RESPONSIBLE GAMBLING TRUST MACHINES RESEARCH PROGRAMME

Tracked play on B1 gaming machines in British casinos

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SUMMARY

1. Technology increasingly permits the tracking of individuals' gambling over time. Resulting research which investigates patterns of behaviour has lead to the development of tools which may have the potential to detect problematic play, triggering interventions which might mitigate harm. However, most data sets made available to the research community relate to online gambling. At least in the public domain, there has therefore been little analysis of tracked data for players using gaming machines and in particular little hitherto has been known about how players use gaming machines in British casinos.

2. Rank Group plc is Britain's largest casino operator and provided us with data collected across its estate from customers using a loyalty card to play at tables or on machines. More than 85,000 individuals are represented in the data set which describes players' activities over periods of up to six years (though coverage is greater for more recent years as the loyalty card scheme has extended). The data set describes activity at both tables and on machines. Data for table games are likely to be imprecise since they have to be inputted by busy staff but the information on machine play is collected automatically by the gaming machine. Machine play is the focus of this Report.

3. The unit of observation in our analysis is the visit: one visit to the casino by one player. For each visit, information available includes such as amount won or lost and duration of play (allowing us to construct a measure of intensity of play). There is limited information about the player; but we do have age, gender and (from residential postcode) the social profile of the neighbourhood where the client lives and how far away that is from the nearest casino.

4. Our agreed research brief was threefold. First, to organise the data in such a way as to show typical and atypical patterns over dimensions such as frequency of play, levels of player expenditure and time spent playing the machines. Second, to investigate the impact of players winning or losing on decisions on when to return to the casino to play again (this related to between-session loss-chasing). Third, to examine the extent to which atypical behaviour by players tends to be transient or else persistent over time.

5. About 28% of all visits to the casino where gambling took place (we exclude visits where the player used the loyalty card only for food and beverage) involved the use of gaming machines and in about 21% of visits the only gambling was on machines. The proportion of machine-visits has been increasing over time. Female visits were much more likely than male visits to include use of machines (correspondingly male visitors were more likely to play table games).

6. A large majority of users visit only very occasionally, often only once. Nevertheless significant numbers gamble at the casino regularly. For example, in 2014, more than 1,200 customers were recorded as gambling at the casino on more than 100 occasions (i.e. twice a week or more). Naturally such customers account for a disproportionate share of all casino visits.

7. Levels of play are usually modest. The median (typical) duration of play on gaming machines is close to or a little below one hour. In half of all visits, the player either wins money on the machines or loses an amount up to the range £20-£25 (depending on year). While it cannot be ruled out that some such visits will harm the player, we note that such levels of expenditure and time are not dissimilar to those associated with other leisure activities such as visits to restaurants, cinemas and public houses.

8. While typical use of gaming machines is at a modest level, there are significant numbers of players who engage in visits with 'high' expenditures of money and time, where the notion that many of them may experience harm is more plausible. For example, more than 11% of machine visits include more than three hours of play on the machines and more than 7% of visits end up with the player losing more than £200.

9. While losses above £200 are relatively common, losses very seldom reach the high hundreds of pounds. This is likely to be related to regulatory limits on the level of stakes and the speed of play. Given the return-to-player offered by the machines (which is very likely to be close to a player's return from several hours of play), duration of continuous play even at maximum stake and maximum speed would have to be very long indeed for losses to go higher.

10. We measure intensity of play by average loss per minute spent gambling on machines. We trace how this varies by time of day. Intensity of play is sharply higher late at night and through the early hours. Since high intensity of play may be a marker for poorly controlled gaming, we recommend further research, in this and other contexts, on how gambling behaviour varies by time of day. We note that casino staff training and procedures should take into account that customers attending the casino during the night may be particularly vulnerable to harm.

11. Between-session loss-chasing is widely accepted as a marker for problem gambling. Indeed both problem gambling screens employed in the British Gambling Prevalence Survey (BGPS) asked respondents whether and how often they returned another day to try to win back losses. Nearly all BGPS machine gamblers who endorsed this item also endorsed other items directly indicative of harm. We constructed a statistical model to account for variation in the time to next visit to the casino. It controlled for players' past behaviour, allowing a focus on the effect of unusually high losses experienced on the last visit. Applied to the whole sample of players with

at least fifty recorded visits, modelling revealed that typical behaviour was for losses to deter future gambling, i.e. each unit increase in loss on a visit increased the predicted time to the next visit. Thus typical behaviour exhibits loss-aversion rather than loss-chasing.

12. We then estimated the model at the individual rather than the aggregate level. Just over 2% of the approximately 15,000 players we studied showed a statistically significant tendency to return to play sooner than usual after losing more than their typical loss. These ‘chronic loss-chasers’ were disproportionately likely to be young, male and ‘heavy’ players (in terms of how much they usually spent on a machine visit).

13. This exercise revealed patterns of individual behaviour over the whole data period. Next we tested for more episodic loss-chasing behaviour. For each player, we estimated the model for rolling six-month periods (with play assessed each month on the basis of behaviour in the preceding six months). 27% of all players had at least one six month period when they had a statistically significant tendency to between-session loss-chasing.

