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A Causality Analysis of Lottery Gambling and Unemployment in Thailand*

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Abstract

Gambling negatively affects the economy, and it brings unwanted financial, social, and health outcomes to gamblers. On the one hand, unemployment is argued to be a leading cause of gambling. On the other hand, gambling can cause unemployment in the second-order via gambling-induced poor health, falling productivity, and crime. In terms of significant effects, previous studies were able to establish an association, but not causality. The current study examines the time-sequence and contemporaneous causalities between lottery gambling and unemployment in Thailand. The Granger causality and directed acyclic graph (DAG) tests employ time-series data on gambling- and unemployment-related Google Trends indexes from January 2004 to April 2021 (208 monthly observations). These tests are based on the estimates from a vector autoregressive (VAR) model. Granger causality is a way to investigate causality between two variables in a time series. However, this approach cannot detect the contemporaneous causality among variables that occurred within the same period. The contemporaneous causal structure of gambling and unemployment was identified via the data-determined DAG approach. The use of time-series Google Trends indexes in gambling studies is new. Based on this data set, unemployment is found to contemporaneously cause gambling, whereas gambling Granger causes unemployment. The causalities are circular and last for four months.

Keywords: Betting, Directed Acyclic Graph, Google Trends, Granger Causality

JEL Classification Code: E24, L83

1. Introduction

Gambling can be defined as "is the wagering something of value ("the stakes") on an event with an uncertain outcome with the intent of winning something of value. Gambling thus requires three elements to be present: consideration (an amount wagered), risk (chance), and a prize" (Williams et al., 2017). Approximately 26% of the world's population engages in gambling (Casino.org, 2021). In terms of prevalence rate, Asia is the region with the highest gambling activities (Williams et al., 2012) and spending (Coleman, 2021). For most individuals, gambling is considered a recreational and enjoyable social activity. However, some people become pathological gamblers, who heavily invest time and money in gambling and suffer personal, social, family, and financial problems (Hodgins et al., 2011).

On the one hand, if it is legalized, gambling can provide economic benefits such as employment and tax revenue (Conner & Taggart, 2009). Economists have also acknowledged the benefits to consumers from the rising utility on gambling and falling prices of entertainment due to increased gambling competition (Productivity Commission, 1999). On the other hand, gambling negatively affects the economy (Walker & Sobel, 2016) and brings unwanted financial, social, and health outcomes to individual gamblers (Muggleton et al., 2021).

2. Literature Review

Unemployment is commonly believed to be one of the leading causes of gambling. This common belief is supported by theory. Tversky and Kahneman (1974) explained causality

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using an availability heuristic. It is easier for the unemployed to imagine the prize won from gambling than to assess the low probability of winning. Nyman (2004) proposed that the unemployed gamble to obtain something for nothing so that they did not have to work to earn income, whereas Abbott et al. (1995) argued that the unemployed chose gambling as a means of escaping from harsh economic situations. Albers and Hübl (1997) and Boreham et al. (1996) noted that the unemployed have a lot of free time so that they could afford the time spent on gambling. In addition, the unemployed tend to suffer from depression and low self-esteem. These poor mental-health conditions reduce self-efficacy to resist an urge to gamble (Sharpe & Tarrier, 1993). Finally, gambling can be considered rational. Gambling income is a source of income that helps improve the welfare of unemployed youths in Africa (Mustapha & Enilolobo, 2019; Wanjohi, 2012).

The employed accumulate tension and frustration from work. Gambling provides them with opportunities to gain feelings of self-reliance and control (Herman, 1967; Merton, 1938). For this reason, the employed tend to gamble more, whereas the unemployed gamble less.

Empirical studies have identified positive effects of unemployment on gambling, for example, Boreham et al. (1996) for Australia, Castrén et al. (2013) for Finland, Mustapha and Enilolobo (2019) for Nigeria, Vongsinsirikul (2012) for Thailand, and Muggleton et al. (2021) for the United Kingdom. Negative effects were reported by Çakıcı et al. (2015) for North Cyprus and Changpetch (2017) and Manprasert (2014) for Thailand, whereas non-significant effects were reported by Albers and Hübl (1997) for Germany, Arge and Kristjánsson (2015) for Iceland, Wanjohi (2012) for Kenya, and McConkey and Warren (1987) for the United States.

Muggleton et al. (2021) cautioned that significant effects could result from the association between unemployment and gambling, not necessarily the causality of unemployment to gambling. The association may result from the causality of gambling to unemployment.

The way gambling causes unemployment is second-order. Gambling eventually leads to unemployment via low productivity due to poor physical and mental health and loss of available time, and crime due to financial problems (Langham et al., 2016). Empirical evidence that supports the positive effects of gambling on unemployment includes Chun et al. (2011), Hofmarcher et al. (2020), and Ladouceur et al. (1994), for example. In a study based in the United Kingdom, Wardle et al. (2018) found that the samples ranked unemployment as the most significant effect of gambling.

