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Describing the Determinants of Problem Gambling in South Africa – A Longitudinal Approach

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Abstract In this study, an enhanced model describing the temporal determinants of problem gambling in South Africa is established using the National Longitudinal Study of Gambling Behaviour (NLSGB) dataset. Various conceptual ambiguities evidenced in the literature, particularly those associated with the Problem Gambling Severity Index (PGSI) screen, are explored. Gambling severity classification, as per the PGSI, is unstable over time. Evidence suggests that the standard PGSI cut-off score of 8 may be replaced by a score of 10 in some cases. For robustness, concurrent use of the PGSI and the Diagnostic and Statistical Manual of Mental Disorders (DSM) measurement criteria for problem gambling is advised. Although it remains undetermined whether problem gambling is best understood as an ordinal or a continuous disorder, the bounded natures of the PGSI and DSM scoring-systems make the statistical analyses of these tools most consistent with an ordinal structure; use of continuous structures cause statistical complications.

Keywords problem gambling, addiction, screening, measurement, panel data

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LIST OF ACRONYMS

Akaike's Information Criterion (AIC; Akaike, 1987)

Barrett's Impulsivity Scale-11 (BIS-11; Patton et al., 1995)

Bayesian Information Criterion (BIC; Schwarz, 1978)

Beck's Anxiety Inventory (BAI; Beck et al., 1988)

Beck's Depression Inventory-II (BDI-II; Beck et al., 1996)

Canadian Problem Gambling Index (CPGI; Ferris & Wynne, 2001)

Diagnostic and Statistical Manual of Mental Disorders (DSM)

DSM, 3rd Edition (DSM-III)

DSM, 4th Edition (DSM-IV)

DSM, 4th Edition, Multiple Response Version (DSM-IV-MR; Fisher, 2000)

DSM, 5th Edition (DSM-V)

General Self-Efficacy Scale (GSE; Schwarzer & Jerusalem, 1995)

Kessler Psychological Distress Scale (K10; Kessler et al., 2002)

List of Threatening Experiences Questionnaire (LTE-Q; Brugha et al.,1985)

National Longitudinal Study of Gambling Behaviour (NLSGB; Hofmeyr et al., 2011)

National Urban Prevalence Study of Gambling Behaviour (NUPSGB; Ross et al., 2010)

Perceived Social Support – Family Scale (PSS-Fa; Procidano and Heller, 1983)

Perceived Social Support – Friend Scale (PSS-Fr; Procidano and Heller, 1983)

Perceived Stress Scale (PSS; Cohen et al., 1983)

Problem Gambling Severity Index (PGSI)

South Oaks Gambling Screen (SOGS; Lesieur & Blume, 1987)

South Oaks Gambling Screen-Revised (SOGS-R; Abbott & Volberg, 2000)

World Health Organization (WHO) Alcohol, Smoking and Substance Involvement Screening Test (ASSIST; WHO ASSIST Working Group, 2002)

1. INTRODUCTION

Problem gambling is broadly defined as the impaired control over one's gambling behaviour, characterized by a "disordered or diseased state that deviates from normal, healthy behaviour" (Blaszczynski & Nower, 2001). The fact that problem gambling is held to have negative personal, familial and financial consequences for both the individual player, as well as others in his or her social network or community (Ferris et al., 1999), makes this disorder, not only a medical concern, but also a socio-economic concern. In order to address this, a thorough understanding of the problem gambling disorder, particularly regarding its behaviour over time, is essential.

The identification, treatment and prevention of problem gambling require an extensive investigation of the social, psychological and biological characteristics associated with this disorder (Blaszczynski & Nower, 2001). Although several studies have been performed toward this end, the problem gambling field is still a relatively new area of study (Petry, 2005) and, in this way, the ambiguities associated with problem gambling become increasingly obvious as the literature grows.

In particular, with different studies adopting different theoretical approaches toward the analysis of problem gambling, there does not exist one single conception of the disorder. Although the existence of these differing conceptual understandings does not have a significant influence on the risk factors commonly identified by such studies (risk factors investigated are rather influenced by the social and cultural context in which the study takes place) it has led to the establishment of different means by which problem gambling is screened.

Although the Problem Gambling Severity Index (PGSI) is largely held to be the preferred screen in the case of general population studies (Kincaid et al., 2012), it has been criticized on basis of arbitrariness in its classification of "high risk" problem gambling (the standard cut-off score of 8 is thought to be too low), as well as on the basis of failing to fully embody the Diagnostic and Statistical Manual of Mental Disorders (DSM) definition of problem gambling by amalgamating two conflicting approaches to the disorder (Kincaid et al., 2012). Explicitly, there is much debate over whether problem gambling should be understood as an ordinal disorder that is explained by an addiction-centered model or whether problem gambling should be understood as a disorder existing on a continuous spectrum of severity that is better explained by a problem-centered model (Blaszczynski & Nower, 2001).

With that said, the main aim of the current study is to establish a model that identifies a well-defined set of risk factors associated with problem gambling behaviours over time, in a South African context. In doing so, the aforementioned ambiguities presented in the literature surrounding problem gambling are addressed.

The dataset used in this study is derived from the National Longitudinal Study of Gambling Behaviour (NLSGB; Hofmeyr et al., 2011), a panel dataset collected over a period of 18 months. Although this dataset has been used in a previous report conducted by Hofmeyr et al. (2011), this report was performed prior to the completion of the final wave. Additionally, the particular group of ambiguities identified by the current study has not yet been explored.

2. LITERATURE

2.1. PREVALENCE OF PROBLEM GAMBLING

Over the last several decades, there has been a global trend towards the progressive relaxing of legislation surrounding gambling (Cocker & Winstanley, 2015). This, coupled with the consequent unprecedented access to gambling opportunities, has resulted in the propogation of gambling behaviour in various parts of the world.

Recent studies conducted in the United States (Cocker & Winstanley, 2015), Canada (Cocker & Winstanley, 2015), Europe (Wardle et al., 2011) and Australia (Delfabbro, 2009) found that between 70% and 90% of the adult population over the age of 16 repoted some level of gambling participation. These numbers demonstrate the relative pervasiveness of gambling within the general population. More perilously, across studies and countries, prevalence rates for problem gambling tend to fall between 0.5% (Scholes-Balog et al., 2013) and 5% (Marmurek et al., 2014).

With the advent of legalized gambling in South Africa in 1996, by way of the Constitution of the Republic of South Africa (Act 108 of 1996), and the ensuing establishment and rapid expansion of the South African gambling sector (Collins & Barr, 2009), gambling activity in South Africa has demonstrated marked growth over the past two decades; with approximately 57% of the adult population reporting participation in some form of gambling (Quarterly Labour Force Survey, 2012). While this prevalence rate appears to fall below that of the rest of the world, the prevalence rate for self-reported problem gambling was found to be as high as 7% of the adult population (Quarterly Labour Force Survey, 2012).

2.2. CONCEPTION OF PROBLEM GAMBLING

Problem gambling is conceptualized on the basis of theoretical models. Since researchers in the past have taken varying approaches to the profiling of problem gambling and have thus developed varying theories regarding its aetiology, no single conception of problem gambling exists. Taber (1987) describes the conceptualization of problem gambling as follows:

> "Problem, excessive and pathological gambling can be conceptualized in terms of addictionology, biology, genetics, disease process, values clarification, forensic responsibility, learning failure, developmental disorder, anthropological matrix, social dynamic, impulse control, economic man, political resource theory, and, yes, in terms of statistical learning theory and schedules of reinforcement."

Theorists tend to agree that, given the numerous dimensions of problem gambling, it is unrealistic to rely on one single model or theory to fully describe problem gambling (Ferris, et al., 1999). Although all existing models illustrate an interaction of key variables in the onset and development of problem gambling (Blaszczynski & Nower, 2001), the specific variables considered in each case are determined on the basis of the terms in which problem gambling is understood. Different models outline a different process by which gambling activity evolves from the point of "initial participation" to a state of "impaired control" (Blaszczynski & Nower, 2001). In this way, relying on one model to fully describe problem gambling tends to act as a "perceptual filter" (Ferris, et al., 1999) and thus raises the risk of suppressing some properties of problem gambling while limiting the focus to others (Brown, 1987). This has the consequence of "impoverishing gambling research" and restricting the scope of the results (Brown, 1987). As a result, gambling literature has come to embrace the wide variety of models and conceptions surrounding the aetiology of problem gambling.

2.3 MEASURES OF PROBLEM GAMBLING

The changing conceptions and understandings of problem gambling have led to the development of a range of measurement tools that are used in the study of problem gambling. In particular, measurement tools have been developed for the screening, assessment, diagnosis and treatment of gambling addiction, as well as for the purposes of various population-based surveys (Abbott et al., 2004).

With early conceptualizations of problem gambling taking a chiefly clinical approach, the measurement tools were constructed from a dominantly psychological perspective (Abbott et al., 2004). Being the only "rigorously developed and tested" measurement tool at the time (Lesieur & Blume, 1987), the South Oaks Gambling Screen (SOGS; Lesieur & Blume, 1987) soon became the dominant measurement tool in gambling research. Partly based on the DSM-III criteria for problem gambling, this empirically developed tool was established specifically for the screening of problem gambling in clinical populations (Holtgraves, 2007). With the widespread use of this screen in clinical studies, it was not long until the SOGS was adopted by studies on the distribution and possible controls of problem gambling (Abbott et al., 2004). Following its growing popularity, alternative versions of this screen were soon developed. In particular, a revised version of the SOGS (SOGS-R; Abbott & Volberg, 2000) was established in direct response to criticism surrounding the lifetime timeframe of the questions upon which the original 20-item screen are based (Lesieur & Blume, 1987). With this, both current problem gamblers as well as problem gamblers in remission were identified as "problem gamblers" by the SOGS (Holtgraves, 2007). Therefore, in an attempt to confine the results to current problem gamblers only, the SOGS-R, which is based on questions asked within a one-year timeframe, was developed (Holtgraves, 2007).

With the more recent expansion in research surrounding problem gambling, the SOGS is no longer an adequate screen for problem gambling. This is due to three factors in particular. First, the clinical setting to which the SOGS is confined renders the SOGS insufficient in large survey sample prevalence studies. Specifically, this inaptness is attributed to the "uncomfortably high" rate of false positives that result when the SOGS is applied in general nonclinical populations (Kincaid et al., 2012). Second, the strictly dichotomous approach taken by the SOGS implies that problem gamblers can be "separated from normality by the presence of characteristic symptoms" (Kincaid et al., 2012). In this way, a respondent is either classified as a problem gambler or not (Holtgraves, 2007). This, in conjunction with the fact that the SOGS does not include less severe behavioral factors, renders the SOGS unable to identify people in the process of becoming problem gamblers (Strong et al., 2003). Third, the 1994 introduction of new criteria for the diagnosis of problem gambling in the DSM-IV rendered much of the DSM-III-based SOGS tool clinically out of date (Fisher, 2000).

In the absence of a fully tested alternative to the SOGS, Fisher (2000) developed the DSM-IV-MR, a multiple response version of DSM-IV, which directly adapts the DSM-IV criteria for use in the general adult population. The DSM-IV-MR consists of a 10-item analysis with 7 items measuring the common gambling behaviours outlined by the DSM-IV and the remaining 3 items measuring the adverse consequences of problem gambling outlined by the DSM-IV. Initially established for use in clinical populations, the DSM-IV-MR items were phrased as 'yes' or 'no' questions; each item is given a score of either 1 for 'yes' or 0 for 'no'. In order to adapt the criteria for use in a non-clinical setting, however, Fisher (2000) employed a Likert scale by which the respondents are given four response options: 'often', 'sometimes', 'once or twice' and 'never'. Accordingly, when employed in non-clinical populations, the items on the scale are scored as follows: a 'yes' for the 7 items measuring the common gambling behaviours is inferred from 'often'; a 'yes' for the 3 items measure adverse consequences of problem gambling is inferred from 'often', 'once or twice' or 'sometimes'. The threshold score for a problem gambling diagnosis is 5.

Following this, gambling research saw the emergence of a multiplicity of new measurement tools, such as the Gamblers Anonymous screen, the Victorian Gambling Screen and, of particular importance, the PGSI screen. The PGSI, which is the scored module of the Canadian Problem Gambling Index (CPGI; Ferris & Wynne, 2001), acts as the most prominent alternative to the SOGS. In fact, in a study performed by Mcmillen and Wenzel (2007), which sought to compare the value of the PGSI, the

SOGS and the Victorian Gambling Screen, it was found that the PGSI encompasses the best "measurement properties" of the three screens.