14. To gain more insight into the persistence of atypical behaviour, we looked at players who recorded visits involving an unusually high level of expenditure or duration of play on machines. For example, for each quarter, we considered players who had lost more than £100 on at least one visit in the quarter. We then checked whether they had repeated the behaviour in any or all subsequent quarters. We followed the same procedure for players who had spent more than five hours on the machines in a single visit. In each case, less than half of players ‘reoffended’ in the immediately following period. Eleven quarters later, less than 30% repeated high-spend behaviour and less than 10% had done so throughout the intervening period. In the case of high-duration, the threshold of five hours was set to capture behaviour that was more extreme relative to the mean. Here only about 3% of those who had such a long session in the first quarter proved to be persistent ‘offenders’ by quarter 11.

15. Extreme behaviour is therefore often self-correcting. This does not imply that much harm has not been experienced in the meantime. Indeed heavy play may be self-correcting just because it proves to be unsustainable in terms of its impact on players’ lives. For those who design experiments for algorithm-driven interventions to be initiated where heavy play is detected, the results are a reminder that the proportion of those targeted who have to show improvement for the experiment to be judged successful will always be high: most extreme behaviour disappears with time anyway. Moreover, we show that the process of self-correction extends over multiple periods, implying that follow-up is required through a long period if the impact of interventions on behaviour is properly to be evaluated.

1 INTRODUCTION

1.1 Background

This Report is linked to the suite of research, commissioned by The Responsible Gambling Trust, which examines issues related to the use of gaming machines in Great Britain. The Trust's focus on gaming machines was motivated by long-standing concerns among that gaming machines may carry greater potential for harm than many other gambling activities. In contrast to apparently 'softer' products such as lotto draws, machine gaming is fast-paced, has high event frequency and presents an immediate opportunity for the player to chase losses. Moreover the technology allows the player to be manipulated, for example through visual and sound stimuli and through the building into the games of a high frequency of near-wins (which creates excitement and encourages the player to believe that a win is more likely than it actually is).

Data from prevalence surveys worldwide appear to confirm that machine gaming is indeed strongly associated with problems.[1] As an illustration, Table 1.1 below shows results from analysis of the 2010 British Gambling Prevalence Survey[2], which interviewed nearly 8,000 individuals face-to-face. It shows the proportions of problem gamblers among those who had taken part in various gambling activities in the past year and among those who took part in the activities on a regular (monthly or more) basis. Assessment of whether a gambler was a problem gambler was made by applying the DSM-IV problem gambling screen devised by the American Psychiatric Association. This looks for indicators of both addiction issues (for example, preoccupation with gambling or the need to gamble with increasing amounts of money) and harmful consequences (for example, risking relationships/ employment as a result of gambling or borrowing because of financial stress from gambling). The number of endorsements of the individual items in the screen determines whether the subject is counted as a problem gambler. According to the data in the Table, problem gamblers account for a higher proportion of those who take part in machine gaming compared with some other popular activities (and the proportion is much higher for regular than for occasional players).

Of course, correlation between participation in machine gaming and propensity of players to exhibit gambling harm (as proxied by the status of 'problem gambler') is not evidence of causation. It may be that concentration of problem gamblers among users of machines is explained by a tendency for machines to attract (as opposed to create) problem gamblers. Indeed

[1] A review of evidence from many jurisdictions is provided in R.A. St-Pierre, D.M. Walker, J. Derevensky & R. Gupta. 'How availability and accessibility of gambling venues influence problem gambling: A review of the literature', *Gaming Law Review and Economics*, 18:2:150-172, 2014.

[2] H. Wardle, A. Moody, S. Spence, J. Orford, R. Volberg, D. Jotangia, M. Griffiths, D. Hussey & F. Dobbie, *British Gambling Prevalence Survey 2010* (London: The Stationery Office), 2011.

this hypothesis is consistent with analysis using 2007 Prevalence Survey which found that individual activities did not ‘predict’ problem gambling once the statistical model included the number of gambling activities.[3] The authors concluded that some activities, such as machine gaming, “might be indicators of unhealthy involvement [in gambling] rather than critical factors for gambling-related problems themselves”.

Table 1.1. Problem gambling prevalence by gambling activity

	past-year participants	regular participants
National Lottery	1.3%	1.5%
bingo	2.9%	4.1%
scratch cards	2.5%	4.0%
slot machines	4.0%	8.7%
FOBT machines	8.8%	13.3%
horse betting	2.9%	9.1%
casino games	6.8%	13.9%

But, whatever the directions of causation, it is still the case that the high concentration of problem gamblers among machine players justifies that greater regulatory attention be paid to the machine gaming sector than to many other forms of gambling. First, problem gamblers represent a very vulnerable group and care must be taken to ensure that the harm they suffer from gambling is limited if possible. Second, the concentration of problem gamblers in venues where machine gaming is offered presents an opportunity to reach out to a group which is generally hard to reach, for example through provision for interventions triggered by observing problematic patterns of play.

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[3] D.A. LaPlante, S.E. Nelson, R.A LaBrie & H.J. Shaffer, ‘Disordered gambling, type of gambling and gambling involvement in the British Gambling Prevalence Survey 2007’, *European Journal of Public Health*, 21:4:532-537, 2009. The pattern was the same in the data from the 2010 Survey: see Fig. 6.2 in the Report (footnote 2 above). International evidence supports that it is the breadth of gambling engagement that presents the greater risk rather than isolated participation in individual activities. For Finland, 16,000 individuals were questioned for the country’s 2011 Prevalence Survey. Heiksanen & Toikka identified a group termed ‘omnivores’ where individuals consumed nearly all available gambling product types and found a problem gambling prevalence-rate of more than 30%. See M. Heiksanen & A. Toikka, ‘Clustering Finnish gambler profiles based on the money and time consumed in gambling activities’, *Journal of Gambling Studies*, e-publication ahead of print, DOI 10.1007/s10899-015-9556-8, 2015.