Finally, the association may also be due to reciprocal determinism (Bandura, 1986). In a literature review, Hodgins et al. (2011) concluded a bidirectional relationship between gambling and psychiatric disorders. Because poor mental health leads to unemployment, the bidirectional relationship supports the reciprocal determinism of gambling and unemployment.

Whether unemployment causes gambling or gambling causes unemployment, or the relationship is bidirectional and cannot be concluded from empirical evidence. A direct test for causality has not yet been performed (Muggleton et al., 2021). The current study tests the causality relationship between lottery gambling and unemployment in Thailand.

Thailand is an interesting country for gambling studies. Compared with the global prevalence rate of 26% (Casino.org, 2021), Thailand's rate is 45.52%. Heavy gamblers account for 9.45% of the population (Komonpaisarn, 2020). This study focuses specifically on lottery gambling because this is the country's most popular game (Research Centre for Social and Business Development, 2020; Wannathepsakul, 2011).

Granger causality tests (Granger, 1969) and directed acyclic graph (DAG) contemporaneous causality tests (Swanson & Granger, 1997) were conducted based on time series data for lottery gambling and unemployment variables from January 2004 to April 2021 (208 monthly observations). In previous studies, Granger causality tests were applied to examine short-term causality among economic variables such as exchange rates and stock prices by Lee and Brahmasrene (2019), and national income, money supply, and deposit interest rate by Yuliadi (2020). DAG causality tests were employed, for example, by Khanthavit (2019) to check for causality relationship between weather and stock prices.

Although the Granger causality test is a statistical test for predictive causality (Diebold, 2007), the tests are useful. They are developed with respect to the fact that unemployment causes (gambling causes) necessarily lead to gambling effects (unemployment effects). Awokuse et al. (2009) noted that the Granger causality test could not detect the contemporaneous causality among variables that occurred within the same period. Nevertheless, if contemporaneous relationships exist, DAG tests will be able to detect them.

Empirical studies on gambling are traditionally based on self-report, cross-sectional, and small-sample data (Volberg, 2004). Prevalence and unemployment levels are necessarily misstated if gamblers do not provide true answers (Harrison et al. 2020). In terms of gambling expenditure, it is possible that the reported amount is inaccurate. Gamblers could have memory biases (Toneatto et al. 1997). In certain studies (Ladouceur et al., 1994) given population sizes, small sample sizes were insufficient for analyses (Volberg, 2007). Moreover, cross-sectional data limit the ability to test for a time-sequence relationship between gambling and unemployment (Muggleton et al., 2021). Muggleton et al. (2021) tested the relationship between gambling and future unemployment status. The test was possible due to the longitudinal data for U.K. samples from the Lloyds Banking Group, the United Kingdom's largest retail bank.

In this study, the lottery gambling and unemployment variables are Google Trends indexes based on Thailand's Google queries for lucky numbers and job applications, respectively. The use of Google Trends data for gambling studies is new. Google Trends is useful for measuring gambling activities. The index provides deep insights into population behavior (Nuti et al., 2014). Because the gambling index is a national index, it should be able to proxy for the gambling activities of lottery gamblers across the country. To measure the unemployment level, the job-related Google Trends index is superior to the unemployment rate. The index is available immediately and for all time periods, whereas the unemployment rate is available with a lag or sometimes unavailable (Pavlicek & Kristoufek, 2015).

3. Research Method and Data

3.1. The Models

3.1.1. Time-Sequence, Granger Causality

Let G_t and U_t denote the gambling and unemployment levels at time t, respectively. This study model the dynamics of G_t and U_t using bivariate vector autoregression (*VAR*). With respect to the Wold representation theorem, the dynamics can be well approximated by the *VAR* of the finite order p(*VAR*(p)) (Lütkepohl, 2005). Equation (1) is the *VAR*(p) equation:

$$\boldsymbol{Y}_t = B_0 + \sum_{i=1}^{p} B_i \boldsymbol{Y}_{t-i} + \boldsymbol{e}_t \tag{1}$$

where the variable vector $\boldsymbol{Y}'_{t-i} = [G_{t-i}, U_{t-i}]$ and the residual vector $\boldsymbol{e}'_t = \left[e_t^G, \varepsilon_t^U\right]$. $\boldsymbol{e}_t$ has a zero-mean vector and a Ω covariance matrix. The intercept-coefficient vector B'_0 is $\left[b_0^G, b_0^U\right]$; the (2×2) slope coefficient matrix B_i is $\begin{bmatrix} b_i^{GG} & b_i^{GU} \\ b_i^{UG} & b_i^{UU} \end{bmatrix}$. The study chooses the optimal lag p using the Bayesian information criterion (BIC); the BIC consistently gives a lag order under general conditions (Zivot & Wang, 2006).