This measurement tool was developed with the particular intention of providing a measurement tool that is able to determine the prevalence of problem gambling in the general population (Sharp et al., 2012). Unlike the dichotomous approach taken by the SOGS, the DSM-IV-MR and other predecessors, the PGSI is developed with the aim of presenting a more dimensional approach to problem gambling whereby gamblers are separated into four different subgroups of problem gambling that correspond to four different risk statuses: no risk, low risk, moderate risk and high risk (Kincaid et al., 2012). More explicitly, the PGSI consists of a 9-item analysis with 4 items measuring common gambling behaviors and the remaining 5 items measuring common adverse consequences of problem gambling (Holtgraves, 2007). Each item is scored on a scale of 1 to 3 according to the frequency with which the respondent experiences each behavior/consequence. The individual's final score is then calculated by totaling the score for each item. A score of 0 implies no risk, a score of 3 or less implies low risk, a score between 3 and 8 implies moderate risk and a score of 8 or more implies high risk of problem gambling. With this, the PGSI represents a progression of problem gambling. Critics have, however, raised concern over the arbitrariness of the definition of these problem gambling subgroups (Kincaid et al., 2012). Furthermore, it has been suggested that the standard cut-off score of 8 is perhaps too low (Kincaid et al., 2012), which results in an insufficiently exclusive classification of problem gambling. On this note, Kincaid et al. (2012) proposes that a cut-off score of 10 is perhaps more appropriate.

A further criticism of the PGSI is that, much like the SOGS, it does not adequately embody the DSM-IV criteria for problem gambling (Svetieva & Walker, 2008). Although the PGSI definition for problem gambling echoes the spirit of the DSM-IV criteria, the PGSI items fail to follow suit (Svetieva & Walker, 2008). In this way, the PGSI seems to present an amalgamation of two conflicting conceptions of problem gambling (Kincaid et al., 2012). On the one hand, it defines problem gambling as a problem-centered model derived from "problems in living" (Kincaid et al., 2012). On the other hand, however, it also accepts that problem gambling is an addiction-centered model, characterized by a loss of control (Kincaid et al., 2012). Therefore, along with the aforementioned criticisms surrounding its arbitrariness in defining subgroups of problem gambling, the PGSI has also been criticized on the basis of inconsistency between concept and measurement (Svetieva & Walker, 2008).

This shortcoming is worsened by the introduction of new criteria for the diagnosis of problem gambling in the DSM-V, which has moved problem gambling from the impulse-control disorder classification to the addictive disorder classification. It has also lowered the threshold from a score of 5 to a score of 4 and removed the committing of illegal acts as a stand-alone criterion. To this end, a number of DSM-IV-based screens similar to the DSM-IV-MR tool described above have been adapted to this new definition. For instance, studies conducted by Denis et al. (2012) and Petry et al. (2013) adjusted the National Opinion Research Centre DSM-IV Screen for gambling problems (NODS), which was partly derived from the DSM-IV-MR tool, to the new DSM-V criterion by dropping any items that related to committing illegal acts and decreasing the threshold for diagnosis from 5 to 4. The results showed that such adjustments yielded consistent diagnoses relative to the standard classification system.

2.4. RISK FACTORS

Despite the varying conceptions and understandings of problem gambling, the associated theoretical models are by no means "mutually exclusive" (Blaszczynski & Nower, 2001). The gambling literature shows a great deal of overlap regarding the potential "risk factors" that have been identified by the different theories and their respective models.

Common risk factors associated with problem gambling come from various domains. From a demographic perspective, studies tend to consider factors such as age, gender, education, income and employment status.

Cross-sectional studies performed by Ladouceur et al. (1999), Bandolfi et al. (2000), Volberg et al. (2001), Jackson et al. (2008) and Johansson et al. (2009) all agree that males are at increased risk for gambling and problem gambling. Furthermore, longitudinal studies conducted by Winters et al. (2002) and Haytbakhsh et al. (2006) found that male gender was an independent predictor of problem gambling in young adulthood. Similarly, a longitudinal study surrounding the protective factors of problem gambling found that female gender independently decreased the odds of problem gambling in young adulthood (Scholes-Balog et al., 2013).

In consort with the cross-sectional findings of Potenza et al. (2001) and Granero et al. (2013), Ladouceur et al. (1999), Bandolfi et al. (2000) and Volberg et al. (2001) again agreed on the increased risk for younger respondents. Moreover, along with the increased *prevalence* of problem gambling among younger respondents, Granero et al. (2013) found the *severity* of the disorder to be higher among younger respondents. Despite these compelling findings, however, it has been suggested that the relationship between problem gambling and age may in fact be due to a cohort effect by which more recently born individuals are at greater risk of developing gambling-related problems (Slutske et al., 2003). Alternatively, it has been suggested that the nature of this relationship may be due to a developmental effect by which gambling-related problems tend to peak during adolescence and then resolve naturally with the transition to adulthood (Shaffer & Hall, 1996). To this end, in a longitudinal study that prospectively examined changes in problem gambling at the transition from adolescence to adulthood, Winters et al. (2002) found that the overall prevalence of past-year problem gambling did not differ significantly over the 7 years of study. There was, however, a significant increase in the number of individuals at-risk of becoming problem gamblers, which appeared to coincide with an increase in gambling participation. Accordingly, these longitudinal results contradict the results of the cross-sectional research by suggesting that the risk of problem gambling may actually be higher among adults than among adolescents.

According to cross-sectional research, the relationship between education and problem gambling is not entirely clear. While a study performed by Volberg et al. (2001) failed to identify a significant relationship between level of education and problem gambling, Melntyre et al. (2007) found convincing results illustrating the prevalence of lower levels of education among problem gamblers. A similar result was obtained in a study by Kennedy et al. (2010), which found that problem gamblers are far less likely to have some sort of tertiary education than are non-problem gamblers. This lack of clarity is echoed in longitudinal research. Although a 1-year longitudinal study conducted by Wiebe et al. (2003) failed to establish a clear relationship between level of education and problem gambling, a longitudinal study conducted by Abbott et al. (2013) found significant prevalence increases among individuals with low levels of education between 1998 and 2009.

The relationship between problem gambling and income is an interesting one. In general, studies have found higher rates of problem gambling among relatively low income subjects (Abbott et al., 2014), but lower rates of problem gambling among the lowest income groups (Dellis et al., 2013). For example, in a study conducted by Davidson and Rogers (2010), although there was lower gambling participation at both income extremes, lower personal income categories were found to be associated with higher rates of problem gambling. Longitudinal research surrounding this relationship is particularly scarce and requires further attention.

The relationship between employment status and gambling participation and severity varies from country to country (Dellis et al., 2013). For example, a study conducted in New Zealand found a higher risk associated with being employed (Abbott & Volberg 2000), while a study conducted in Australia found a higher risk associated with being unemployed or in in part-time employment (Davidson & Rodgers, 2010) and a study conducted in Canada found a higher risk associated with the unemployed and students (Ministry of Public Safety and Solicitor General, 2003).

Over the past decade, a number of authors have drawn attention to the significance of investigations into the comorbidities of probem gambling. According to Sharp et al. (2014), this serves to increase the understanding of the determinants of probem gambling beyond socio-economic factors, which, in turn, offers greater insight into the aetiological pathways of problem gambling. From the comorbid disorder domain, studies commonly consider symptoms of depression, anxiety, psychological distress, impulsivity, alcohol abuse and substance abuse.

According to Scherrer et al. (2005), problem gamblers often report poorer mental health than non-gamblers. This poor mental health is most commonly manifested in depression, anxiety and psychological distress. In a study conducted by McCormick et al. (1984), it was found that 76% of problem gamblers in the study suffered from major depressive disorder. As noted by the authors, an interesting question is whether the depression generates a motivation to escape these feelings through gambling or if the gambling losses spawn the depression. Although the participants in this particular study were unable to report reliably the temporal relationship between early gambling and early depressive episodes, this question has been addressed in a number of later studies and the results are mixed. For instance, Beaudoin and Cox (1999) examined the characteristics of 57 adults seeking treatment for problem gambling. Approximately 40% of the sample reported gambling to relieve themselves of unpleasant feelings. These results suggest that, for some people, gambling may act as a coping mechanism for depression. Conversely, a study performed by Kennedy et al. (2010), which found high incidences of problem gambling among patients diagnosed with major depressive disorder, elucidated the direction of causality with 70% of the problem gamblers in the study reporting that the onset of the mood disorder occurred prior to the onset of the gambling problem (Kennedy et al., 2010). This same study further found evidence of a lower reported quality of life among problem gamblers.

In terms of anxiety, cross-sectional gambling research conducted by Ste-Marie et al. (2006) and Oei et al. (2008) identified a significant positive relationship between anxiety and problem gambling. Correspondingly, a longitudinal study conducted by Slutske et al. (2005) found that higher scores on measures of anxiety at age 18 were associated with higher levels of problem gambling at age 21.

Relatedly, a longitudinal study conducted by Winters et al. (2002) found that psychological distress at a young age was predictive of adult problem gambling. Similarly, a longitudinal study conducted by Wiebe et al. (2003) found that an increased level of psychological distress was associated with an increase in problem gambling severity between the two waves. Further, when examining a broad set of risk factors simultaneously, Wiebe et al. (2003) found psychological distress to be the only significant variable in predicting increases in problem gambling severity.

According to literature, high levels of impulsivity are demonstrated in three ways: first, in the inability to stop or inhibit a behavior regardless of its consequences (Barratt & Patton, 1983); second, in the tendency to act without anticipating the consequences of the action (Eysenck & Eysenck, 1977); third, in an excessive sensitivity to immediate reinforcement and a relative insensitivity to punishment (White et al., 1994). Various studies have explored the relationship between impulsivity and problem gambling but the results remain mixed. In a retrospective study conducted by Carlton and Goldstein (1987), it was found that adult problem gamblers displayed higher levels of impulsivity during childhood. More recently, a longitudinal study conducted by Vitaro et al. (2001) found that impulsivity was predictively related to gambling two years later. Additionally, a longitudinal study conducted by Edgerton et al. (2014) found impulsivity to be the only predictor to affect the rate of change in gambling severity across time. In contrast, however, a longitudinal study conducted by Barnes et al. (2005) suggests that impulsivity is not a significant predictor of problem gambling. This result was echoed in a cross-sectional study conducted by Marmurek et al. (2014).

Alcohol and substance abuse are perhaps the most commonly considered comorbid risk factors in gambling literature. A significant positive relationship between alcohol consumption and problem gambling has been identified by both Feigelman et al. (1995) and Ladouceur et al. (1999). This association is manifest in respondents reporting a lifetime alcohol problem (Feigelman et al., 1995) as well as respondents reporting high levels of alcohol consumption in the month prior to the operation of the relevant study (Ladouceur et al., 1999). Furthermore, a longitudinal study conducted by Vitaro et al. (2001) found that alcohol abuse predicted an increase in gambling problems one year later.

In a similar vein, a number of studies have identified a strong positive association between drug use and problem gambling (Johansson et al., 2009). In particular, Winters et al. (1993) clarified that the incidence of problem gambling is positively related to the frequency of drug use. Following this, Feigelman et al. (1995) went further to find the relationship between problem gambling and drug use particularly prevalent amongst heroin users. More recently, a longitudinal study conducted by Winters et al. (2002) found substance abuse to be a strong predictor of problem gambling seven years later.

Along with the findings related to drug abuse, Feigelman et al. (1995) found strong correlates between smoking tobacco and problem gambling. This result was again reached in a study conducted by McGrath et al. (2012), which found that smoking tobacco was not only strongly associated with the incidence of problem gambling, but also with the amount of money spent on gambling and the reasons for gambling. These results suggest that smoking and gambling have common "neurobiological, genetic and environmental influences" (McGrath et al., 2012). Moreover, in a longitudinal study, Haytbakhsh et al. (2006) found heavy tobacco use to be an independent predictor of problem gambling in later years.

A recent study by Grant et al. (2009) investigated the interaction between psychiatric disorders (Axis I and Axis II), nicotine dependence and problem gambling. Among non-nicotine dependent respondents, problem gambling was found to be strongly associated with acute psychopathology for most of the psychiatric disorders considered (Grant et al., 2009). Among nicotine dependent respondents, however, this relationship was not uniform. Furthermore, when holding each psychiatric disorder variable constant (one at a time) significant associations between nicotine dependency and problem gambling emerged in the cases of most psychiatric disorders (Grant et al., 2009). From this result, the authors concluded that nicotine in fact stimulates the relationship between problem gambling and psychiatric disorders and even accounts for a portion of the "elevated risks of psychopathology" associated with excessive levels of gambling activity (Grant et al., 2009).

Another domain from which risk factors are often drawn is that of cognitive distortions. Problem gamblers have been found to differ systematically from non-risk gamblers in their cognitive processes relating to confidence calibration and control (Goodie, 2005). In particular, problem gamblers exhibit cognitive distortions that can generally be described as the "expectancy of a personal success probability inappropriately higher than the objective probability would warrant" (Johansson et al., 2009). According to Cocker and Winstanley (2015), the increased presence of cognitive distortions identified in problem gamblers is one of the most important factors leading to the disorder.