This Report is about machine gaming in one particular class of venue, namely casinos. The British Gambling Prevalence Survey did not separately report the problem gambling rate among slots players who use casino machines though it is possible to make a calculation from the raw data since respondents who had played slots games were asked at what types of venue they had played. However, the confidence interval would be very wide given that few slots players had in fact played in a casino.

Most slot machines in Great Britain are located in non-gambling-specific venues where maximum stakes and prizes are much lower than in casinos and these may be less attractive to those at risk of harmful play. These are grounds for supposing that the prevalence-rate may well be higher among casino machine players than the figures for slots players generally (shown in Table 1.1). Moreover, some machine play in casinos will be in conjunction with consumption of the other gambling product on offer at these venues, table games. From Table 1.1 above, participation in casino games is particularly strongly associated with problem gambling. Indeed prevalence-rates for casino games are very similar to the high rates reported for FOB-T machines found in bookmaker shops, which have been the subject of considerable controversy regarding their potential for harm. All this suggests that there is a compelling need to improve knowledge about the behaviour of casino machine players. In the last Triennial Review of maximum stakes and prizes for gaming machines, it was noted that very little was in fact known that could inform regulatory decisions.[4]

This study is intended to fill part of the knowledge gap. It is enabled to do so by Britain's largest casino operator having made available a large data set which records details of play during visits by each of more than 85,000 customers over six years. Data on individual play, collected in an automated way, has the potential to be much more informative than data collected by prevalence surveys. These latter may be subject to bias because, for example, heavy gamblers have a different propensity than others to agree to participate in the survey. Further, while prevalence surveys typically inquire as to participation in and frequency of various gambling activities, they rarely seek to find out the level of expenditure on play. Where they have done so, data have proved unreliable. For example, the average response by gamblers in the British Gambling Prevalence Survey on how much a gambler had won or lost over a period was in the territory of gambler win rather than house win. Tracked data enable direct observation of player losses and therefore enable answers to questions such as 'how many players experience heavy losses?'.

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https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/249274/Triennial_Review_of_Gaming_Machine_Stake_and_Prize_Limits_Impact_Assessment.pdf

Provision of individual-level gambling data for research is, however, unusual outside the online sector.[5] To our knowledge, there is only one previous project in the World where researchers have been able to exploit such data in respect of gambling at land-venue casinos. Like us, Narayanen & Manchanda[6] analysed data generated by players using loyalty cards. Their data set related to two years of play by nearly 200,000 customers of a single (unnamed) casino in the South Western United States (outside Nevada). Their principal focus was on estimation of the extent of 'addiction' among casino patrons (most of whom were machine players, given the dominance of machines over table games in the American industry). Their use of the term 'addiction' reflected the definition used in economics where it refers to individuals whose decisions on how much of a product to purchase in one period are influenced by their past levels of consumption. In common parlance, such consumers get a 'taste' for the product and this may be reflected in levels of consumption which increase over time. More neutral language might call this 'habit formation' since it does not necessarily imply harmful consumption. Nevertheless, it is of interest that the proportion of players they estimated to be 'addicted' was not dissimilar to estimates of problem gambling rates for American casino players and that behaviour consistent with 'addiction' was more likely to build up among regular than among occasional players and more likely among Hispanics than among Caucasians. This suggests that their concept of addiction is at least correlated with the more general concepts of problem gambling and gambling harm.[7]

As with Narayanan & Manchanda, our data set had the limitation that there was no information on whether individuals at any point in time were 'problem gamblers' or were otherwise experiencing harm from gambling. However, although we could not identify problem gamblers

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[5] A particularly well known example of an online operator providing data for research was that of the collaboration between Bwin and the Division of Addiction, Cambridge Health Alliance. Resulting analyses of patterns of play in online sports betting and casino games are reviewed in D.A. Laplante, S.E. Nelson, R.A. LaBrie & H.J. Shaffer, 'Challenges for the normal science of Internet gambling', chapter 9 in R.J. Williams, R.T. Wood & J. Parke, *Routledge International Handbook of Internet Gambling* (London: Routledge), 2012.

[6] S. N. Narayanan & P. Manchanda, 'An empirical analysis of individual level casino gambling behavior', *Quantitative Marketing and Economics*, 10:27-62, 2012.

[7] In a second strand in their research, they examined the responsiveness of the amount of play to incentives (comps) offered by the casino in marketing directed at individuals. They found that those whom they identified as 'addicted' were twice as responsive as those with no sign of 'addiction'. Our data set included no information on, for example, individuals receiving marketing material or being offered incentives other than those applicable to all those enrolled in the loyalty programme. We have no reason to believe that the operator engaged in the same marketing techniques as those found in the American industry where exploitation of loyalty card data appears to be more systematic. Nevertheless the impact of marketing programmes on individual gamblers' behaviour might prove an appropriate topic for future research should relevant data become available.

in the data set, we were able to track behaviour to help assess the extent of patterns of play associated with problem gambling, such as regular heavy play or chasing losses.