If unemployment (gambling) does not Granger cause gambling (unemployment), from Equation (1), then $b_1^{GU} = \ldots = b_p^{GU} = 0\left(b_1^{UG} = \ldots = b_p^{UG} = 0\right)$. Under the null hypothesis of Granger non-causality, the F-statistic is distributed as an F variable with $(p + 1, N - 2p - 1)$ degrees of freedom. N denotes the number of observations.

3.1.2. DAG Contemporaneous Causality

The contemporaneous causal structure of gambling and unemployment can be identified via the data-determined DAG approach, which is based on the *VAR* residuals via the Ω covariance matrix.

Let $Pr\left(e_t^G, e_t^U\right)$ be the joint density of residuals $\left[e_t^G, e_t^U\right]$. Equation (2) describes the density of the product decomposition (Pearl, 2000).

$$Pr\left(e_t^G, e_t^U\right) = \prod_{k=G,U} Pr(e_t^k \mid pa^k) \tag{2}$$

where pa^k is the subset of $\left[e_t^G, e_t^U\right]$ that causes e_t^k and $Pr(e_t^k \mid pa^k)$ is the density of e_t^k, conditioned on pa^k.

This study estimates the DAG using the Peter-Clark (PC) causal search algorithm (Spirtes & Glymour, 1991) from the relationship in Equation (2). Five types of DAG relationships between an $\left(e_t^G, e_t^U\right)$ pair are possible. These can be represented by graph edges:

(1) No edge $\left(e_t^G \;\; e_t^U\right)$ indicates independent e_t^G and e_t^U.
(2) Undirected edge $\left(e_t^G — e_t^U\right)$ indicates their correlation, but not causation.
(3) Uni-directed edge $\left(e_t^G \rightarrow e_t^U\right)$ indicates the causality from e_t^G to e_t^U.
(4) Uni-directed edge $\left(e_t^G \leftarrow e_t^U\right)$ indicates the causality from e_t^U to e_t^G.
(5) Bi-directed edge $\left(e_t^G \leftrightarrow e_t^U\right)$ indicates the bidirectional causality between e_t^G and e_t^U.

If unemployment (gambling) contemporaneously causes gambling (unemployment), the DAG relationship $\left(e_t^U \rightarrow e_t^G\right)$ $(e_t^G \rightarrow e_t^U)$ must be significant.

The PC algorithm is based on hypothesis testing for significant correlations and partial correlations between residuals. The significance level is set at 10% because the sample of 208 observations is not very large (Glymour et al., 2004). The correlations were estimated using the adjusted Spearman rank correlation. The statistic is preferred to the Pearson correlation when the residuals are not normally distributed (Teramoto et al., 2014).

3.2. The Data

3.2.1. Google Trends Indexes

The data is monthly Google Trends indexes, based on Thailand's Google queries for lucky numbers and job applications (https://trends.google.co.th/trends/?geo=TH). The time series sample covers January 2004 to April 2021 (208 monthly observations). The query for lottery gambling is เลขเด็ด (*Lek̄h dĕd*, meaning lucky number) in Thai, whereas the search query for job application is สมัครงาน (*S̄mạkhr ngān*, meaning job application).

The choice for สมัครงาน follows previous studies (Naccarato et al., 2018) that used the job-application query in local languages. As for the choice for เลขเด็ด, Pravichai and Ariyabuddhiphongs (2015) reported that Thai lottery gamblers searched for lucky numbers. Internet sites are among the most popular sources (Scott, 2017). Alternative queries for lottery gambling are เลขล็อค (*Lekh̄ l̆xkh*) and หวยเด็ด (*H̄wy dĕd*), whose meanings are very close to the lucky number. The two queries are not considered in this study. They are much less popular in the Google Trends comparison (https://trends.google.co.th/trends/explore?geo=TH&q=เลขเด็ด,เลขล็อค,หวยเด็ด).

3.2.2. Descriptive Statistics

In the analyses, the gambling and unemployment indexes are detrended and deseasonalized. The detrending variable is logged time, whereas the deseasonalizing variables are month-of-the-year dummies. Descriptive statistics of the treated variables are reported in Table 1.