The two principal dimensions of this domain are the illusion of control and the gambler's fallacy. According to Clark (2014), the illusion of control concerns the "irrelevant features of a game that create a sense that one is developing some kind of skill over an outcome that is in fact determined by chance alone". In a preliminary study conducted by Langer (1975), it was found that problem gamblers are commonly unable to differentiate between "chance-determined events" and "skill-determined events" (Langer, 1975). More recently, Orgaz and Matute (2013) found that problem gamblers exhibited a higher level of perceived control over a non-contingent response–outcome association compared to that of the healthy participants. This result was reiterated in a study conducted by Barrault and Varescon (2013), which found that the illusion of control was a good predictor of problem gambling, particularly amongst poker players.

According to Ejova et al. (2013), the gambler's fallacy is a well-documented belief about the sequencing of chance-based outcomes. Specifically, it is the belief that random sequences tend to self-correct, producing a 'head' after a series of 'tails' when flipping a coin, a 'red' after a series of 'blacks' in roulette, and a win after a series of losses on slot machines (Oskarsson et al., 2009). In a study conducted by Goodie and Fortune (2013), a notably strong relationship between adherence to the gambler's fallacy and the incidence of problem gambling was uncovered. Additionally, Marmurek et al. (2014) found associations between correlates of problem gambling severity and the gambler's fallacy.

Despite the lack of longitudinal research in the area, the strong association between cognitive distortions and the manifestation of problem gambling in general has led to the theory that such distorted beliefs play a causative role in the establishment, progression and maintenance of problem gambling (Lund, 2011). Intuitively, this assumption of causality is based on the notion that these biases likely precipitate gambling as they lead to dysfunctional decision making under risk or ambiguity (Cocker & Winstanley, 2015). Empirically, this assumption of causality is based on the increased incidence and magnitude of cognitive distortions as gambling severity worsens. For example, social gamblers demonstrate a greater degree of cognitive distortions in relation to gambling compared to non-gamblers (Källmén et al., 2008) and, in turn, problem gamblers demonstrate a greater degree of cognitive distortions in relation to gambling compared to non-risk gamblers (Joukhador et al., 2003). Furthermore, studies conducted by Gonzalez-Ibanez et al. (2005) and Leung and Cottler (2009) found that behavioural treatments aimed at correcting these irrational beliefs are valuable in promoting gambling cessation. Relatedly, in a longitudinal study conducted by Oei and Gordon (2008), it was found that the persistence of cognitive distortions following problem gambling treatment is linked to a higher likelihood of relapse. Collectively, these findings imply that cognitive distortions are linked to gambling acquisition, maintenance and severity.

An additional cognitive-based factor, which does not necessarily conform to the domain of cognitive distortion but is often strongly linked, is gambling self-efficacy. In general, gambling self-efficacy refers to one's belief as to whether or not one could resist an opportunity to gamble in a given situation (Casey et al. 2008). A low level of gambling self-efficacy has been found to relate to the acquisition, maintenance, and treatment of problem gambling (Sylvain et al., 1997). For example, in a study conducted by Weinstock et al. (2007), a low level of gambling self-efficacy was found to be associated with greater problem gambling behavior among college students. Similar results were obtained by May et al. (2003) among adults with a history of gambling. Interestingly, it has also been found that gamblers who possessed a low gambling self-efficacy tend to demonstrate greater levels of gambling-related cognitive bias (Casey et al., 2008).

Family and peer influences have also been identified as an important component in the development of problem gambling. The social learning perspective suggests that family members and friends can often act as significant models for gambling. In a review of studies concerning this relationship, Hardoon and Derevensky (2002) found that up to 68% of problem gamblers report gambling with family and up to 82% of problem gamblers report gambling with friends. Several further studies have shown a link between parental gambling and offspring gambling. For example, Lorenz & Shuttlesworth (1983) reported that 20% of problem gamblers were raised in environments that involved gambling problems. Similarly, a longitudinal study conducted by Winters et al. (2002) found exposure to parental gambling in adolescence to be a significant independent predictor of problem gambling in adulthood. Moreover, results obtained in a study conducted by Oei and Raylu (2004) showed a strong association between parents' gambling cognitions and gambling behaviors and offspring gambling cognitions and behaviors. In addition, many adolescents report that they gamble because their friends do (Griffiths, 1990) and, over time, problem gamblers have been reported to replace old friends with gambling associates (Gupta & Derevensky, 2000). Congruently, Lussier et al. (2014) found peer and neighborhood risk to be associated with the onset and increased levels of gambling problems.

Another common risk factor, which does not necessarily conform to a particular domain, is the availability of gambling to the respondent (Johansson et al., 2009). Ladouceur et al. (1999) performed a longitudinal study that directly tested the effect of greater access to gambling on the incidence of problem gambling by comparing the prevalence of problem gambling in a specific community before and after the opening of several new gambling venues (Johansson et al., 2009). The results showed a clear and prevalent positive relationship between access to gambling and problem gambling, which is the same result put forward by Campbell and Lester (1999). Furthermore, it is held that the risk associated with the availability of gambling is not necessarily confined to the physical access of gambling venues but also extends to the reception of gambling as a practice within a particular community (Blaszczynski & Nower, 2001). That is, an "environment in which gambling is socially accepted, encouraged and promoted" is likely to foster a greater degree of problem gambling (Blaszczynski and Nower, 2001).

Although there clearly exists a group of risk factors that are commonly identified by gambling studies, it is certainly not the case that every study will identify the exact same group of risk factors. That is, with the unique social, economic and physiological context of each study, it is unrealistic to expect every community to reflect the same characteristics and hence the same determinants for gambling addiction. Therefore, although the above discussion on common risk factors will help guide the present study, which is specific to South Africa, it is insufficient to draw any convincing conclusions.

2.5. STABILITY, PROGRESSION AND ABATEMENT

Most of the research on gambling and problem gambling relies on cross-sectional samples and retrospective accounts (Abbott & Clarke, 2007). Although this research has resulted in the identification of a wide range of risk factors and correlates of problem gambling, it is severely limited in its capacity to assess changes in gambling behaviour over time and to adequately determine causal connections. As a result, there is a significant degree of ambiguity and debate surrounding the trajectory of problem gambling over time. This is a particularly important area of research as, in order to devise the optimal methods of treatment, it is necessary to characterize the natural rates of problem gambling development and abatement (LaPlante et al., 2008).

According to conventional wisdom, disordered gambling is intractable and escalating (LaPlante et al., 2008). This view is endorsed by the DSM, which describes the course of problem gambling as chronic and progressive (American Psychiatric Association, 2000). More explicitly, Lesieur (1984) characterizes problem gambling as a downward spiral by which the worsening of gambling-related issues leads to a greater desire to gamble and, as a result, a further exacerbation of the problem.

Contrary to this idea that disordered gambling is always progressive and enduring, recent prospective research reveals that problem gambling tends to be more transitory and episodic than enduring and chronic at the individual level (Slutske et al., 2003). In an extensive review that analyzed five recent longitudinal studies, LaPlante et al. (2008) made three important discoveries. First, no evidence was found to support the notion that individuals cannot recover from disordered gambling. Second, no evidence was found to support the idea that individuals who have more severe gambling problems are less likely to improve than individuals who have less severe gambling problems. Third, no evidence was found to support the idea that individuals who have some gambling problems are more likely to worsen than individuals who do not have gambling problems. According to Slutske et al. (2003), such findings suggest that natural recovery may be the rule rather than the exception.

Despite these convincing results, however, it is important to consider the possibility of "addiction hopping" (LaPlante, 2008). More specifically, emerging perspectives on addiction suggest that it can manifest in multiple ways. In this view, individuals can experience numerous transitions between different expressions of addiction over time. Consequently, it is possible that, even though the individuals in the aforementioned studies tended toward improvement in gambling behaviour, such behaviour might have been temporarily replaced by a different type of disordered behaviour. In this way, it is important that the trajectories of other disorders are accounted for when analyzing the trajectory of problem gambling in a given sample.

2.6. ECONOMIC MODELLING

Traditionally, regression modeling is used to study the relationships among variables. In particular, when describing some quantitative variable – the dependent variable – as a function of, or in relation to, two or more factors of interest – the independent variables – multiple linear regression analysis is typically employed. Briefly, this involves fitting a linear equation to observed data. In general, any relationship observed is characterized in terms of the strength of the relationship. More explicitly, whether or not each independent variable should be retained in the model is determined according to a range of relationship-strength measures. One of the most attractive features of multiple regression analysis is its automatic provision of regression coefficients, proportion of variance and correlational measures of various kinds, all of which are types of relationship-strength measures.

Although it is common knowledge that correlation does not imply causation, this fact is sometimes overlooked in the employment of multiple regression analysis. In some cases, two variables are correlated simply through chance. In other cases, there is a causal link, not because one of the variables is affecting the other, but rather because they are both responding to an external driving force. The latter occurence is known as spurious causation and, if misinterpreted as direct causation, has the potential to discredit the results and conclusions.

Despite this caveat, traditional multiple regression analysis is often used to infer causality (Kincaid, 2012). It is for this reason that Kincaid (2012) promotes the use of graphical approaches to causality. In particular, Kincaid (2012) focuses on what he terms horizontal mechanisms. The function of horizontal mechanisms is to describe the intervening causes between two variables, at the same level, that make for a continuous process (Kincaid, 2012).

Essentially, the need for such mechanisms to identify spurious causation relies on whether one is looking to confirm that a causal relationship exists or whether one is looking to determine the size of the causal relationship (Kincaid, 2012). On the one hand, having a mechanism in the sense of a causal intermediary and relevant structure at the same level is useful, but not essential, in confirming a causal relation between two variables (Kincaid, 2012). Specifically, although identifying horizontal mechanisms allows one to provide more stringent tests and stronger evidence, intervening mechanisms are sufficient but not necessary to rule out spurious causation. This is because it is possible to determine whether or not a causal relationship is confounded without having information on the intervening steps between cause and effect. Explicitly, if one suspects that a causal relation is confounded and one can identify all of the possible confounders, controlling for these confounders will either make the correlation go away, in which case confounding exists, or it will make no difference to the correlation, in which case confounding can be ruled out (Kincaid, 2012).

On the other hand, however, having a mechanism in the sense of a causal intermediary and relevant causal structure at the same level is necessary in estimating the size of the causal relationship (Kincaid, 2012). This is because acute bias and inferential inaccuracy ensues from assuming the wrong intervening mechanisms and causal structure when estimating the size of a given cause (Kincaid, 2012).

There are three cases in particular where understanding mechanisms in the sense of causal structure is essential to avoid bias in effect size estimates. The first case involves controlling for a variable that is the joint effect of the two variables of interest. This will bias the effect size upward (Kincaid, 2012). In this way, the strategy of throwing every possible variable in, which is adopted in standard multiple regression practices, is counterproductive in estimating effect size when the variables are colliders (Kincaid, 2012). The second case involves including an intermediate variable in a multiple regression aimed at estimating the effect sizes of more distal causes. This produces a bias in the other direction (Kincaid, 2012). The third case, which is less about causality and more about inferences from sample to population (Kincaid, 2012), involves controlling for irrelevant variables. This increases the likelihood that size estimates of all the variables will be biased downward and, hence, the causal effect size estimates will be inaccurate (Kincaid, 2012). Again, this moral goes against the standard practice of controlling for every variable that comes to mind.

Nevertheless, the standard practice of multiple regression analysis can be improved upon by employing an explicit causal model. There are various ways to do this. According to Kincaid (2012), the most systematic method involves using an explicit model to identify the dependencies and independencies and then testing these findings against associations reflected in the data. This however, falls beyond the scope of this paper.

3. DATASET

3.1. BACKGROUND

The NLSGB began from a sample of randomly recruited adults who participated in the prior National Urban Prevalence Study of Gambling Behaviour (NUPSGB; Ross et al., 2010). For the purposes of the NLSGB, the researchers aimed to recruit a roughly equal number of subjects into each of the four PGSI risk categories. High scorers were thus significantly oversampled and there were not enough moderate risk and high risk NUPSGB subjects to fill these NLSGB sub-samples. Accordingly, additional self-reported problem gamblers were recruited to meet these goals.

The NLSGB is a 15-month, 6-wave panel study that focuses on the short-run determinants of gambling behaviour. Conducted in the Johannesburg, Durban, Cape Town and Tshwane metropoles of South Africa, the research team visited a sample of approximately 300 gamblers every three months for the duration of the study. Due to dropouts, the number of participants decreased over the course of the study, with only 248 participants remaining in the final wave.

The study is based on a face-to-face survey conducted by way of a questionnaire. The first 14 response categories of the questionnaire concern the respondents' personal and household demographics. The respondents were then presented with 17 response categories concerning gambling behaviour and influences. Following this, the gamblers were screened for problem gambling using both the PGSI and the DSM-IV-MR. Other standard measurement instruments used in the questionnaire include: Beck's Depression Inventory-II (BDI-II; Beck et al., 1996); Beck's Anxiety Inventory (BAI; Beck et al., 1988); Barrett's Impulsivity Scale-11 (BIS-11; Patton et al., 1995); the Kessler Psychological Distress Scale (K10; Kessler et al., 2002); the List of Threatening Experiences Questionnaire (LTE-Q; Brugha et al.,1985); the Perceived Stress Scale (PSS; Cohen et al., 1983); the General Self-Efficacy Scale (GSE; Schwarzer & Jerusalem, 1995); the Perceived Social Support – Friend Scale (PSS-Fr; Procidano and Heller, 1983); the Perceived Social Support – Family Scale (PSS-Fa; Procidano and Heller, 1983) as well as the World Health Organization (WHO) Alcohol, Smoking and Substance Involvement Screening Test (ASSIST; WHO ASSIST Working Group, 2002).