Our brief for the Report, agreed with the Responsible Gambling Trust, was two-fold. The first objective was to examine data from across players to learn about typical and atypical patterns of play as described by, for example, lengths of visit and amounts lost. The second objective was to study and model player-level behaviour, specifically: (i) How do players react to experiencing wins and losses? If they lose more than usual, do they stay away from the casino for a longer period of time or return sooner than they would typically?; and (ii) Do behavioural characteristics of individual players vary over time? For example, one player may exhibit risky behaviour only on a small number of visits to a casino, whilst for the majority of his or her visits, will behave more conservatively.[8]

The structure of the Report is as follows. The rest of this Introduction sets the scene by describing the context: the casino sector in Great Britain, the place of machine gaming within it, the operator from which we obtained data and the regulations applicable to machine play. Chapter 2 describes the data set and the types of information it includes. Chapter 3 presents a descriptive picture of machine gaming in casinos as derived from the data. Chapters 4 and 5 examine particular types of behaviour which are often said to be associated with problematic play.

1.2 Casinos in Great Britain

At the most recent official count, March 31, 2015, there were 148 casinos operating in Great Britain.[9] All except two of these had licences granted under the terms of the Gaming Act (1968). The other two held 'Gambling Act (2005) licenses'. The 2005 Act authorised sixteen local

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[8] The commissioning also required that we assess the viability of using loyalty card data from the casino sector for research that would inform future regulatory decisions. However, this requirement was met in an earlier Report, published in December, 2015, which used a shorter run of the present data: D. Forrest, I.G. McHale & H. Wardle, *Evaluating the Impact of the Uplift of Stakes and Prizes on B1 Gaming Machines in Casinos* (London: Responsible Gambling Trust), 2015. This earlier Report focused on the very particular question of how players responded to the increase in stake and prize limits introduced in 2014. The present Report has a wider scope with a brief for more detailed examination of individual behaviour.

[9] This statistic, and several others in this and the following section, are taken from *Industry Statistics, April 2010 to March 2015*, published by the Gambling Commission in November, 2016 (http://www.gamblingcommission.gov.uk/Gambling-data-analysis/statistics/Industry-statistics.aspx).

authorities to permit casinos with a wider range of activities (and a greater number of machines) than was allowed by the earlier legislation.[10]

In terms of gross gaming yield (the amount lost by players), which was £1.2b in 2014-5, casinos comprise the third largest gambling sector in Great Britain though this is still well behind the National Lottery and betting (each of which took £3.2b). On the other hand, in terms of participation, the place of casinos within gambling was more marginal. Survey data indicate that barely 1% of adults played 'casino games' in 2015.[11] The combination of relatively high revenue and low participation implies that, on average, gamblers in casinos spend more heavily than gamblers in other leading sectors.

In British casinos, table games generate far more revenue than machines. In 2014-5, table games accounted for 85.5% of gross gaming yield (with roulette the highest earner) and machines 14.5%. This is almost the reverse of the numbers for America where machine gaming not only accounts for the bulk of the revenue but is also, typically, physically dominant in the casino space. By the yardstick of revenue, casinos represent the largest gambling sector in the United States and there is a much higher participation than in Great Britain, with up to a third of adults attending in any given year. The customer base has a strikingly older demographic than in Britain with more than half of visits being made by the over-fifties.[12] It is plausible that the failure of the British industry to increase and diversify participation is explained by the prohibition on 'machine shed' casinos where machine gaming is the dominant activity. This model has proved popular when introduced into culturally similar jurisdictions in Australia and Canada as well as America.

1.3 Machines in British casinos

The regulatory framework which governs machine gaming in Great Britain distinguishes categories of machine according to the type of venue where they are permitted and specifications regarding maximum stake and prize levels and speed of play. The general principle is that the greater the potential for losing money, the greater the restriction on access. Thus category D machines have a maximum stake of only 10 pence (and prize of £5) but are widely available in premises which children are permitted to enter and where indeed it is legal for them to play the

[10] Since the date of the last count, two more 2005 Act casinos have been opened.

[11] *Participation in Gambling and Problem Gambling 2015- Full Report*, published by the Gambling Commission in February, 2016 (http://www.gamblingcommission.gov.uk/Gambling-data-analysis/Gambling-participation/Gambling-participation-data/Gambling-participation-survey-data.aspx).

[12] www.statista.com › Industries › Sports & Recreation › Gambling.

machines. Category C machines carry a higher maximum stake (£1) and prize (£100) but may be placed only in 'adult' environments such as public houses.[13] Category B machines are permitted still higher stakes and prizes but are restricted to adult-only, gambling-specific venues, namely betting premises, casinos and bingo halls.[14]

Category B is divided into three sub-categories. A very large majority of the more than 2,800 machines located in casinos in 2014-5 were B1 machines. This number of just over 2,800 is close to being twenty times the number of casinos (as reported in Section 2.2 above) because, except in the two premises licensed under the 2005 Act, there is a regulatory limit of twenty machines per casino. Typically, a venue will offer the full number of twenty and it will not include other categories of machine, presumably because it would be commercially unrewarding to cater for wider tastes by using up some of the quota to provide, say, category C machines.