The Jarque-Bera statistic, based on the sizes of skewness and excess kurtosis, cannot reject the normality hypothesis for gambling; it rejects the hypothesis for unemployment at the 99% confidence level. The fact that the normality hypothesis is rejected for unemployment supports the use of the adjusted Spearman rank correlation in the DAG analysis. The first-order autocorrelation ($AR(1)$) coefficients are positive and significant for the two variables, suggesting their autocorrelation properties. Finally, the augmented Dickey-Fuller (ADF) test rejects the non-stationarity hypothesis for both gambling and unemployment. The $AR(1)$ and ADF statistics ensure that the dynamics of gambling and unemployment are well described by a $VAR(p)$ model.

Table 1: Descriptive Statistics

Statistic	Gambling	Unemployment
Average	0.0000	0.0000
Standard Deviation	16.0067	7.4781
Skewness	0.2766	–0.2928
Excess Kurtosis	0.0158	2.5345
First-Order Autocorrelation	0.9017***	0.6898***
Jarque-Bera Statistic	3.9813	60.1281***
Augmented Dickey–Fuller Statistic	–4.0256***	–6.9343***

***denotes significance at the 99% confidence level.

4. Empirical Results

4.1. The *VAR*(*p*) Model and Granger Causality Tests

The $VAR(p)$ model is estimated for $p = 1,\ldots,6$. The gambling and unemployment variables are detrended and deseasonalized, and the intercept vector B_0 is constrained to a zero vector. The BIC for $VAR(1)$ is the smallest at 12.8743, such that one lag is optimal. The parameter estimates for the $VAR(1)$ model are reported in Panel 2.1 of Table 2. For gambling, the coefficient for its own lag is significant, whereas the coefficient for lagged unemployment is non-significant. The coefficients for both lagged gambling and unemployment are significant in the unemployment equation.

The test results for Granger causality are reported in Panel 2.2 of Table 2. For the parameter-constrained model under the null hypothesis of Granger non-causality, the F statistic is distributed as an F variable with (1.206) degrees of freedom. The test cannot reject the hypothesis of Granger non-causality from unemployment to gambling. It rejects the hypothesis of non-causality from gambling to unemployment at the 95% confidence level. Gambling Granger causes unemployment. The causality relationship is time-sequential.

Table 2: Tests for Granger Causality

Panel 2.1 Vector Autoregression Model of Order One

Lagged Variable	Variables	
	Gambling	Unemployment
First-Lagged Gambling	0.8723***	0.0490**
First-Lagged Unemployment	0.1048	0.6436***

** and *** denote significance at the 95% and 99% confidence levels, respectively.

Panel 2.2 Granger Causality Tests

Test	*F* (1,206)
Unemployment does not Granger cause gambling.	2.6374
Gambling does not Granger cause unemployment.	4.6592**

**denotes significance at the 95% confidence level.

4.2. DAG Causality Test

The residuals from the $VAR(1)$ model are used to estimate the DAG model. The 10% significance level was selected to establish the relationship. The PC algorithm found a significant uni-directed edge, $(U_t \rightarrow G_t)$. The edge indicates a contemporaneous causality from unemployment to gambling.

5. Discussion

5.1. Causality Relationships Between Lottery Gambling and Unemployment

This study uncovers the causal relationships between lottery gambling and unemployment in Thailand. First, unemployment causes gambling in the same month. In Panel 2.1 of Table 2, the slope coefficient of lagged gambling in the unemployment equation is positive and significant. Once the unemployed start to gamble, gambling activities subsequently lead to higher unemployment in the following month.

The DAG contemporaneous causality from unemployment to gambling supports the common belief and theories that unemployment causes gambling. This result is consistent with traditional gambling studies that used cross-sectional data.

Langham et al. (2016) explained Granger causality from gambling to unemployment. The effects of gambling on unemployment are second-order; it takes time for the effects to show. This finding is consistent with Muggleton et al. (2021), who reported a positive relationship between gambling and future unemployment status in the United Kingdom.

The finding of Granger causality has important implications on previous studies, based on cross-sectional data, on the effects of gambling on unemployment. The significant effects do not indicate causality from gambling to unemployment, but the association between the two variables. It is likely that this association is from the contemporaneous causality of unemployment to gambling.

5.2. Impulse Response Functions

The findings that (i) unemployment contemporaneously causes gambling, and (ii) gambling Granger causes unemployment in the following month implies that unemployment in the following month will contemporaneously cause gambling in that month. The causes and effects are continuous and circular. It is interesting to examine how long these circular relationships will continue.

To answer this question, impulse response functions (IRFs) of gambling and unemployment are estimated for months 0 to 6 (Enders, 1995). With respect to the significant uni-directed edge $(U_t \rightarrow G_t)$, the structural factorization for contemporaneous causation between the residuals is set from unemployment to gambling. That is, the residuals $\begin{bmatrix} e_t^G \\ e_t^U \end{bmatrix}$ equals $A\begin{bmatrix} w_t^G \\ w_t^U \end{bmatrix}$, where $A = \begin{bmatrix} a^{GG} & a^{GU} \\ a^{UU} & 0 \end{bmatrix}$ and $\Omega = AA'$. The variables w_t^G and w_t^U are independent gambling and unemployment shocks, respectively.