3.2. NATIONAL LONGITUDINAL STUDY REPORT

In 2011, Hofmeyr et al. produced a report on the first five waves of the NLSGB data. This report made a number of interesting findings. First, it was established that gambling participation declined over the course of the study, while the average amount of time and money spent on gambling was relatively stable over this period. Second, gambling severity classification was found to be relatively unstable across waves. Third, when considering the association between certain mental disorders and problem gambling behaviour, Hofmeyr et al. (2011) found positive relationships between problem gambling severity and anxiety, depression, impulsivity and alcohol use, respectively. As noted by the authors, these results suggest that it is imperative that individuals are screened for other co-occurring disorders when being assessed for problem gambling behaviour.

4. METHOD

4.1. VARIABLE CONSTRUCTION

Most of the variables used in this study are taken from the NLSGB dataset. Nonetheless, for the purposes of model construction, it was necessary to define and generate a number of variables that are not explicitly defined in the dataset. This is with regard to both independent variables and dependent variables.

4.1.1. Independent Variables

Social Influence measures the degree to which the respondent is influenced by the gambling behaviours of family and friends. This is an ordinal variable ranging from 0 to 2, constructed by summing two separate binary variables. First, *Friends or Family Gamble*, which is equal to 1 if the respondent's family or friends gamble often. Second, *Gamble with Friends or Family*, which is equal to 1 if the respondent gambles with friends or family often.

Childhood Influence measures the degree to which the respondent was subjected to gambling during childhood. *Childhood Influence* is an ordinal variable ranging from 0 to 3, constructed by summing three separate binary variables. First, *Exposure*, which is equal to 1 if the respondent was often around gambling during childhood. Second, *Friends*, which is equal to 1 if the respondent's childhood friends gambled often. Third, *Gambling Problem*

Exposure, which is equal to 1 if the respondent's friends or family suffered from gambling problems during the respondent's childhood.

Cognitive Bias measures the level of cognitive distortions demonstrated by the respondent. *Cognitive Bias* is an ordinal variable ranging from 0 to 6, constructed by summing two separate ordinal variables. First, *Illusion of Control*, which measures the degree to which the respondent exhibited an inability to differentiate between "chance-determined events" and "skill-determined events". This variable ranges from 0 to 4 and is defined by the respondent's response to four questions relating to the roles of luck and experience in gambling success. Second, *Gambler's Fallacy*, which measures the respondent's understanding of the sequencing of chance-based outcomes. This variable ranges from 0 to 2 and is defined by the respondent's response to two questions relating to probability depictions.

Gambling Self-Efficacy measures one's belief as to whether or not one could resist an opportunity to gamble in a given situation. *Gambling Self-Efficacy* is an ordinal variable ranging from 0 to 3, defined by the respondent's response to three questions relating perceived control over gambling behaviour.

4.1.2. Dependent Variables

The first set of dependent variables to be dealt with comprises two binary forms of the *PGSI Score* dependent variable. These two binary dependent variables differ only in cut-off score. The one *PGSI Score* binary dependent variable is equal to one if the respondent's total PGSI score was 8 or above and zero otherwise. The other *PGSI Score* binary dependent variable is equal to one if the respondent's total PGSI score was 10 or above and zero otherwise.

Next, the *Ordinal PGSI Score* variable was constructed. That is, a dependent variable that measures the PGSI score on a scale of 0 to 3 whereby 0 is indicative of "no risk" of problem gambling, 1 is indicative of "low risk" of problem gambling, 2 is indicative of "moderate risk" of problem gambling and 3 is indicative of "high risk" of problem gambling.

Similarly, the *Ordinal DSM-V-MR Score* variable, which is derived from the DSM-IV-MR tool established by Fisher (2000), was created. This is a dependent variable that measures problem gambling severity according to the new DSM-V criteria. Explicitly, *Ordinal DSM-V-MR Score* is measured using the DSM-IV-MR tool but omits the question relating to illegal activities and decreases the cut-off score from 5 to 4 so as to conform to the updated DSM-V definition of problem gambling. Similarly to *Ordinal PGSI Score*, *Ordinal DSM-V-MR Score* measures this adjusted DSM-V-MR score by way of four equally spaced groups ordered on a scale of 0 to 3 whereby 0 is indicative of "no risk" of problem gambling, 1 is indicative of "low risk" of problem gambling, 2 is indicative of "moderate risk" of problem gambling and 3 is indicative of "high risk" of problem gambling.

The final set of dependent variables to be considered comprises a continuous version of the aforementioned *Ordinal PGSI Score* dependent variable, *Continuous PGSI Score*, and a continuous version of the *Ordinal DSM-V-MR Score*. These variables are constructed by calculating each respondent's total PGSI score and total DSM-V-MR score, respectively. Both of these variables are truncated at zero and, in this way, do not exhibit a normal distribution. In order to deal with the non-normal distribution of these dependent variables, Tobit regression methods, which allow for censoring, are, in some cases, employed in conjunction with standard linear regression methods when dealing with these variables.

4.2. STATISTICAL ANALYSIS

Statistical regressions were employed for a number of purposes throughout this study. In the first place, stability tables and transition probabilities were used to analyze the temporal behaviour of problem gambling severity under various circumstances.

Next, random effects and fixed effects logistic regressions were performed using a binary *PGSI Score* dependent variable with the standard cut-off score of 8 and a set of risk factors proposed to be relevant in explaining the behaviour of problem gambling over time. To this end, Akaike's Information Criterion (AIC; Akaike, 1987) and Bayesian Information Criterion (BIC; Schwarz, 1978) analyses were employed so as to ensure a well-defined approach to model selection. That is, variables were added to and dropped from the model, one-by-one, so as to identify a model composition that reflects the lowest AIC and BIC values. Following this, further random effects and fixed effects logistic regressions were performed to test whether the standard PGSI cut-off score of 8 would perhaps be more appropriately defined by a cut-off score of 10. For this cause, a binary *PGSI Score* dependent variable with a cut-off score of 10 was regressed on the group of risk factors newly established in this study.

Moreover, for the purpose of examining problem gambling behaviour over time in line with the problem-centered view, a random effects Tobit regression, a random effects linear regression and a fixed effects linear regression were performed using both the *Continuous PGSI Score* and the *Continuous DSM-V-MR Score* dependent variables. Furthermore, it is important to note that in all cases concerning random effects and fixed effects models, the Hausman Specification Test was employed to determine the preferred model of the two.

Finally, in order to assess the effect of treating problem gambling as an ordinal disorder, as opposed to a continuous disorder, ordered logit random effects models were employed using both the *Ordinal PGSI Score* and the *Ordinal DSM-V-MR Score* dependent variables. These results were then compared to the respective random effects linear regression models described in the previous paragraph.

It is worth noting that, although the approach to model selection employed by this study made exclusive use of AIC and BIC analyses, significance tests were considered for comparative purposes throughout the analysis of results. That is, although variables were at no point added/dropped on the basis of significance test results, such results were considered purely for the exploration of differences existing between certain regression results. Importantly, while differences in statistical significance are by no means decisive, they do offer some meaningful insight.

5. RESULTS

5.1. PROBLEM GAMBLING SEVERITY STABILITY AND PERSISTENCE

A primary advantage of collecting panel data, as opposed to cross-sectional data, is that it permits the analysis of temporal trends in variables. Of central interest to the present study is the stability, trajectory and abatement of problem gambling behaviour and severity over time. In particular, given the relatively short period of time between the waves of the study, the focus is on the short-run stability and persistence of gambling severity.

TABLE I presents a tabulation of the PGSI categories across all 6 waves of the NLSGB data. The "Overall" column summarizes results in terms of person-years, which, essentially, refers to one observation at one point in time. Explicitly, there are 653 observations of individuals classified as "No Risk" gamblers; 264 observations of individuals classified in the "Low Risk" category, 330 observations of individuals classified as "Moderate Risk" gamblers and 399 observations of individuals classified in the "Problem Gambler" category. Therefore, in 39.67% of the data, individuals were classified as "No Risk" gamblers; in 16.04% of the data, individuals were classified in the "Low Risk" category; in 20.05% of the data, individuals were classified as "Moderate Risk" gamblers and in 24.24% of the data, individuals were classified in the "Problem Gambler" category.

TABLE I.
Stability of PGSI categories

	Overall		Between		Within
PGSI Category	Frequency	Percent	Frequency	Percent	Percent
No Risk	653	39.67	227	76.17	51.37
Low Risk	264	16.04	161	54.03	28.95
Moderate Risk	330	20.05	182	61.07	34.73
Problem Gambler	399	24.24	177	59.40	40.44
Total	1646	100	747	250.67	39.89

The "Between" column in TABLE I repeats this breakdown in terms of people, rather than person-years. From this, 227 people (76.17%) were classified as "No Risk" gamblers at some point across the 6 waves of the study; 161 people (54.03%) were classified in the "Low Risk" category, 182 people (61.07%) were ever classified as "Moderate Risk" gamblers and 177 people (59.40%) were classified in the “Problem Gambler” category. Summing these figures yields a grand total of 747 individuals (250.67%). This means that there are people in the sample who were classified into different categories of gambling severity across the 6 waves.

Lastly, the “Within” column in TABLE I shows the fraction of time that respondents were classified in the various categories of gambling severity. More explicitly, conditional on an individual ever having been classified as a “No Risk” gambler, 51.37% of that individual’s observations fell into that gambling severity category over the 6 waves of study. Similarly, conditional on an individual ever having been classified in the “Low Risk” category, 28.95% of that individual’s observations fell into that gambling severity category. Again, conditional on an individual having ever been classified as a “Moderate Risk” gambler, 34.73% of that individual’s observations fell into the category. Finally, conditional on an individual ever having been classified in the “Problem Gambler” category, 40.44% of that individual’s observations fell into that category over the period of study. Essentially, these figures measure the stability of the various gambling severity categories over time. Accordingly, the “Low Risk” category is the least stable, followed by the “Moderate Risk” category, then the “Problem Gambler” category and, finally, the “No Risk” category. By implication, individuals who were ever classified in the “No Risk” or the “Problem Gambler” categories were more likely to stay in those categories than people classified in the “Low Risk” and the “Moderate Risk” categories. Of note is the total figure of 39.89% at the bottom of the “Within” column, which is the normalized between weighted average of the within percents and thereby provides a measure of the overall stability of the gambling severity categories.

In general, the figures provided in TABLE I imply that gambling severity classification is markedly unstable over time. This appears to be the case throughout the severity continuum.

Relatedly, TABLE II shows the transition probabilities of gambling severity categories across the waves of the study. The rows of the table represent the initial categories while the columns represent the final categories. Accordingly, the principal diagonal of the table shows the likelihood that an individual classified in a particular gambling severity category in one wave will remain in that category by the next wave. This complements the results of the preceding analysis since TABLE II reveals that individuals classified in the “No Risk” category or the “Problem Gambler” category are more likely to remain there between waves (61.50% and 44.16%, respectively) than are the “Low Risk” and “Moderate Risk” gamblers (25.94% and 34.51%, respectively).

TABLE II.
Transition probabilities of PGSI categories

	Final Value				
Initial Value	No Risk	Low Risk	Moderate Risk	Problem Gambler	Total
No Risk	61.50	15.89	9.91	12.71	100
Low Risk	42.92	25.94	17.92	13.21	100
Moderate Risk	23.59	17.25	34.51	24.65	100
Problem Gambler	22.08	12.30	21.45	44.16	100
Total	41.32	16.19	19.07	22.70	100

Interestingly, between waves, “Problem Gambler” individuals have an almost equal probability of moving to the “No Risk” category (22.08%) and to the “Moderate Risk” category (21.45%). Similarly, “Moderate Risk” gamblers have an almost equal probability of moving to the “No Risk” category (23.59%) and to the “Problem Gambler” category (24.65%). Finally, although both likelihoods are low, “No Risk” gamblers have a higher probability of moving to the Problem Gambler” category (12.71%) than to the “Moderate Risk” category (9.91%).

Although this transition matrix is very interesting, it was noted by LaPlante (2008) that the stability and trajectory of problem gambling severity must be considered in light of “addiction hopping”. That is, individuals can experience numerous transitions between different expressions of addiction over time and it is thus important that the existence of other addiction disorders are accounted for when analyzing the stability and trajectory of problem gambling severity.

To this end, TABLE III shows the transition probabilities of gambling severity categories across waves for individuals who suffer from another form of addiction – tobacco addiction – and may thus be considered to have “addictive personalities”. In contrast, TABLE IV shows such transition probabilities for individuals who do not suffer from tobacco addiction and are thus considered to have “non-addictive personalities". Importantly, for the purposes of this analysis, a tobacco addict is defined as someone who reportedly smokes either "daily" or "weekly" as per the WHO ASSIST screen.

