet on mobile device, internet using desktop computer) of each gambling activity. Annual gambling frequency was calculated by standardising each response to an estimated yearly frequency then summing these yearly frequencies across gambling activities.</td>
</tr>
<tr>
<td><strong>Gambling expenditure</strong></td>
<td>Assessed as ‘In the past 12 months, approximately how much money, on average, did you spend during each session of [gambling activity]?’ for each specific gambling activity. Total annual gambling expenditure was calculated by multiplying gambling frequency with session expenditure estimates for each activity then summing these yearly gambling expenditures across all gambling activities. Gambling expenditure was assessed only in terms of amount of money lost.</td>
</tr>
<tr>
<td><strong>Gambling expenditure as a proportion of income</strong></td>
<td>Assessed using expenditure data and gross annual personal income, assessed as ‘Could you please tell me your approximate annual personal income before tax?’. Categories were in $10,000 increments (from less than $10,000 to $150,000 or more). To derive expenditure as a proportion of income, we used the mid-point of each category’s range to represent the respective income category (e.g. $10,000 to $19,999 became $15,000). For the final income category (e.g. $150,000 more) in which no mid-point exists, the same $5,000 interval that was applied (i.e. $155,000). The midpoint income value was then converted to the median disposable income (10). Total annual gambling expenditure was then divided by the median disposable income value to derive gambling expenditure as a proportion of income.</td>
</tr>
</tbody>
</table>

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proportion of income. Estimates exceeding 100% were recoded to 100%.
Figure 1. Risk-curves using categorical gambling consumption for PGSI (full scale) outcomes. Note: Equal magnitude = Gambling categories plotted on x-axis with equal magnitude; Rescaled to midpoint = Gambling categories plotted on x-axis using the midpoint of each category; Rescaled/reduced range = Gambling categories plotted on x-axis using the midpoint of each category and dropping the final category; Mean scores and proportions presented for continuous and binary outcomes, respectively.
### Table 2. Bootstrapped linear and logistic regression model estimates of gambling consumption and gambling problems and harms risk-curves

<table>
<thead>
<tr>
<th></th>
<th>Continuous outcome</th>
<th></th>
<th>Binary outcome</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b</td>
<td>95% CI</td>
<td>p</td>
<td>b</td>
</tr>
<tr>
<td><strong>PGSI all items</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear</td>
<td>0.24</td>
<td>(0.12, 0.35)</td>
<td>&lt;0.001</td>
<td>0.77</td>
</tr>
<tr>
<td>Quadratic</td>
<td>-0.01</td>
<td>(-0.03, 0.02)</td>
<td>0.604</td>
<td>-0.03</td>
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<tr>
<td>Expenditure</td>
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</tr>
<tr>
<td>Linear</td>
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<td>(0.23, 0.57)</td>
<td>&lt;0.001</td>
<td>1.23</td>
</tr>
<tr>
<td>Quadratic</td>
<td>-0.02</td>
<td>(-0.04, -0.00)</td>
<td>0.037</td>
<td>-0.09</td>
</tr>
<tr>
<td>Proportion of income</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear</td>
<td>0.44</td>
<td>(0.23, 0.66)</td>
<td>&lt;0.001</td>
<td>1.26</td>
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<tr>
<td>Quadratic</td>
<td>-0.03</td>
<td>(-0.05, -0.00)</td>
<td>0.028</td>
<td>-0.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td><strong>PGSI negative consequences items</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear</td>
<td>0.22</td>
<td>(0.12, 0.33)</td>
<td>&lt;0.001</td>
<td>0.72</td>
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<td>(-0.03, 0.01)</td>
<td>0.574</td>
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<tr>
<td>Expenditure</td>
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</tr>
<tr>
<td>Linear</td>
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<td>(0.21, 0.56)</td>
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<td>1.17</td>
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<td>(-0.04, 0.00)</td>
<td>0.084</td>
<td>-0.09</td>
</tr>
<tr>
<td>Proportion of income</td>
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<td></td>
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<tr>
<td>Linear</td>
<td>0.43</td>
<td>(0.20, 0.66)</td>
<td>&lt;0.001</td>
<td>1.32</td>
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<td>Quadratic</td>
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<td>(-0.06, 0.00)</td>
<td>0.061</td>
<td>-0.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>SGHS all items</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Linear</td>
<td>0.30</td>
<td>(0.20, 0.40)</td>
<td>&lt;0.001</td>
<td>1.03</td>
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<td>Expenditure</td>
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<tr>
<td>Linear</td>
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<td>(0.29, 0.63)</td>
<td>&lt;0.001</td>
<td>0.90</td>
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<td>(-0.05, -0.00)</td>
<td>0.034</td>
<td>-0.05</td>
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<tr>
<td>Proportion of income</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>Linear</td>
<td>0.50</td>
<td>(0.31, 0.69)</td>
<td>&lt;0.001</td>
<td>0.95</td>
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<tr>
<td>Quadratic</td>
<td>-0.03</td>
<td>(-0.06, -0.01)</td>
<td>0.001</td>
<td>-0.06</td>
</tr>
</tbody>
</table>

Note: bolded effects with p < 0.05
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The shape of gambling risk-curves

Figure 2. Risk-curve shapes using continuous gambling consumption
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