The IRFs are graphically represented in Figure 1. The solid lines indicate the levels, and the dotted lines represent the two standard deviation bands. The shock of gambling has an effect on unemployment in months 1 to 4, whereas the shock of unemployment also affects gambling in months 1 to 4. (The response of gambling to unemployment in month 0 is significant at the 90% confidence level). The circular causality lasts four months.

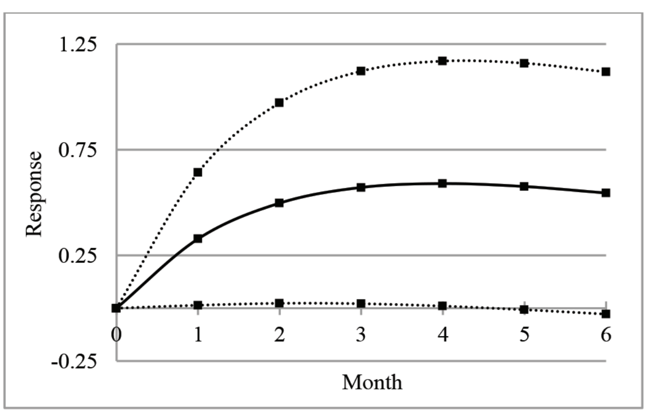

Figure 1.1: Response of Unemployment to Gambling

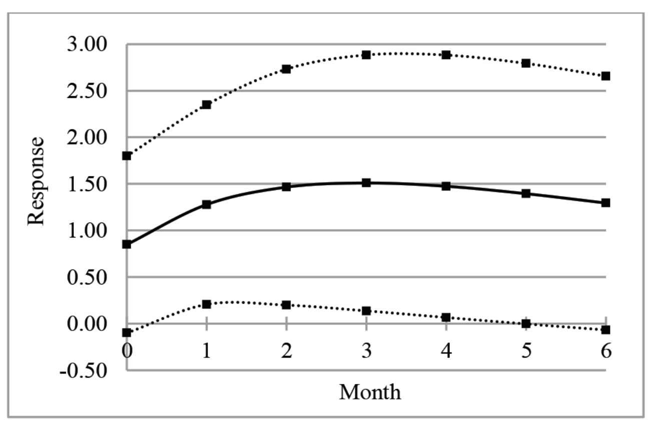

Figure 1.2: Response of Gambling to Unemployment

Figure 1: Impulse Response Functions

5.3. Underground Lottery

In Thailand, the lottery consists of government and underground lotteries. In the past, the underground lottery was more popular than the government lottery (Wannathepsakul, 2011). Recently, the reverse is the case (Research Centre for Social and Business Development, 2020). This study relies on the Google Trends index as a proxy for lottery-gambling activities. The behavior of the index from February 27, 2021, to April 30, 2021, is illustrated in Figure 2 and is similar for the entire sample period. Lottery numbers are drawn on the first and the sixteenth days of each month. The square markers indicate the levels on the number-drawing dates; gambling activities are most active on the draw dates.

Because the supply of government lottery is lowest on the number-drawing day, the search is expected to be by underground lottery gamblers. Underground lottery dealers accept bets until 3.30 p.m. before the first-prize number is drawn. Despite this, the Google Trends index should be able to proxy lottery gambling activities. The Research Centre for Social and Business Development (2018) reported that most lottery gamblers buy tickets from both government and underground lotteries.

5.4. Robustness Check

As a robustness check, the tests are repeated using the unemployment-rate data and the lottery-gambling Google Trends index. Unemployment rates were retrieved from the CEIC Data database (https://www.ceicdata.com/en). The sample period is from January 2004 to December 2021.

The correlation of the raw (detrended and deseasonalized) unemployment rate with the raw (detrended and deseasonalized) gambling index is 0.60 (0.03). Tests are based on detrended and deseasonalized variables. The study imputes the missing unemployment rates for April to June 2020 based on their linear interpolation levels.

When the unemployment rate data is used, gambling Granger causes unemployment, but unemployment does not Granger cause gambling. At the 10% significance level, the DAG test cannot detect any relationship between unemployment and gambling. However, when the significance level is set at 20%, the uni-directed edge ($U_t \rightarrow G_t$) is significant. Unemployment contemporaneously causes gambling. The results are consistent with those for the Google Trends data.