TABLE III.
Transition probabilities of PGSI categories for addictive personalities

Initial Value	Final Value: No Risk	Low Risk	Moderate Risk	Problem Gambler	Total
No Risk	59.05	18.10	13.33	9.52	100
Low Risk	36.67	31.67	18.33	13.33	100
Moderate Risk	21.25	15.00	30.00	33.75	100
Problem Gambler	19.28	12.05	28.92	39.76	100
Total	35.67	18.29	22.26	23.78	100

Remarkably, a comparison of TABLE III and TABLE IV explicates that, between waves, addictive personalities have a lower probability of remaining in the "Problem Gambler" category (39.76%) than do non-addictive personalities (45.73%). Similarly, addictive personalities have a lower probability of remaining in the "No Risk" category (59.05%) than do non-addictive personalities (62.84%). Moreover, of the other three categories, "Problem Gambler" addictive personalities are most likely to move to the "Moderate Risk" category (28.92%) whereas "Problem Gambler" non-addictive personalities are most likely to move to the "No Risk" category (23.62%).

TABLE IV.
Transition probabilities of PGSI categories for non-addictive personalities

Initial Value	Final Value: No Risk	Low Risk	Moderate Risk	Problem Gambler	Total
No Risk	62.84	14.21	9.29	13.66	100
Low Risk	45.24	23.81	15.87	15.08	100
Moderate Risk	26.11	19.75	32.48	21.66	100
Problem Gambler	23.62	12.56	18.09	45.73	100
Total	44.22	16.27	16.63	22.88	100

In general, these inferences are all in support of the "addiction-hopping" hypothesis as they provide evidence for the notion that, even though the problem gamblers may tend toward improvement in gambling behaviour over time, such behaviour might be temporarily replaced by a different type of disordered behaviour. In this way, individuals suffering from multiple addiction disorders are likely skewing the trajectories of problem gambling. This highlights the importance of understanding factors that affect gambling severity over time.

5.2. FACTORS AFFECTING PROBLEM GAMBLING

As the focus of this paper is, essentially, problem gambling, a good base-point in understanding the factors that affect disordered gambling behaviour over time is a model that adequately describes the factors that determine the probability of an individual being diagnosed as a problem gambler as per the PGSI. To this end, a binary *PGSI Score* dependent variable with a cut-off score of 8 was regressed on a set of risk factors proposed to influence gambling behaviour over time. The proposed set of risk factors was compiled in light of the relevant literature and the fitness of the model was assessed using a systematic approach to model selection: AIC and BIC analyses. That is, seemingly interesting and theoretically-relevant variables were added to the model (one at a time) and AIC and BIC results were noted with the individual addition and exclusion of each variable so as to ensure that the fitness of the model was in fact increasing in the process. The results obtained from running this model with the binary PGSI Score dependent variable with a cut-off score of 8 are presented in TABLE V.

TABLE V.

Random effects logistic regression and fixed effects logistic regression of proposed set of risk factors using a binary *PGSI Score* dependent variable with a cut-off score of 8

	Random Effects		Fixed Effects	
Variable	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
Female	-0.27	(0.33)		
Age	0.01	(0.01)	0.37	(0.52)
Years of Education	0.10	(0.08)		
Employment Status	0.89***	(0.34)	-0.23	(0.55)
Log Income	0.06	(0.05)	0.03	(0.08)
K10 Score	0.08***	(0.02)	0.08**	(0.03)
BAI Score	0.01	(0.02)	0.01	(0.02)
BDI Score	0.01	(0.02)	0.02	(0.03)
BIS Score	0.03	(0.02)	0.03	(0.03)
WHO ASSIST - Highest Drug Score	0.04	(0.04)	0.12*	(0.07)
WHO ASSIST - Alcohol Score	0.09	(0.26)	-0.02	(0.40)
Cognitive Bias	0.14*	(0.09)	0.14	(0.12)
Gambling Self-Efficacy	-0.48***	(0.13)	-0.50***	(0.17)
Social Influence	0.45**	(0.18)	0.52**	(0.22)
Childhood Influence	0.19	(0.15)		
Wave 2	-0.84**	(0.41)	-1.24**	(0.52)
Wave 3	-1.20**	(0.48)	-1.47**	(0.66)
Wave 4	-0.63	(0.41)	-1.02	(0.66)
Wave 5	-0.67	(0.42)	-1.25*	(0.75)
Wave 6	-0.46	(0.41)	-1.01	(0.96)
Constant	-7.39***	(1.83)		

Note: Both regressions performed on NLSGB dataset
Standard errors in parentheses
***** represents significance at the 1% level***
*** represents significance at the 5% level*
** represents significance at the 10% level*

TABLE V presents the estimates from two different logistic models of factors that may influence gambling behaviour over time. The first set of estimates listed in TABLE V is from a random effects model. A random effects model takes into account the panel structure of the NLSGB data and employs the assumption that the variation across individuals is random and uncorrelated with the included independent variables. This model is particularly useful when there is reason to believe that differences across individuals influence gambling behaviour over time.

A number of interesting risk factors are of note. First, the positive coefficients on *Employment Status* (0.89) and *K10 Score* (0.08), both of which are significant at the 1% level, imply that being employed and suffering from psychosocial distress, respectively, are associated with a higher probability of being a problem gambler. Similarly, the positive coefficient on *Social Influence* (0.45), which is significant at the 5% level, suggests that being surrounded by individuals who gamble frequently is related to a higher probability of problem gambling. Furthermore, the positive coefficient on *Cognitive Bias* (0.14), significant at the 10% level, indicates that a greater demonstration of cognitive distortions, such as an illusion of control or adherence to the gambler's fallacy, is associated with a higher probability of suffering from problem gambling.

Correspondingly, the negative coefficient on *Gambling Self-Efficacy* (-0.48), which is significant at the 1% level, implies that greater ability to control gambling behaviour is related to a lower probability of problem gambling. Additionally, the negative coefficients on *Wave 2* (-0.84) and *Wave 3* (-1.20), both significant at the 5% level, suggest that, as the study progressed, the probability of being diagnosed with problem gambling declined relative to that observed in Wave 1 of the study. Importantly, in light of the NLSGB's massive oversampling based on one cohort of PGSI score observations, this decline in average PGSI score over the course of the subsequent waves is unsurprising.

Although generally attractive, the random effects model rests on a number of stringent statistical assumptions, which often go unfulfilled by a dataset. It is for this reason that a fixed effects model is considered.

A fixed effects model encompasses the panel structure of the dataset and is used to analyze the impact of time-varying variables. Accordingly, the model investigates the relationship between predictor and response variables within an individual. When using this model, it is assumed that characteristics within the individual may impact or bias the predictor or outcome variables and must therefore be controlled for. Simply, the fixed effects estimator removes the impact of any time-invariant characteristics of a person from the predictor variables in a model, which permits the assessment of the net effect of each predictor variable. The fundamental insight from this model is that the removal of time-invariant effects means that any changes in gambling severity must be due to influences other than those fixed characteristics.

Some differences between the two models presented in TABLE V are of note. Firstly, the *Female*, *Years of Education* and *Childhood Influence* variables have been omitted from the fixed effects model. This is to be expected in a fixed effects context, as these variables are unlikely to vary within adult individuals over time, particularly given the short timeframe associated with this study. Additionally, the coefficient on *Employment Status* (-0.23), which was positive and highly significant in the random effects model, is negative and no longer significant in the fixed effects model. Thus, being employed is associated with a lower probability of problem gambling in this model. Likewise, the coefficient on *Cognitive Bias*, although unchanged in magnitude, is no longer significant in the fixed effects model. The loss of significance associated with these variables is likely due to the generally slow change in employment status and demonstration of cognitive bias over time, making these factors less likely to cause significant changes in an individual over the short period of the study. Conversely, the coefficient on *Wave 5*, which was not significant in the random effects model, is significant at the 10% level and has increased in magnitude (from -0.67 to -1.25) in the fixed effects model.

Furthermore, it is interesting to note that, in general, the size of the coefficient estimates found to be significant (at the 1% level, the 5% level or the 10% level) in both models do not change massively between the two cases. Nevertheless, where changes do occur, the coefficient appears to be greater (in absolute value) in the fixed effects model *Gambling Self-Efficacy* (-0.48 in the random effects model and -0.50 in the fixed effects model), *Social Influence* (0.45 in the random effects model and 0.52 in the fixed effects model), *Wave 2* (-0.84 in the random effects model and -1.24 in the fixed effects model) and *Wave 3* (-1.20 in the random effects model and -1.47 in the fixed effects model) all suggest a slightly more intense association with the probability of being a problem gambler in the fixed effects model.

In general, the models presented in TABLE V suggest a handful of factors that influence the probability of problem gambling over time. A robust finding across the two models is that psychological distress and social influences are positively related to problem gambling, while gambling self-efficacy is negatively related to problem gambling.

In order to determine the preferred model, the Hausman Specification Test was employed. By evaluating the consistency of an estimator against an alternative, less efficient but consistent estimator, this test determines whether a statistical model corresponds to the data. Due to higher efficiency, the null hypothesis for this test is that random effects is the preferred model; under the alternative, fixed effects is at least consistent and is therefore preferred. When performed on the two models presented in TABLE V, the Hausman Test returned a chi-squared statistic of 18.09 and a p-value of 0.3833. Accordingly, the null hypothesis cannot be rejected and random effects is the preferred model.

5.3. PGSI CUT-OFF POINTS

The next action of the study involves addressing the aforementioned criticisms regarding the broadness of the "high risk" category (Kincaid et al., 2012). More specifically, the standard cut-off score of 8 was evaluated against the suggested cut-off score of 10 (Kincaid et al., 2012). To this end, a binary *PGSI Score* dependent variable with a cut-off score of 10 was regressed on the proposed set of risk factors established above. TABLE VI presents the estimates from two different logistic models.

Again, the first set of estimates listed in TABLE VI is from a random effects model. A number of interesting risk factors are of note. The positive coefficients on *K10 Score* (0.08) and *BIS Score* (0.05), both of which are significant at the 1% level, suggest that high levels of psychological distress and impulsivity are associated with a greater probability of problem gambling over time. Similarly, the positive coefficient on *Employment Status* (0.94), significant at the 5% level, implies that being employed is related to a higher probability of suffering from problem gambling.

On the other hand, the negative coefficient on *Gambling Self-Efficacy* (-0.36), significant at the 1% level, suggests that the self-perceived ability to control gambling behaviour is associated with a lower probability of problem gambling over time. Finally, the negative coefficients on *Wave 2* (-1.21), *Wave 3* (-1.39) and *Wave 5* (-1.35), all significant at the 5% level, propose that, as the study progressed, the probability of being diagnosed with problem gambling declined relative to that observed in Wave 1 of the study. Again, in light of the sample construction, this finding is expected.

TABLE VI.

Random effects logistic regression and fixed effects logistic regression of proposed set of risk factors using a binary *PGSI Score* dependent variable with a cut-off score of 10

	Random Effects		Fixed Effects	
Variable	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
Female	0.13	(0.34)		
Age	0.02	(0.01)	1.002	(0.70)
Years of Education	0.12	(0.08)		
Employment Status	0.94**	(0.37)	-0.03	(0.77)
Log Income	0.07	(0.05)	0.02	(0.09)
K10 Score	0.08***	(0.03)	0.11**	(0.04)
BAI Score	0.01	(0.02)	0.02	(0.03)
BDI Score	-0.001	(0.02)	-0.01	(0.03)
BIS Score	0.05***	(0.02)	0.07**	(0.03)
WHO ASSIST - Highest Drug Score	0.05	(0.04)	0.17**	(0.09)
WHO ASSIST - Alcohol Score	-0.26	(0.30)	-0.03	(0.59)
Cognitive Bias	0.05	(0.09)	0.20	(0.16)
Gambling Self-Efficacy	-0.36***	(0.14)	-0.12	(0.20)
Social Influence	0.18	(0.19)	-0.07	(0.27)
Childhood Influence	0.01	(0.15)		
Wave 2	-1.21**	(0.49)	-1.88**	(0.74)
Wave 3	-1.39**	(0.57)	-1.75**	(0.85)
Wave 4	-0.52	(0.44)	-1.00	(0.82)
Wave 5	-1.35**	(0.54)	-2.63**	(1.04)
Wave 6	-0.38	(0.42)	-1.59	(1.23)
Constant	-9.75***	(2.07)		

Note: Both regressions performed on NLSGB dataset
Standard errors in parentheses
**** represents significance at the 1% level*
*** represents significance at the 5% level*
** represents significance at the 10% level*

The second set of estimates listed in TABLE VI is from a fixed effects model. Some changes are of note. First, for the same reasons provided with regard to TABLE V above, the *Female*, *Years of Education* and *Childhood Influences* variables have been omitted from the fixed effects model. Moreover, the coefficient on *Employment Status* (-0.03), which was both positive and significant at the 5% level in the random effects model, is negative and no longer significant in the fixed effects model. This mirrors the findings presented in TABLE V. Similarly, the coefficient on *Gambling Self-Efficacy* (-0.12), although unchanged in direction, is smaller in absolute value and is no longer significant in the fixed effects model. This loss of significance suggests that, in general, one's self-perceived ability to stop gambling does not exhibit much change over time. Conversely, the coefficient on *WHO ASSIST – Highest Drug Score* (0.17), which was not significant at even the 10% level in the random effects model, is significant at the 5% level in the fixed effects model. The positive nature of this coefficient suggests that drug addiction is associated with a higher probability of problem gambling.