For most of the period covered by the data set analysed in this Report, the maximum stake on these B1 machines was set by the regulations at £2. The maximum prize was £4,000. Machines within given premises could be linked to provide a common jackpot but this was still restricted to £4,000.

In January, 2014, regulations were changed to be less restrictive, an intervention commonly referred to in discussion of industry issues as 'Uplift'. Uplift raised the maximum stake to £5 and the maximum prize to £10,000. Where machines were linked within premises, the maximum jackpot could now be set as high as £20,000. By early February, 2014, the operator whose data we use had modified all machines in its estate to accommodate these new limits.

The new regulations for B1 machines made no change with respect to speed of play. The minimum game cycle (which is the minimum gap between successive spins) remained at 2.5 seconds.

Earlier research published by The Responsible Gambling Trust (footnote 7 above) concluded that Uplift had led to a modest increase, of the order of 7%, in casino net revenue from B1 gaming

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[13] Children are allowed to enter many public houses but only under adult supervision; and they may not play the machines.

[14] The specification for Category A machines places no limit on stakes and prizes but they are permitted only in 'regional casinos' as defined in the Gambling Act (2005). However, no regional casinos have been authorised.

machines.[15] This was broadly what the industry had expected according to its submissions to the consultation exercise conducted as part of the preceding Triennial Review of regulations. In their submissions, operators had typically emphasised that they thought they were more constrained in growing revenue by the limit of twenty machines per casino than by the then current limits on stake and prize levels.

1.4 The operator

The data set we analyse was provided to the researchers by Rank Group plc prior to the commissioning of research by the Responsible Gambling Trust. To ensure the independence of any work undertaken subsequently, there was a written Agreement that analysis based on the data set could be published without reference of the work back to Rank.

Rank Group, whose venues are branded as 'Grosvenor Casinos' or 'G Casinos', is the largest operator in Great Britain. For most of the six years covered by the data set, its estate included 35-38 casinos.[16] These were fairly evenly distributed geographically and included a range of types of location: city centre, edges of city centres, suburbs, free-standing, part of leisure complexes, etc. There is therefore every reason to expect that data on Rank customers would be representative of players across the whole sector and that conclusions with respect to player behaviour would be generalisable to the whole player population, at least those outside the 'high end' London casinos (which often don't have gaming machines anyway).

[15] Based on analysis of individual-level data, the Report noted that there was a tendency for a disproportionate share of the extra revenue to have come from players who were young, who played late at night or who were resident in deprived areas. These are all circumstances thought to be associated with problematic play. However, the data on individuals did not include information on whether they were 'problem gamblers'. Therefore the evidence that there was an increase in the share of revenue linked to problematic play must be regarded as suggestive rather than definitive.

[16] By March 31, 2015, it operated 63 of the 148 casinos in Great Britain (but neither of the 2005 Act casinos). The increase to 63 had been achieved by takeover of the Gala Coral Group in 2014. Our data do not include activity at these new acquisitions.

2 THE DATA

2.1 Loyalty card data

The data made available to us track individual players' behaviour over time *but only when they use their Rank loyalty cards while playing*. Even if the questions have no definitive answers, it is therefore still appropriate to begin by considering:

(i) whether patterns of play observed among loyalty card users collectively are likely to be illustrative of patterns of play among the totality of casino customers over the time period;

and

(ii) whether the set of play recorded for a given individual in the data set is likely to be an adequate representation of all play by that individual over the time period.

These questions concern the risk that samples of players and of play are biased.

In the context of Rank Group's casinos, any bias appears unlikely to arise at the point of recruitment on to the loyalty card scheme. Until the provisions of the Gambling Act (2005) came into force, British casinos had been members-only establishments and membership cards were required to gain entry. Although this is no longer a legal necessity, the old culture of access control has survived at Rank's casinos. A customer must either have been issued with a card in the past or sign up for one to secure entry. Effectively therefore all customers gambling at these casinos are members of the player card scheme.

On the other hand, it is not compulsory to use the player card when gambling. There is some incentive to do so because the player card also serves as a loyalty card with 'rewards' attached to spending money. 'Play points' are awarded for any transaction at any casino in the estate (or online) whenever the customer uses the card while playing table games or slots or buying food and beverage. When sufficient points have been accumulated, a customer can convert them to vouchers for use in the casino or else they can be spent on electronic consumer goods offered in a catalogue.[17]

Evidently these incentives are insufficient to persuade customers always to use their card when gambling. The earlier Report on Uplift for The Responsible Gambling Trust was able to compare

[17] Details of the scheme and levels of rewards are given at secure.grosvenorcasinos.com/play-points.

(for 23 casinos over a period of nearly two years) the volume of gaming machine activity that appeared in the tracked individual-level data with the volume recorded in the casinos' financial records. This exercise indicated that tracked play accounted for only about 23% of the actual house win from gaming machines. This raises the possibility that tracked play is unrepresentative of all play because choices over whether to use a card are non-random and may reflect non-observed player characteristics which impinge on playing patterns. Unfortunately there is no firm empirical basis on which the risk of such bias can be assessed; but perhaps there is some reassurance from the earlier Report (p. 39) which showed that weekly volumes of tracked losses and total losses were at least highly correlated. This implies that variation of tracked machine play from week to week was responding to the same factors as machine play generally. At least on one level, tracked and non-tracked play therefore appear to respond to common drivers, suggesting that players who use cards and those who do not may not be so dissimilar to each other.[18]