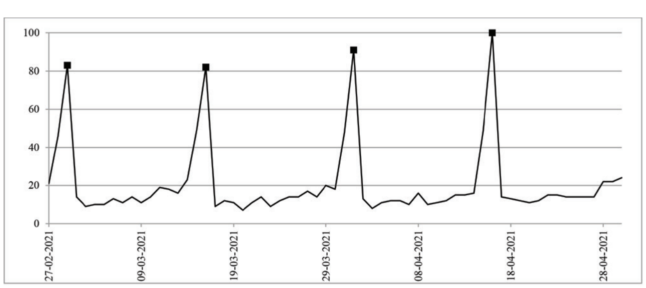

Figure 2: Google Trends Index for Lottery-Gambling Activities

6. Conclusion

In most gambling studies, the significant effects of unemployment on gambling, or vice versa, do not necessarily imply causality from one variable to the other, rather their association. The tests were not direct causality tests. Granger and DAG tests were conducted for time-sequence and contemporaneous causalities between lottery gambling and unemployment in Thailand. The results reveal that unemployment contemporaneously causes gambling, whereas gambling Granger causes unemployment. The findings support common beliefs and theories regarding the causality of unemployment to gambling. They also support the explanation of the second-order effects of gambling on unemployment.

In this study, the interesting causalities are between lottery gambling and unemployment. However, unemployment (gambling) is one of the possible causes and effects of gambling (unemployment) (Changpetch, 2017; Shakur et al., 2020). Other variables were possible, but these were not addressed in this study and are left for future research.

References

Abbott, D. A., Cramer, S. L., & Sherrets, S. D. (1995). Pathological gambling and the family: Practice implications. *Families in Society*, *76*(4), 213–219. https://doi.org/10.1177%2F104438949507600402

Albers, N., & Hübl, L. (1997), Gambling market and individual patterns of gambling in Germany. *Journal of Gambling Studies*, *13*, 125–144. https://doi.org/10.1023/A:1024999217889

Arge, E. F., & Kristjánsson, S. (2015). *The effects of unemployment on gambling behavior in Iceland: Are gambling rates higher in unemployed populations?* Reykjavík, University of Iceland.

Awokuse, T. O., Chopra, A., & Bessler, D. A. (2009). Structural change and international stock market interdependence: Evidence from Asian emerging markets. *Economic Modelling*, *26*(3), 549–559. https://doi.org/10.1016/j.econmod.2008.12.001

Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. In D. Marks (Ed.), *The health psychology reader* (pp. 94–106). Englewood Cliff, NJ: Prentice-Hall.

Boreham, P., Dickerson, M., & Harley, B. (1996). What are the social costs of gambling? The case of the Queensland machine gaming industry. *Australian Journal of Social Issues*, *31*(4), 425–442. https://doi.org/10.1002/j.1839-4655.1996.tb01288.x

Çakıcı, M., Çakıcı, E., & Karaaziz, M. (2015). A lifetime of prevalence and risk factors of the problem and pathologic gambling in North Cyprus. *Journal of Gambling Studies*, *32*(1), 11–23. https://doi.org/10.1007/s10899-015-9530-5

Casino.org. (2021). *Global industry in recent years*. https://www.casino.org/features/gambling-statistics/#:~:text=World

Castrén, S., Basnet, S., Pankakoski, M., Ronkainen, J., Helakorpi, S., Uutela, A., & Lahti, T. (2013). An analysis of problem gambling among the Finnish working-age population: A population survey. *BMC Public Health*, *13*, 519. https://doi.org/10.1186/1471-2458-13-519

Changpetch, P. (2017). Gambling consumers in Thailand. *Asian Social Science*, *13*(5), 136–143. https://doi.org/10.5539/ass.v13n5p136

Chun, J. S., Cho, S., Chung, I., & Kim, S. (2011). The economic and psychological impact of problem gambling in South Korea. *Asian Journal of Gambling Issues and Public Health*, *2*(1), 29–38. https://doi.org/10.1186/BF03342123

Coleman, L. (2021). *Global gambling statistics & facts 2021*. https://gamblingngo.com/guides/gambling-stats-facts/

Conner, T. W., & Taggart, W. A. (2009). The impact of gaming on the Indian nations in New Mexico. *Social Science Quarterly*, *90*(1), 50–70. https://doi.org/10.1111/j.1540-6237.2009.00602.x

Diebold, F. X. (2007). *Elements of forecasting* (4th ed.). Cincinnati: South-Western. Retrieved from

Enders, W. (1995). *Applied Econometrics Time Series*. New York, NY: John Wiley & Sons.