Moreover, it is again interesting to note that, in general, the size of the coefficient estimates found to be significant (at the 1% level, the 5% level or the 10% level) in both models do not change massively between the two cases. Nevertheless, where changes do occur, the coefficient appears to be greater (in absolute value) in the fixed effects model. For instance, *K10 Score* (0.08 in the random effects model and 0.11 in the fixed effects model), *BIS Score* (0.05 in the random effects model and 0.07 in the fixed effects model), *Wave 2* (-1.21 in the random effects model and -1.88 in the fixed effects model), *Wave 3* (-1.39 in the random effects model and -1.75 in the fixed effects model) and *Wave 5* (-1.35 in the random effects model and -2.63 in the fixed effects model) all suggest a slightly more intense association with the probability of being a problem gambler in the fixed effects model.

Overall, the models presented in TABLE VI reveal a number of factors that influence the probability of problem gambling over time when the "high risk" category is narrowed. A particularly robust finding across the two models is that psychological distress and impulsivity are positively related to problem gambling.

In order to determine the preferred model, the Hausman Specification Test was employed. When performed on the two models presented in TABLE VI, the Hausman Test returned a chi-squared statistic of 24.78 and a p-value of 0.0998. Accordingly, the null hypothesis cannot be rejected and random effects is again the preferred model.

In light of the above, an assessment of the differences between a cut-off score of 8 and a cut-off score of 10 can be conducted by comparing the two random effects models presented above. These results are represented in TABLE VII.

From these results, it is clear that changing the cut-off score from 8 to 10 has an influence on both the statistical significance of certain risk factors as well as the size of the effect of these variables on the risk of problem gambling. Firstly, one variable in particular proves to be more significant in the case of a cut-off score of 10. That is, the

BIS Score estimate, which is not at all significant when the cut-off score is 8, is significant at the 1% level when the cut-off score is 10. The size of this estimate has also increased slightly from 0.03 to 0.05. This suggests that limiting diagnosis to individuals who exhibit more severe characteristics of problem gambling results in a stronger and more pertinent association between impulsivity and the probability of problem gambling.

Conversely, the *Social Influence* estimate, significant at the 5% level when the cut-off score is 8, is not significant when the cut-off score is 10. The effect size of this factor has also decreased from 0.45 to 0.18. This suggests that limiting diagnosis to individuals who exhibit more severe characteristics of problem gambling results in a weaker and less significant association between being surrounded by people who gamble frequently and the probability of problem gambling. Likewise, the *Cognitive Bias* estimate, significant at the 10% level when the cut-off score is 8, is not significant when the cut-off score is 10. This change in significance is also associated with a decrease in effect size from 0.14 to 0.05. Again, this implies that limiting diagnosis to individuals who exhibit more severe characteristics of problem gambling results in a weaker and less significant relationship between the exhibition of cognitive distortions and the probability of problem gambling. Moreover, the *Employment Status* estimate, significant at the 1% level when the cut-off score is 8, decreased to the 5% level when the cut-off score is 10. Unlike the *Social Influence* and *Cognitive Bias* estimates, however, the magnitude of the *Employment Status* estimate has increased from 0.89 to 0.94. This suggests that that limiting diagnosis to individuals who exhibit more severe characteristics of problem gambling results in a stronger but slightly less significant relationship between being employed and the probability of problem gambling.

Furthermore, it is interesting to note that the size of the coefficient estimates found to remain at the same level of significance in both cut-off score cases do not change massively between the two cases. For instance, the coefficient on *K10 Score* (0.08) remains unchanged. This implies that limiting diagnosis to individuals who exhibit more severe characteristics of problem gambling has no influence on the relationship between psychological distress and the probability of being a problem gambler. The coefficient on *Gambling Self-Efficacy*, however, decreases in absolute value from -0.48 when the cut-off score is 8 to -0.36 when the cut-off score is 10. This implies that, although limiting diagnosis to individuals who exhibit more severe characteristics of problem gambling has no influence on the significance of the association between self-perceived ability to control gambling behaviour and the probability of problem gambling, it does weaken the association.

TABLE VII.

Random effects logistic regression of proposed set of risk factors using a binary *PGSI Score* dependent variable with a cut-off score of 8 and a binary *PGSI Score* dependent variable with a cut-off score of 10

	Cut-Off Score of 8		Cut-Off Score of 10	
Variable	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
Female	-0.27	(0.33)	0.13	(0.34)
Age	0.01	(0.01)	0.02	(0.01)
Years of Education	0.10	(0.08)	0.12	(0.08)
Employment Status	0.89***	(0.34)	0.94**	(0.37)
Log Income	0.06	(0.05)	0.07	(0.05)
K10 Score	0.08***	(0.02)	0.08***	(0.03)
BAI Score	0.01	(0.02)	0.01	(0.02)
BDI Score	0.01	(0.02)	-0.001	(0.02)
BIS Score	0.03	(0.02)	0.05***	(0.02)
WHO ASSIST - Highest Drug Score	0.04	(0.04)	0.05	(0.04)
WHO ASSIST - Alcohol Score	0.09	(0.26)	-0.26	(0.30)
Cognitive Bias	0.14*	(0.09)	0.05	(0.09)
Gambling Self-Efficacy	-0.48***	(0.13)	-0.36***	(0.14)
Social Influence	0.45**	(0.18)	0.18	(0.19)
Childhood Influence	0.19	(0.15)	0.01	(0.15)
Wave 2	-0.84**	(0.41)	-1.21**	(0.49)
Wave 3	-1.20**	(0.48)	-1.39**	(0.57)
Wave 4	-0.63	(0.41)	-0.52	(0.44)
Wave 5	-0.67	(0.42)	-1.35**	(0.54)
Wave 6	-0.46	(0.41)	-0.38	(0.42)
Constant	-7.39***	(1.83)	-9.75***	(2.07)

Note: Both regressions performed on NLSGB dataset
Standard errors in parentheses
**** represents significance at the 1% level*
*** represents significance at the 5% level*
** represents significance at the 10% level*

In general, the comparison conducted by way of the results presented in TABLE VII suggests that increasing the cut-off score from 8 to 10 has various effects. This provides evidence for the suggestion that the temporal problem gambling behaviour of individuals with a PGSI Score of 8 or 9 tends to differ from that of individuals with a PGSI Score of 10 and above. This claim is further supported by the transition matrix presented in TABLE VIII, which replaces the 8-threshold between the "Moderate Risk" category and the "Problem Gambler" category represented in TABLE II with a 10-threshold.

A cursory comparison of TABLE VIII and TABLE II does not present any surprising results. Individuals classified in the 10-threshold "Problem Gambler" category are less likely to remain there between waves (34.58%) than are individuals classified in the 8-threshold "Problem Gambler" category (44.16%). Correspondingly, individuals classified in the 10-threshold "Moderate Risk" category are more likely to remain there between waves (43.15%) than are individuals classified in the 8-threshold "Moderate Risk" category (34.51%). These changes in severity persistence are expected; it makes sense that decreasing the size of the "Problem Gambler" category will decrease the probability of remaining in that category, while increasing the size of the Moderate Risk category will increase the probability of remaining there.

TABLE VIII.
Transition probabilities of PGSI categories using a cut-off score of 10

Initial Value	Final Value				
	No Risk	Low Risk	Moderate Risk	Problem Gambler	Total
No Risk	61.50	15.89	13.27	9.35	100
Low Risk	42.92	25.94	23.11	8.02	100
Moderate Risk	23.00	16.80	43.15	17.05	100
Problem Gambler	22.43	10.75	32.24	34.58	100
Total	41.32	16.91	26.41	15.36	100

More interestingly, between waves, the 8-threshold "Problem Gambler" individuals have an almost equal probability of moving to the "No Risk" category (22.08%) and to the "Moderate Risk" category (21.45%), whereas the 10-threshold "Problem Gambler" individuals have a notably higher probability of moving to the "Moderate Risk" category (32.34%) than to the "No Risk" category (22.43%). Relatedly, the 8-threshold "Moderate Risk" gamblers have an almost equal probability of moving to the "No Risk" category (23.59%) and to the "Problem Gambler" category (24.65%), whereas the 10-threshold "Moderate Risk" gamblers have a higher probability of moving to the "Low Risk" category (23.00%) than to the "Problem Gambler" category (17.05%). These two findings provide further evidence to suggest that there is a difference in the temporal problem gambling behaviour of individuals with a PGSI Score of 8 or 9 and individuals with a PGSI score of 10 and above. Specifically, individuals with a PGSI score of 10 and above tend to exhibit less fluctuation in problem gambling severity.

Moreover, a comparison of the transition matrix for addictive personalities illustrated in TABLE IX and the transition matrix for non-addictive personalities illustrated in TABLE X, which simply replace the 8-threshold with a 10-threshold in TABLE III and TABLE IV, respectively, provide further evidence for these differences in behaviour. In particular, between waves, addictive personalities have a slightly higher probability of remaining in the 10-threshold "Problem Gambler" category (35.59%) than do non-addictive personalities (33.59%).

TABLE IX.
Transition probabilities of PGSI categories for addictive personalities using a cut-off score of 10

Initial Value	Final Value				
	No Risk	Low Risk	Moderate Risk	Problem Gambler	Total
No Risk	59.05	18.10	16.19	6.67	100
Low Risk	36.67	31.67	20.00	11.67	100
Moderate Risk	23.08	14.42	43.27	19.23	100
Problem Gambler	15.25	11.86	37.29	35.59	100
Total	35.67	18.29	29.27	16.77	100

This result is in stark-contrast with the findings associated with the 8-threshold "Problem Gambler" category, which provided solid evidence for "addiction hopping". Accordingly, increasing the cut-off to 10 seems to eliminate the presence of "addiction-hopping" and thus may offer a more reliable perception of the stability and trajectory of problem gambling behaviour and severity.

TABLE X.
Transition probabilities of PGSI categories for non-addictive personalities using a cut-off score of 10

Initial Value	Final Value				
	No Risk	Low Risk	Moderate Risk	Problem Gambler	Total
No Risk	62.84	14.21	13.11	9.84	100
Low Risk	45.24	23.81	23.81	7.14	100
Moderate Risk	24.09	18.64	40.00	17.27	100
Problem Gambler	25.74	11.03	29.41	33.82	100
Total	44.22	16.27	24.29	15.21	100

5.4. PROBLEM-CENTERED APPROACH

Next, the aforementioned criticism regarding the failure of the PGSI to fully embody the DSM criteria for problem gambling is addressed. Specifically, the PGSI seems to present an amalgamation of two conflicting conceptions of problem gambling (Kincaid et al., 2012). On the one hand, in line with the DSM criteria, it defines problem gambling as a problem-centered model derived from "problems in living" (Kincaid et al., 2012). On the other hand, however, it also accepts that problem gambling is an addiction-centered model, characterized by a loss of control (Kincaid et al., 2012).

A preliminary assessment of this criticism was conducted by determining the correlation between the *Ordinal PGSI Score* variable and the *Ordinal DSM-V-MR Score*. As described above, the new DSM-V criteria for problem gambling was employed in place of the outdated DSM-IV criteria so as to ensure relevant results. A correlation coefficient of 0.5132 was found between *Ordinal PGSI Score* and *Ordinal DSM-V-MR Score*. This low degree of correlation indicates that the PGSI and the DSM-V-MR capture different areas of the problem gambling disorder.

Further evidence for this claim was found when testing for commonalities among individuals who dropped out between waves. Explicitly, while individuals who dropped out were found to display significantly higher DSM-V-MR scores than those who remained through all 6 waves of study, no significant difference in PGSI score was found between the two groups. Interestingly, individuals who dropped out were also found to display significantly higher levels of impulsivity than those who remained through all 6 waves of study. In light of all this, it is clear that, for completeness, it is imperative that both the PGSI and the DSM measures are considered when examining gambling behaviour.

A key feature of the problem-based approach is the movement away from the dichotomous definition of problem gambling. The models described above are based on binary dependent variables and therefore assume that an individual is either at risk of problem gambling or is not. In this way, the risk factors considered simply affect the subject's probability of being a problem gambler, rather than the level or degree of problem gambling behaviour exhibited by the subject. In order to consider the determinants of problem gambling on a continuous spectrum of "low" to "high", the *Continuous PGSI Score* dependent variable was regressed on the set of risk factors proposed above.