It is a limitation of research based on analysis of tracked data that one does not observe all gambling activity by an individual gambler. In the present context, certain players may use their cards on some plays but not on others; this could even be due to cognitive bias on the part of the player who may believe that use of the card affects the chance of winning (for example, the player believes, if he is winning, that identifying him will enable the house to stop him winning again, thus retrieving the money it has lost). Such behaviour may bias conclusions to be drawn from the data. More generally, and this applies even to data sets from gambling operators (such as online) where all play is account-based, the player may still use other land- or online-providers where his or her gambling is not observed. Again, the choice to go elsewhere may even be influenced by activity seen in the data set. For example, an individual loses heavily at the Grosvenor Casino one day and therefore decides it is an unlucky venue for him and shifts to a Genting Casino. Such a player's behaviour would bias researchers in the potentially misleading direction of finding that players who lose heavily respond with a period of abstention.

These limitations to the use of tracked data have to be noted.[19] However, its advantages to researchers seeking to understand gambling behaviour have also been argued to be strong. Its use avoids the weaknesses associated with the common reliance on self-report data, such as bias

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[18] Anecdotal evidence was collected in the form of opinions sought from staff in Grosvenor casinos. The typical view was that use of cards was more associated with average players than with those who were either very low-level/ occasional gamblers (who could not hope to spend enough to gain significantly from player points) or very heavy gamblers (whom staff thought could just not be bothered to use cards; an alternative explanation might be that heavy players might be less comfortable about records of their gambling being kept).

[19] For an overview of general issues surrounding research using tracked play data, see S. Gainsbury, 'Player account-based gambling: potential for behaviour-based research methodologies', *International Gambling Studies*, 11:2:153-171, 2011.

from individuals' choices over whether to take part in the survey and recall errors. Crucially it introduces a longitudinal dimension into the data, enabling study of how individuals' gambling behaviour evolves over time. And, in terms of policies to minimise harm, tracked data have the potential to predict future patterns of play, possibly enabling targeted interventions aimed at those who appear to be at risk of harm.

2.2 What information is there on the players?

All the data supplied to us had been anonymised and the player was identified by account number rather than name. Rank in fact holds only limited personal information on the holder of each account: we had the gender of the individual and his or her year of birth. But, in addition, the postcode associated with the account could be used to generate two further variables, *distance* and *deprivation*, which we were able to employ in the analysis below.

distance

By using Geographical Information Systems (GIS) software, we were able to add to each player's information the distance (km.) from his or her residential address to the nearest Rank casino. This might not always be the casino the customer used on any particular visit (for example, sometimes a players may use a casino near work or when making a multi-purpose trip to the city centre). The variable could therefore be thought of as representing not the cost of any particular visit to a casino but rather ease of everyday access to a casino facility. We expected that visit frequency might be lower for those with higher journey cost; we also had in mind that those who had higher fixed costs for a visit might typically spend either less or more once at the casino (less because they have already spent relatively heavily to reach the casino *or* more because they choose to make fewer but more intensive visits).

deprivation

Residential postcode, while not of course telling us anything certain about the wealth or poverty of the individual, does give access to socio-economic information about the neighbourhood in which he or she lives. Neighbourhoods here are identified with Local Super Output Areas which are geographically engineered to represent about 1,500 residents and 650 households. Except in rural areas, this implies a quite small geographical area (the Local Super Output Area is the smallest geographical unit for which Census data are reported).

In England, the official Index of Multiple Deprivation presents a single index for each Local Super Output area. Based primarily on Census data, it takes into account a wide range of measures of, for example, health, educational achievement and income. Corresponding indices for Scotland and Wales are constructed similarly though the measures used in their calculation vary slightly.

Our binary variable *deprivation* flags players whose postcode places them in one of the 30% most deprived areas in the country. In our data set, players appear to be drawn roughly equally from across the ten deciles of areas ranked by deprivation and the 30% most deprived areas are only slightly overrepresented (32.5%). However, it is of interest whether residents of deprived areas, on average, behave any differently from other players: area deprivation is, from British and international evidence, a well-established risk factor for many problematic behaviours including problem gambling.[20]

2.3 What information is there on players' gambling activity?

A customer who uses a card for any transaction at a Rank casino (including its online casino) is entitled to player points within the loyalty card scheme. Rank therefore attempts to capture all customer activity and, at land-venue casinos, this applies to table games, e-roulette, machine gaming and purchase of food and beverage.[21]

In the case of machine gaming, it is reasonable to assume that the data are generally accurate as regards, for example, the length of time for which a customer plays and the net financial outcome from the session. Exact start and end times are recorded according to when the player inserts and subsequently removes his or her card from the machine. Some errors may occur because of player behaviour (for example, failing to remove the card when play has been completed) or because of machine idiosyncrasies (for example, one meter in the machine has just six digits; when it resets, it records a misleading figure for player loss). Such anomalies require cleaning of the data, as described in the following section. But, by and large, machine-generated data may be regarded as sufficiently precise and reliable for use in statistical modelling.

This is not the case for data describing player activity at tables. Here the dealer is responsible for entering details of how much the player has staked and it is not an easy task, especially at busy

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[20] See pp. 116-117 in J. Orford, *Power, Powerlessness and Addiction* (Cambridge: Cambridge University Press), 2013.