Glymour, C., Scheines, R., Spirtes, P., & Ramsey, J. (2004). *TETRAD-IV new Manual*. www.phil.cmu.edu/projects/tetrad_download/files/new_manual.pdf

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*(3), 424–438. https://doi.org/10.2307/1912791

Harrison, G. W., Lau, M. I., & Ross, D. (2020). The risk of gambling problems in the general population: A reconsideration. *Journal of Gambling Studies*, *36*, 1133–1159. https://doi.org/10.1007/s10899-019-09897-2

Herman, R. D. (1967). Gambling as work: A sociological of the racetrack. In R. D. Herman (Ed.), *Gambling* (pp. 87–104). New York, NY: Harper & Row.

Hodgins, D. C., Stea, J. N., & Grant, J. E. (2011). Gambling disorders. *Lancet, 378*(9806), 1874–1884. https://doi.org/10.1016/s0140-6736(10)62185-x

Hofmarcher, T., Romild, U., Spångberg, J., Persson, U., & Håkansson, A. (2020). The societal costs of problem gambling in Sweden. *BMC Public Health*, *20*, 1921. https://doi.org/10.1186/s12889-020-10008-9

Khanthavit, A. (2019). Causality of weather effects on stock returns and volatility. *Human Behavior, Development, and Society*, *20*(2), 29–40. https://so01.tci-thaijo.org/index.php/hbds/article/view/162024

Komonpaisarn, T. (2020). *The social cost of gambling in Thailand*. Bangkok: Chulalongkorn University.

Ladouceur, R., Boisvert, J., Pépin, M., Loranger, M., & Sylvain, C. (1994). Social cost of pathological gambling. *Journal of Gambling Studies*, *10*, 349–409. https://doi.org/10.1007/BF02104905

Langham, E., Throne, H., Browne, M., Donaldson, P., Rose, J., & Rockloff, M. (2016). Understanding gambling-related harm: A proposed definition, conceptual framework, and taxonomy of harms. *BMC Public Health*, *16*, 80. https://doi.org/10.1186/s12889-016-2747-0

Lee, J. W., & Brahmasrene, T. (2019). Long-run and short-run causality from exchange rates to the Korea composite stock price index. *Journal of Asian Finance, Economics, and Business*, *6*(2), 257–267. https://doi.org/10.13106/jafeb.2019.vol6.no2.257

Lütkepohl, H. (2005). *A new introduction to multiple time series analysis*. Berlin: Springer. https://doi.org/10.1007/978-3-540-27752-1

Manprasert, S. (2014). The study of gambling behavior in Thailand. *NIDA Economic Review*, *8*(1), 35–72. http://econ-test.nida.ac.th/components/com_booklibrary/ebooks/2.pdf

McConkey, C. W., & Warren, W. E. (1987). Psychographic and demographic profiles of state lottery ticket purchasers. *Journal of Consumer Affairs*, *21*(2), 314–327. https://doi.org/10.1111/j.1745-6606.1987.tb00205.x

Merton, R. K. (1938). Social structure and anomie. *American Sociological Review*, *3*(5), 672–682. https://doi.org/10.2307/2084686

Muggleton, N., Parpart, P., Newall, P., Leake, D., Gathergood, J., & Stewart, N. (2021). The association between gambling and financial, social, and health outcomes in big financial data. *Nature Human Behaviour*, *5*, 319–326. https://doi.org/10.1038/s41562-020-01045-w

Mustapha, S. A., & Enilolobo, O. S. (2019). Effects of gambling on the welfare of Nigerian youths: A case study of Lagos state. *Journal of Gambling Issues*, *43*, 29–44. http://doi.org/10.4309/jgi.2019.43.3

Naccarato, A., Falorsi, S., Loriga, S., & Pierini, A. (2018). Combining official and Google Trends data to forecast the Italian youth unemployment rate. *Technological Forecasting and social change*, *130*, 114–122. https://doi.org/10.1016/j.techfore.2017.11.022

Nuti, S. V., Wayda, B., Ranasinghe, I., Wang, S., Dreyer, R. P., Chen, S. I., & Murugiah, K. (2014). The use of Google Trends in health care research: A systematic review. *PLOS One*, *9*(10), e109583. https://doi.org/10.1371/journal.pone.0109583

Nyman, J. A. (2004). *A theory of demand for gambles.* Minnesota: University of Minnesota.

Pavlicek, J., & Kristoufek, L. (2015). Nowcasting unemployment rates with Google searches: Evidence from the Visegrad Group countries. *PLOS One*, *10*(5), e0127084. https://doi.org/10.1371/journal.pone.0127084

Pearl, J. (2000). *Causality*. Cambridge, UK: Cambridge University Press.

Pravichai, S., & Ariyabuddhiphongs, V. (2015). Superstitious beliefs and problem gambling among Thai lottery gamblers: The mediation effects of number search and gambling intensity. *Journal of Gambling Studies*, *31*, 1633–1649. https://doi.org/10.1007/s10899-014-9517-7

Productivity Commission. (1999). *Australia's gambling industries, report no. 10*. Canberra: AusInfo.