TABLE XI presents the estimates from three different models of factors that may influence gambling behaviour over time. The first set of estimates listed in TABLE XI is from a random effects Tobit model.

A number of variables are of interest. First, the positive coefficients on *K10 Score* (0.14) and *Social Influence* (0.63), both of which are significant at the 1% level, indicate that psychological distress and being associated with people who gamble frequently, respectively, are associated with higher PGSI scores over time. Similarly, the positive coefficients on *Years of Education* (0.21) and *Employment Status* (0.76), both significant at the 5% level, suggest that higher educational attainment and being employed, respectively, are associated with higher PGSI scores. Likewise, the positive coefficients on *BIS Score* (0.03) and *Cognitive Bias* (0.16), both significant at the 10% level, imply that higher levels of impulsivity and displays of cognitive distortions, respectively, are associated with higher PGSI scores.

Conversely, the negative coefficient on *Gambling Self-Efficacy* (-0.65), significant at the 1% level, suggests that a greater degree of self-perceived ability to control gambling behaviour is related to lower PGSI scores. Moreover, the negative coefficients on *Wave 2* (-1.04), *Wave 3* (-1.35), *Wave 5* (-1.63) and *Wave 6* (-1.18), significant at either the 1% level or the 5% level, imply that, again, as expected, as the study progressed, the average PGSI score declined relative to that observed in Wave 1 of the study.

TABLE XI.

Random effects Tobit regression, random effects linear regression and fixed effects linear regression of proposed set of risk factors using a *Continuous PGSI Score* dependent variable

	Tobit		Random Effects		Fixed Effects	
Variable	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
Female	-0.16	(0.41)	-0.20	(0.44)		
Age	0.002	(0.02)	0.004	(0.02)	0.37	(0.48)
Years of Education	0.21**	(0.10)	0.22**	(0.10)	0.29	(0.65)
Employment Status	0.76**	(0.37)	0.69*	(0.38)	-0.17	(0.55)
Log Income	0.06	(0.05)	0.05	(0.05)	-0.02	(0.06)
K10 Score	0.14***	(0.03)	0.14***	(0.03)	0.12***	(0.03)
BAI Score	0.02	(0.02)	0.02	(0.02)	0.03	(0.03)
BDI Score	0.03	(0.03)	0.03	(0.03)	0.06*	(0.03)
BIS Score	0.03*	(0.02)	0.03*	(0.02)	0.04	(0.03)
WHO ASSIST - Highest Drug Score	0.06	(0.05)	0.06	(0.05)	0.08	(0.06)
WHO ASSIST - Alcohol Score	0.29	(0.33)	0.28	(0.34)	0.16	(0.42)
Cognitive Bias	0.16*	(0.09)	0.16*	(0.09)	0.17	(0.12)
Gambling Self-Efficacy	-0.65***	(0.14)	-0.65***	(0.14)	-0.62***	(0.17)
Social Influence	0.63***	(0.20)	0.63***	(0.20)	0.52**	(0.24)
Childhood Influence	0.25	(0.19)	0.26	(0.20)		
Wave 2	-1.04**	(0.46)	-1.02**	(0.45)	-0.96*	(0,50)
Wave 3	-1.35***	(0.49)	-1.32***	(0.49)	-1.27**	(0.57)
Wave 4	-0.72	(0.47)	-0.69	(0.47)	-0.77	(0.62)
Wave 5	-1.63***	(0.47)	-1.63***	(0.47)	-2.04***	(0.73)
Wave 6	-1.18**	(0.48)	-1.16**	(0.48)	-1.43*	(0.84)
Constant	-4.12**	(2.02)	-4.31**	(2.12)	-18.10	(20.30)

Note: All regressions performed on NLSGB dataset
Standard errors in parentheses
**** represents significance at the 1% level*
*** represents significance at the 5% level*
** represents significance at the 10% level*

The second set of estimates listed in TABLE XI is from a random effects linear regression model. These results are remarkably similar to those obtained from the random effects Tobit regression model. One slight difference is that there appears to be a decrease in the statistical significance of the *Employment Status* estimate from the 5%

level to the 10% level, which is accompanied by a decrease in the effect size from 0.76 to 0.69.

The third set of estimates listed in TABLE XI is from a fixed effects linear regression model. A number of differences between this model and the previous two are worth noting. First, *Female* and *Childhood Influence* have been omitted. This is likely due to the time-invariant nature of these two variables. Interestingly, unlike in the case of the binary *PGSI Score* dependent variable, *Years of Education* has not been omitted from the current model. Furthermore, however, unlike in the other two models presented in TABLE XI, where the *Years of Education* estimate was found to be significant at the 5% level, this estimate is not significant at even the 10% level in the fixed effects model. Moreover, the coefficient on *Employment Status* (-0.17), which is positive and significant in both preceding models, is negative and no longer significant in the current model. Accordingly, this model predicts that being employed is associated with lower PGSI scores over time. Similarly, the *BIS Score* and the *Cognitive Bias* estimates, both significant at the 10% level in the preceding models, are no longer significant in the current model. These significance losses are likely a result of the slow change expected in one's employment status, impulsive behaviour and cognitive distortions over time. Further more, the *Social Influence* estimate, although still significant in the fixed effects model, has decreased in magnitude from 0.63 in the preceding models to 0.52 in the current model. Conversely, the coefficient on *BDI Score* (0.06), which was not significant in either of the preceding models, is significant at the 10% level in the current model.

In general, the models presented in TABLE XI suggest a handful of factors that influence the level of problem gambling risk, as per the PGSI, over time. A robust finding across the three models is that psychological distress and social influences are positively related to PGSI score, while gambling self-efficacy is negatively related to PGSI score.

The Hausman Specification Test was employed on the latter two models presented in TABLE XI. The results returned a chi-squared statistic of 21.76 and a p-value of 0.2428. Accordingly, the null hypothesis cannot be rejected and random effects is the preferred model.

As noted above, for the sake of completeness, it is imperative that the DSM-V-MR measure is considered alongside the PGSI when examining gambling behaviour. Accordingly, the *Continuous DSM-V-MR Score* dependent variable was regressed on the set of risk factors proposed above.

TABLE XII presents the estimates from three different models of factors that may influence gambling behaviour over time. Again, the first set of estimates listed in TABLE XII is from a random effects Tobit model. A number of significant variables are of note. First, the positive coefficients on *K10 Score* (0.04), *BAI Score* (0.04), *BIS Score* (0.01) *Social Influence* (0.19), all significant at the 1% level, indicate that psychological distress, anxiety, impulsivity and being associated with people who gamble frequently, respectively, are associated with higher DSM-V-MR scores over time. Similarly, the positive coefficients on *Years of Education* (0.05) and *Log Income* (0.03), both significant at the 5% level, suggest that higher educational attainment and higher income, respectively, are associated with higher DSM-V-MR scores. Likewise, the positive coefficient on *Cognitive Bias* (0.04), significant at the 10% level, implies that greater displays of cognitive distortions are associated with higher DSM-V-MR scores.

TABLE XII.

Random effects Tobit regression, random effects linear regression and fixed effects linear regression of proposed set of risk factors using a *Continuous DSM-V-MR Score* dependent variable

	Tobit		Random Effects		Fixed Effects	
Variable	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
Female	-0.01	(0.11)	-0.02	(0.12)		
Age	-0.0004	(0.004)	0.0002	(0.005)	-0.06	(0.13)
Years of Education	0.05**	(0.03)	0.06**	(0.03)	0.18	(0.18)
Employment Status	0.13	(0.10)	0.13	(0.10)	0.17	(0.15)
Log Income	0.03**	(0.01)	0.03**	(0.01)	0.003	(0.02)
K10 Score	0.04***	(0.01)	0.04***	(0.01)	0.03***	(0.01)
BAI Score	0.04***	(0.01)	0.04***	(0.01)	0.03***	(0.01)
BDI Score	-0.01*	(0.01)	-0.01	(0.01)	0.004	(0.01)
BIS Score	0.01***	(0.01)	0.01**	(0.01)	0.005	(0.01)
WHO ASSIST - Highest Drug Score	0.02	(0.01)	0.02	(0.01)	0.03*	(0.02)
WHO ASSIST - Alcohol Score	0.07	(0.09)	0.09	(0.09)	0.16	(0.11)
Cognitive Bias	0.04*	(0.02)	0.05*	(0.02)	0.08***	(0.03)
Gambling Self-Efficacy	-0.11***	(0.04)	-0.10**	(0.04)	-0.04	(0.04)
Social Influence	0.19***	(0.05)	0.19***	(0.05)	0.20***	(0.07)
Childhood Influence	0.02	(0.05)	0.02	(0.05)		
Wave 2	-0.09	(0.13)	-0.07	(0.12)	0.07	(0.13)
Wave 3	-0.11	(0.13)	-0.08	(0.13)	0.11	(0.16)
Wave 4	-0.11	(0.13)	-0.09	(0.13)	0.07	(0.17)
Wave 5	-0.39***	(0.13)	-0.39***	(0.13)	-0.28	(0.20)
Wave 6	-0.24*	(0.13)	-0.23*	(0.13)	-0.07	(0.23)
Constant	-1.92***	(0.54)	-1.96***	(0.57)	-0.86	(5.50)

Note: All regressions performed on NLSGB dataset
Standard errors in parentheses
**** represents significance at the 1% level*
*** represents significance at the 5% level*
** represents significance at the 10% level*

Contrariwise, the negative coefficient on *Gambling Self-Efficacy* (-0.11), significant at the 1% level, suggests that a greater degree of self-perceived ability to control gambling behaviour is related to lower DSM-V-MR scores. The negative coefficient on *BDI Score* (-0.01), significant at the 10% level, implies that higher levels of depression are associated with lower DSM-V-MR scores. Moreover, the negative coefficients on *Wave 5* (-0.39) and

Wave 6 (-0.24), significant at either the 1% level and the 10% level, respectively, indicate that, unsurprisingly, as the study progressed, the average DSM-V-MR score declined relative to that observed in Wave 1 of the study.

The second set of estimates listed in TABLE XII is from a random effects linear regression model. As above, these results are remarkably similar to those obtained from the random effects Tobit regression model. A few slight differences are worth acknowledging. First, the coefficient on *BDI Score*, although unchanged in magnitude, is no longer significant. Along similar lines, the *BIS Score* estimate and the *Gambling Self-Efficacy* estimate, both of which were significant at the 1% level in the Tobit regression, are significant at the 5% level in the current model.

The third set of estimates listed in TABLE XII is from a fixed effects linear regression model. Some differences between this model and the previous two are important to note. First, as in the case of the *Continuous PGSI Score* dependent variable, *Female* and *Childhood Influence* have been omitted from the model, while *Years of Education* has remained. Again, however, unlike in the other two models presented in TABLE XII, where the *Years of Education* estimate was found to be significant at the 5% level, this estimate is not significant at even the 10% level in the fixed effects model. This loss of significance is accompanied by an increase in the magnitude of the effect. Similarly, the *Log Income*, the *BIS Score* and the *Gambling Self-Efficacy* estimates, all of which are significant in the two preceding models, are no longer significant in the current model. In all three cases, these significance losses are accompanied by a decrease in the magnitude of the coefficient. These significance losses indicate slow changes in one's income, impulsive behaviour and self-perceived ability to control gambling behaviour over time.

On the other hand, the coefficient on *WHO ASSIST – Highest Drug Score* (0.03), which was not significant in either of the preceding models, is significant at the 10% level in the fixed effects model. Likewise, the coefficient on *Cognitive Bias* (0.08), which was significant at the 10% level in the two preceding models, is significant at the 1% level in the current model. Finally, the *Wave 5* and *Wave 6* estimates, both significant in the preceding models, are no longer significant in the fixed effects model.

Overall, the models presented in TABLE XII indicate a number of factors that influence the level of problem gambling risk, as per the DSM-V-MR tool, over time. A robust finding across the three models presented in TABLE XII is that psychological distress, anxiety, cognitive distortions and social influences are positively related to DSM-V-MR score. Only the first two models suggest that DSM-V-MR score tended to decline across all waves of the study.

The Hausman Specification Test was employed on the latter two models presented in TABLE XII. The results returned a chi-squared statistic of 33.62 and a p-value of 0.0140. Accordingly, the null hypothesis is rejected at the 5% level and fixed effects is considered the preferred model.

5.5. CONTINUOUS VERSUS ORDINAL

Although, in theory, the problem-centered view of problem gambling advocates that problem gambling should be perceived as an "end-point on a continuum of gambling involvement" (Blaszczynski & Nower, 2001), statistically, there are strong doubts surrounding the treatment of limited, or bounded, dependent variables as continuous (Wright, 1999). In this view, the limited nature of the PGSI scoring-system makes the statistical analysis of this measurement tool most conducive to an ordinal structure (Wright, 1999). This is also true for the DSM scoring-system.