[21] E-roulette refers to the playing of live games taking place at tables in the casino but through terminals located elsewhere on the gaming floor. These are not classified as gaming machines under the Gambling Act (2005) because they are regarded as just an alternative channel for taking part in a table game. It is possible that e-roulette may attract customers who prefer a more private experience than that associated with playing at the roulette table itself.

times, to keep track of every customer who has presented a loyalty card. We did not find any casino employee who thought that the data could be more than very rough-and-ready. Indeed this is acknowledged on the website which sets out the terms and conditions of the loyalty card scheme: "Customers as a condition of taking part in the programme agree that Play Points are awarded on the personal observation of Grosvenor Casino staff which may be subject to error".[22]

For the most part, we therefore avoid using table games data in the statistical analyses we present below. However, we do use entries for activity at tables as indicating whether a particular visit to a casino included table play and this allows us to distinguish between, for example, machine-only visits and 'mixed' visits where a customer plays both machine and table games.

In any case, the core topic of the Report is how players use machines. Here data have the potential to be at varying levels of granularity. Machines record play-by-play but these data are not retained by the operator. Very micro-level analysis was therefore not possible. The level of detail which could be observed was that of a 'rating period'. This is defined when the machine aggregates what has occurred since the last rating. It is not of a consistent length. About twenty minutes is typical but it can be longer or shorter (and very short if the player ends the session just after a rating has been registered). For each rating period, the record includes date of rating, beginning and end time, total amount staked, number of spins and total casino win.

Our analysis aggregates rating periods across a 'visit'. In the analysis, each observation relates to a visit to the casino by a single customer. The beginning of a visit is defined as the time the first gambling activity (machines, tables or e-roulette) is recorded. A visit is deemed to have ended when the last gambling activity is recorded with no further activity for at least two hours. All visits are therefore separated by at least two hours during which the player card has not been used for gambling. This definition of a visit allows two or more visits to be defined for a particular player on a particular day. However, the large majority of visits represented the only visit for the player that day.[23]

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[22] www.grosvenorcasinos.com/play-points

[23] Visits are defined by gambling activity at a land casino. Therefore we discarded data generated by purchase of food and beverage. Similarly our edited data set excludes observations related to online use of the player card.

2.4 Preparation and cleaning of the data

The raw data, as supplied by Rank, consisted of 28,325,489 'ratings' in two files. The files had to be combined and dating and timing had to be reformatted so that consecutive ratings from a single player at a single session could be grouped together. Non-gambling transactions (food and beverage) were removed from the data set.

Player ratings were then combined to form the 'visits' which comprised our unit of observation, as defined above. At this stage, the data set included: 7,416,661 visits by 914,068 players, spread across 43 different casinos (some of which were not in operation throughout the data period). The data were intended to cover a period from 2010 to January 29, 2015. However, a few were dated earlier than 2010 (the earliest May 13, 2008). For these, it was assumed that there had been an error in the recording of the date.

The next step was to 'clean' the data, by which is meant the removal of observations which appeared sufficiently anomalous as to be judged certain or almost certain to contain errors. The criteria for removing observations (visits), similar to those used in the earlier Report on Uplift (footnote 2 above), were as follows:

- remove if transactions were dated before 2010
- remove if the total time spent gaming in a session was negative
- remove if the amount staked was negative
- remove if a visit was recorded as lasting longer than 14 hours
- remove if the player had had a loss more than the loss at the 99.9th percentile (i.e. a loss in the top 0.1% of losses)
- remove if the player had a win greater than the win at the 99.9th percentile (i.e. a win in the top 0.1% of wins)

In each case except the first, we removed *all* observations for a particular player if *any* of his or her visits met the criterion. This is because any erroneous observation would contaminate any modelling of how that player's behaviour evolved over time.

Of the various criteria, negative stakes and negative duration of play are each impossible and therefore the entries must be incorrect. Play longer than 14 hours is implausible. All of the extreme wins and losses meeting either of the final two criteria were numerically close to £1m and this makes it very likely that the numbers were generated because of the way in which one of the meters in the machines resets to zero when it reaches the limit of its six digits. When this issue was investigated for the earlier Report on Uplift (footnote 2 above), it was discovered that, with the extreme values retained, loyalty transactions collectively would have accounted for more than 100% of the casino win from all customers, underlining that these entries are not to be trusted.

After cleaning, we were left with 5,196,251 observations (visits) made by 855,608 players.

3 TYPICAL AND ATYPICAL PLAY

3.1 Introduction

Notwithstanding that loyalty card play may not represent exactly patterns for all customers, the very large data set supplied by Rank presents a unique opportunity for basic stylised facts surrounding machine play in casinos to be put into the public domain. The contribution of this chapter is to draw out key stylised facts to answer questions such as what proportions of gamblers at casinos use machines and how this varies by gender. We ask how many visits to casinos are by regular players and by occasional players. We pay particular attention to identifying typical levels of spending and duration of play and investigate how common it is to play to levels well above what is normal. We address also the issue of intensity of play. Many of the summary tables display separate data for 2012, 2013 and 2014, in case a trend is evident in any of the statistics.[24]

3.2 Frequency of visits and types of visit

Table 3.1 shows, by year, the proportions of players with different numbers of visits. The proportions relate to the set of players with at least one visit in the relevant year. As noted above, visits comprise only casino attendances with gambling activity.