Research Centre for Social and Business Development. (2018). *A 2017 survey report on gambling situations, behaviors, and harms in Thailand.* Bangkok: Faculty of Economics, Chulalongkorn University.

Research Centre for Social and Business Development. (2020). *A 2019 survey report on gambling situations, behaviors, and harms in Thailand: Situations in the provinces.* Bangkok: Faculty of Economics, Chulalongkorn University, Bangkok.

Scott, R. M. (2017). Religion, prosperity, and lottery lore: The linkage of new religious networks to gambling practices in Thailand. In J. Koning & G. Njoto-Feillard (Eds.), *New religiosities, modern capitalism, and moral complexities in Southeast Asia* (pp. 232–245). London: Palgrave Macmillan.

Shakur, E. S. A., As'at, N. H., Aziz, N., Abdullah, S. S., & Rasid N. H. A. (2020). Determining unemployment factors among job-seeking youth in the East Coast of Peninsular Malaysia. *Journal of Asian Finance, Economics, and Business*, *7*(12), 565–576. https://doi.org/10.13106/jafeb.2020.vol7.no12.565

Sharpe, L., & Tarrier, N. (1993). Towards a cognitive-behavioral theory of problem gambling. *British Journal of Psychiatry*, *162*(3), 407–412. https://doi.org/10.1192/bjp.162.3.407

Spirtes, P., & Glymour, C. (1991). An algorithm for fast recovery sparse causal graphs. *Social Science Computer Review*, *9*(1), 62–72. https://doi.org/10.1177%2F089443939100900106

Swanson, N. R., & Granger, C. W. J. (1997). Impulse response functions based on a causal approach to residual orthogonalization in vector autoregression. *Journal of the American Statistical Association*, *92*(437), 357–367. https://doi.org/10.1080/01621459.1997.10473634

Teramoto, R., Saito, C., & Funahashi, S. (2014). Estimating causal effects with a non-paranormal method for the design of efficient intervention experiments. *BMC Bioinformatics*, *15,* 228. https://doi.org/10.1186/1471-2105-15-228

Toneatto, T., Blitz-Miller, T., Calderwood, K., Dragonetti, R., & Tsanos, A. (1997). Cognitive distortions in heavy gambling. *Journal of Gambling Studies*, *13*, 253–266. https://doi.org/10.1023/A:1024983300428

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4175), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Volberg, R. A. (2004). Fifteen years of problem gambling prevalence research: What do we know? Where do we go? *Journal of Gambling Issues*, *10,* 54–81. http://doi.org/10.4309/jgi.2004.10.12

Volberg, R. A. (2007). Population surveys. In: G. Smith, D. C. Hodgins, & R. J. Williams (Eds). *Research and measurement issues in gambling studies* (pp. 33–55). Burlington, MA: Elsevier.

Vongsinsirikul, V. (2012). *Understanding the impact of gambling with special reference to Thailand*. [Unpublished doctoral dissertation]. Birmingham Business School, University of Birmingham.

Walker, D. M., & Sobel, R. S. (2016). Social and economic impacts of gambling. *Current Addiction Reports*, *3*, 293–298. https://doi.org/10.1007/s40429-016-0109-8

Wanjohi, M. U. (2012). Influence of unemployment on youth gambling in Nairobi, Kenya [Unpublished master's research project]. Department of Sociology, University of Nairobi.

Wannathepsakul, N. (2011). *The economics of underground lottery: A perspective of gambling business on socio-economic development*. Bangkok: Chulalongkorn University.

Wardle, H., Reith, G., Best, D., McDaid, D, & Platt, S. (2018). *Measuring gambling-related harms*: A framework for action. Birmingham: Gambling Commission.

Williams, R. J., Volberg, R. A., & Stevens, R. M. G. (2012). *The population prevalence of problem gambling: Methodological influences, standardized rates, jurisdictional differences, and worldwide trends.* Canada: The Ontario Problem Gambling Research Centre & The Ontario Ministry of Health and Long-Term Care.

Williams, R. J., Volberg, R. A., Stevens, R. M. G., Williams, L. A., & Arthur, J. N. (2017). *The definition, dimensionalization, and assessment of gambling participation.* Canada: Canadian Consortium for Gambling Research.

Yuliadi, I. (2020). An analysis of money supply in Indonesia: Vector Autoregressive (VAR) approach. *Journal of Asian Finance, Economics, and Business*, *7*(7), 241–249. https://doi.org/10.13106/jafeb.2020.vol7.no7.241

Zivot, E., & Wang, J. (2006). *Vector autoregressive models for multivariate time series: Modeling Financial time series with S-Plus®* (2nd ed.). New York: Springer.