The extent to which the results are affected by treating a bounded PGSI score dependent variable as continuous, instead of ordinal, is determined by comparing the results of the random effects linear regression using *Continuous PGSI Score* as the dependent variable and the results of a random effects ordered logit using *Ordinal PGSI Score* as the dependent variable. It is important to note that the *Ordinal PGSI Score* dependent variable, which is divided into four equally spaced groups, is used in the ordered logit model instead of the bounded *Continuous PGSI Score* dependent variable as use of the latter would result in a number of insufficient or empty severity groups. These results are presented in TABLE XIII.

From these results, differences in the statistical significance and effect size of some variable estimates are apparent. Firstly, the coefficient on *Years of Education*, significant at the 5% level in the continuous model, is no longer significant in the ordinal model. This loss of significance is accompanied by a decrease in the effect size from 0.22 in the continuous model to 0.07 in the ordinal model. Similarly, the *BIS Score* estimate, although unchanged in magnitude, is no longer significant at the 10% level in the ordinal model. Contrariwise, the *Log Income* and *Childhood Influence* estimates, neither of which is significant in the continuous model, are both significant at the 5% level in the ordinal model. The estimates on *BAI Score* and *WHO ASSIST – Alcohol Score*, neither of which is significant in the continuous model, are both significant at the 10% level in the ordinal model. Additionally, the *Cognitive Bias* estimate, significant at the 10% level in the continuous model, is significant at the 1% level in the ordinal model.

TABLE XIII.

Random effects linear regression of proposed set of risk factors using a *Continuous PGSI Score* dependent variable and random effects ordered logistic regression of proposed set of risk factors using an *Ordinal PGSI Score* dependent variable

	Continuous PGSI Score		Ordinal PGSI Score	
Variable	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
Female	-0.20	(0.44)	-0.32	(0.24)
Age	0.004	(0.02)	-0.01	(0.01)
Years of Education	0.22**	(0.10)	0.07	(0.06)
Employment Status	0.69*	(0.38)	0.41*	(0.21)
Log Income	0.05	(0.05)	0.06**	(0.03)
K10 Score	0.14***	(0.03)	0.06***	(0.02)
BAI Score	0.02	(0.02)	0.02*	(0.01)
BDI Score	0.03	(0.03)	0.01	(0.01)
BIS Score	0.03*	(0.02)	0.02	(0.01)
WHO ASSIST - Highest Drug Score	0.06	(0.05)	0.03	(0.03)
WHO ASSIST - Alcohol Score	0.28	(0.34)	0.32*	(0.19)
Cognitive Bias	0.16*	(0.09)	0.21***	(0.05)
Gambling Self-Efficacy	-0.65***	(0.14)	-0.36***	(0.08)
Social Influence	0.63***	(0.20)	0.39***	(0.11)
Childhood Influence	0.26	(0.20)	0.22**	(0.11)
Wave 2	-1.02**	(0.45)	-0.22	(0.25)
Wave 3	-1.32***	(0.49)	-0.60**	(0.28)
Wave 4	-0.69	(0.47)	-0.25	(0.26)
Wave 5	-1.63***	(0.47)	-0.81***	(0.28)
Wave 6	-1.16**	(0.48)	-0.48*	(0.28)
Constant	-4.31**	(2.12)		

Note: Both regressions performed on NLSGB dataset
Standard errors in parentheses
**** represents significance at the 1% level*
*** represents significance at the 5% level*
** represents significance at the 10% level*

Furthermore, amongst the estimates that are significant at the 1% level in both models, a decrease in the absolute value of the effect size is observed in the ordinal model. Explicitly, *K10 Score* (0.14 in the continuous model and 0.06 in the ordinal model), *Gambling Self-Efficacy* (-0.65 in the continuous model and -0.36 in the ordinal model) and *Social Influence* (0.63 in the continuous model and 0.39 in the ordinal model) all imply a slightly less intense association with the problem gambling severity in the ordinal model.

A robust finding across the two models presented is that employment, psychological distress, displays of cognitive distortions and social influences are positively related to problem gambling severity, while gambling self-efficacy is negatively associated with problem gambling severity. Additionally, as expected, both models report that the average risk of problem gambling tended to decline across waves of the study.

For completeness, the preceding investigation was performed on the DSM-V-MR measure of problem gambling. These results are presented in TABLE XIV.

TABLE XIV.

Random effects linear regression of proposed set of risk factors using a *Continuous DSM-V-MR Score* dependent variable and random effects ordered logistic regression of proposed set of risk factors using an *Ordinal DSM-V-MR Score* dependent variable

	Continuous DSM-V-MR Score		Ordinal DSM-V-MR Score	
Variable	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
Female	-0.02	(0.12)	-0.05	(0.30)
Age	0.0002	(0.005)	-0.002	(0.01)
Years of Education	0.06**	(0.03)	0.12	(0.07)
Employment Status	0.13	(0.10)	0.48	(0.31)
Log Income	0.03**	(0.01)	0.11**	(0.05)
K10 Score	0.04***	(0.01)	0.09***	(0.02)
BAI Score	0.04***	(0.01)	0.06***	(0.02)
BDI Score	-0.01	(0.01)	-0.02	(0.02)
BIS Score	0.01**	(0.01)	0.06***	(0.02)
WHO ASSIST - Highest Drug Score	0.02	(0.01)	0.02	(0.03)
WHO ASSIST - Alcohol Score	0.09	(0.09)	0.19	(0.24)
Cognitive Bias	0.05*	(0.02)	0.20**	(0.08)
Gambling Self-Efficacy	-0.10**	(0.04)	-0.16	(0.11)
Social Influence	0.19***	(0.05)	0.36**	(0.16)
Childhood Influence	0.02	(0.05)	0.05	(0.13)
Wave 2	-0.07	(0.12)	-0.26	(0.36)
Wave 3	-0.08	(0.13)	-0.58	(0.42)
Wave 4	-0.09	(0.13)	-0.45	(0.37)
Wave 5	-0.39***	(0.13)	-1.58***	(0.46)
Wave 6	-0.23*	(0.13)	-1.002**	(0.42)
Constant	-1.96***	(0.57)		

Note: Both regressions performed on NLSGB dataset
Standard errors in parentheses
***** represents significance at the 1% level**
*** represents significance at the 5% level*
** represents significance at the 10% level*

From these results, differences in the statistical significance and effect size of some variable estimates are evident. Firstly, the coefficient on *Years of Education*, significant at the 5% level in the continuous model, is no longer significant in the ordinal model. Unlike the case of the PGSI, this loss of significance is accompanied by an increase in the effect size from 0.06 in the continuous model to 0.12 in the ordinal model. Similarly, the *Gambling Self-Efficacy* estimate is no longer significant at the 5% level in the ordinal model. Furthermore, the *Social Influence* estimate, significant at the 1% level in the continuous model, is significant only at the 5% level in the ordinal model. This decrease in significance is accompanied by an increase in effect size from 0.19 to 0.36.

Conversely, the *BIS Score* estimate, significant at the 5% level in the continuous model, is significant at the 1% level in the ordinal model. Likewise, the *Cognitive Bias* estimate, significant at the 10% level in the continuous model, is significant at the 5% level in the ordinal model. This gain in significance is accompanied by an increase in magnitude from 0.05 to 0.20.

Moreover, it is interesting to note that, in general, the size of the coefficient estimates found to be significant (at the 1% level or the 5% level) in both models do not change massively between the two cases. Nevertheless, the slight changed that do occur show a greater coefficient in the ordinal model. Specifically, *Log Income* (0.03 in the continuous model and 0.11 in the ordinal model), *K10 Score* (0.04 in the continuous model and 0.09 in the ordinal model) and *BAI Score* (0.04 in the continuous model and 0.06 in the ordinal model) all suggest a slightly more intense association with the problem gambling severity in the ordinal model.

A robust finding across the two models is that income, psychological distress, anxiety, impulsivity, displays of cognitive distortions and social influences are positively related to problem gambling severity. Additionally and, again, unsurprisingly, both models report that the average risk of problem gambling tended to decline across waves of the study.

6. DISCUSSION

Several findings of this paper are worth discussing. First, in general, gambling severity classification, as per the PGSI, appears to be unstable over time. When using a PGSI cut-off score of 8, it is revealed that, although there is a notable amount of flux throughout the severity continuum, those classified at the two ends of the distribution have a higher likelihood of remaining there than those classified in the middle. Nevertheless, this is accompanied by strong evidence for the "addiction-hopping" hypothesis, as well as counterintuitive trends associated with inter-category movements between waves of study. When using a cut-off score of 10, although the overall gambling severity stability remains somewhat unstable, there is a higher likelihood of remaining in the "Moderate Risk" category than the "Problem Gambler" category. Additionally, a cut-off score of 10 shows no evidence of "addiction-hopping" and boasts far more intuitive trends associated with inter-category movements between waves of study. This suggests that a cut-off score of 10 adequately differentiates between consistent problem gamblers and fluctuating problem gamblers.

Second, and following from the first point, the difference between a cut-off score of 8 and a cut-off score of 10 extends beyond the high-level stability of problem gambling severity and into the understanding of factors that affect problem gambling severity. In general, replacing the cut-off score of 8 with a cut-off score of 10 in a random effects logistic regression leads to changes in both the significance levels of factor estimates and the effect size of factor estimates that are significant in both models. From this, it can be inferred that the nature of the associations between problem gambling and many of the risk factors proposed in this paper differ depending on whether one is considering all problem gamblers who meet the cut-off score of 8 or only the severe problem gamblers who meet the cut-off score of 10. In sum, whether the PGSI "Problem Gambler" category should be defined by an 8-threshold or a 10-threshold depends on whether the researcher is interested in all individuals who exhibit some kind of problem gambling behaviour or only individuals who show consistent signs of problem gambling.

Third, the low correlation coefficient identified between the PGSI measure for problem gambling and the DSM-V-MR measure for problem gambling supports the criticisms surrounding the failure of the PGSI to adequately emulate the DSM definition of problem gambling. This suggests that, to obtain a complete understanding of problem gambling severity over time, it is imperative that the PGSI screen and the DSM screen are employed concurrently.

Fourth, the results show numerous differences between the random effects linear regression model using *Continuous PGSI Score* as the dependent variable and the random effects ordered logit model using *Ordinal PGSI Score* as the dependent variable. This is true for both the significance levels of variable estimates and the effect size of variable estimates for those risk factors found to be significant in both models. In line with existing literature, this suggests that treating a limited dependent variable as a continuous one poses complications in obtaining a full understanding of that measure over time. Accordingly, the bounded nature of the PGSI scoring-system makes the statistical analysis of this measurement tool most conducive to an ordinal structure, not a continuous one. Although to a lesser extent, these results also apply to the DSM-V-MR scoring-system.

Fifth, there are a number of risk factors that were consistently found to affect the behaviours surrounding problem gambling across almost all models defined in this study. In particular, psychological distress was found to have a robust positive association with problem gambling severity throughout all models considered. Similarly, the expression of cognitive distortions and being associated with frequent gamblers were consistently identified as risks linked to higher levels of problem gambling. Moreover, self-perceived ability to control gambling behaviour was found to be negatively associated with greater degrees of problem gambling across most models.

Some limitations to this study are worth noting. First, a common limitation associated with interview-based data collection processes is the high risk of recall bias. In this way, much of the information contained in the NLSGB data is subject to high risk of measurement error (Sharp et al., 2012). Second, a common limitation associated with longitudinal studies is the regular occurrence of sample attrition over time. Although the NLSGB researchers made every effort to reduce the risk of attrition over time, it still proved to be an issue with approximately 60 individuals dropping out between the first wave and the last wave of the study. Third, the extremely limited amount of tobacco smoking and nicotine dependence data available in the NLSGB dataset limited the extent to which the association between these behaviours (both commonly identified risk factors in the gambling literature) and risk of problem gambling could be evaluated in a South African context. Finally, the use of graphical approaches to the inference of causality was beyond the scope of this study. Understanding the direction of causality between problem gambling and the identified risk factors is a crucial, yet mostly untapped, area of problem gambling research; future studies should focus on this matter.

Despite these limitations, however, the findings of this study are certainly contributive to research regarding excessive gambling activity in South Africa over time. Furthermore, such findings offer some insight regarding certain ambiguities contained in the problem gambling literature.

7. CONCLUSION

In conclusion, this study has successfully established a model that serves to describe the determinants of problem gambling over time in a South African setting. The strength of this model lies in its reflection of many risk factors commonly recognized in the gambling literature, as well as its reflection of risk factors more specific to a South African context. In defining this model, this study further established that, in light of the instability of gambling severity classification over time, the standard PGSI cut-off score of 8 should be replaced by a cut-off score of 10 when the aim of the study is to analyze the problem gambling behaviour of a subset of more persistent and intensive problem gamblers. Moreover, for robustness, this study proposes the use of the PGSI and the DSM measurement criteria concurrently when analyzing problem gambling severity, particularly in panel data. Finally, this study found that the bounded natures of the PGSI and DSM scoring-systems make the statistical analysis of these tools most consistent with an ordinal structure, not a continuous one. This is at odds with the problem-centered view of problem gambling, which promotes the notion that problem gambling is best understood on a continuous spectrum.

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