Table 3.2 displays the proportions of visits featuring different mixes of activities: table games, e-roulette and category B1 gaming machines (CTB1). Tables 3.3 and 3.4 provide similar information but broken down by gender.

Key features from these tables include:

- More than half of all 'active' loyalty card players are minimally active with only one visit registered in the data for the year; for many of these, attendance will be a 'one off' and they will not be observed in any future year in the data set.
- Between about 300 and 500 loyalty card holders (depending on year) visit the casino with an average frequency of three or more visits per week; by the final year, about 1,200 are 'regulars' if the bar is lowered to an average of two or more visits per week.

[24] It should be borne in mind that new, higher stake and prize limits were in place for most of 2014 (machines were adjusted in late January and early February). The earlier Report on Uplift (footnote 2 above) investigated changes in patterns of play in 2014. These were mostly somewhat modest.

- During 2012-14, there was an increase in the proportion of casino visits which included play on B1 machines- by 2014, 27.9% of visits included B1 play (and 20.8% included *only* B1 play).

- Comparing Tables 3.3 and 3.4, a female visit was much more likely than a male visit to feature machine play.

- Females were correspondingly less likely to play table games but there was no significant difference by gender in preference for e-roulette.

In addition to information displayed in the tables, we note also that the proportion of visits which included B1 play was slightly higher late at night. Here and in subsequent analysis, *we define a late visit as one which starts between 9 p.m. and 9 a.m. and/or finishes between midnight and 9 a.m.* In 2014, 29.2% of late visits included play on B1 machines.

Commentary: only a relatively small minority of registered players are observed to be frequent visitors to the casino. But these players deserve special attention. We looked at raw data from the British Gambling Prevalence Survey and found, among slots players, a steep relationship between frequency of play and propensity to be categorised as a PGSI problem or moderate risk gambler.[25] In a review of markers for harm for machine players at licensed betting offices, Wardle, Parke & Excell[26] suggested that the specificity of frequent play (at the level of two or more days per week) as an indicator of 'problem gambler' was high, i.e. a large majority of those surveyed who play frequently were in fact problem gamblers according to a conventional screen.[27] In a related study, the average number of days between visits was significantly lower for players who self-reported 'almost always' having problems with machines than among those who reported no such problems.[28] And in another Report, on developing a predictive model for problem gambling using tracked data of machine players in licensed betting offices, 'number of playing days' was the single most influential variable in the model.[29] With such findings in mind,

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[25] For example, occasional players (less-than-monthly) had a PGSI problem gambling prevalence rate of 0.5% (which was a lower figure than for the population as a whole) whereas 7.8% of monthly-or-more players were problem gamblers- and another 10.6% were moderate-risk.

[26] H. Wardle, J. Parke & D. Excell, *Theoretical Markers of harm for machine play in a bookmaker's* (London: Responsible Gambling Trust), 2014.

[27] Sensitivity was, however, below 50%. This implies that large numbers of problem gamblers would be undetected if reliance were placed only on this single indicator with a threshold of two or more days per week.

[28] See p. 95 in H. Wardle, D. Excell, E. Ireland, N. Llic & S. Sharman, *Identifying problem gambling – findings from a survey of loyalty card customers* (London: Responsible Gambling Trust), 2014.

[29] D. Excell, G. Bobashev, H. Wardle, D. Gonzalez-Ordonez, T. Whitehead, R.J. Morris & P. Ruddle, *Predicting problem gambling: An analysis of industry data* (London: Responsible Gambling Trust), 2014.

the approximately 1,200 customers observed (in the final year of the data set) to play at the casino on either or both of machines and table games on more than 100 occasions would be candidates to be flagged for monitoring and possible intervention were casinos to introduce automated systems to detect potentially harmful play. Of course, it would be feasible to detect other markers, such as increasing play over time, which could trigger intervention, precisely because these frequent players generate sufficient numbers of observations for meaningful trends to be identified as they occur.

Regarding gender preferences over different gambling activities at the casino, results accord closely with international findings. While we observe significant volumes of machine play by both men and women, it is still the case that a female visit is much more than twice as likely as a male visit to feature only machine activity. This is consistent with a tendency noted in the literature for men to have a relatively strong preference for 'strategic games' (e.g. blackjack) and women to have a relatively strong preference for 'non-strategic' games (e.g. slot machines). [30]

Table 3.1. Number of visits by a player in a year

	percent of players in 2012	percent of players in 2013	percent of players in 2014
one visit	57.58	57.08	55.51
2 to 5	29.16	29.14	29.74
6 to 10	6.29	6.33	6.58
11 to 25	4.47	4.59	4.93
26 to 50	1.54	1.75	1.91
51 to 75	0.49	0.54	0.60
76 to 100	0.21	0.25	0.31
101 to 150	0.16	0.21	0.27
more than 150	0.10	0.15	0.20
N	298,388	273,853	257,465

[30] For a review, see chapter 2 in N. Hing, A. Russell, B. Tolchard & L. Nower, *A Comparative Study of Men and Women Gamblers in Victoria* (Melbourne: Victoria Responsible Gambling Foundation), 2014.

Table 3.2. Proportions of visits with different mixes of gambling activities

gambling activity	percent of visits in 2012	percent of visits in 2013	percent of visits in 2014
B1 only visits	16.89	18.98	20.78
e-roulette only visits	25.19	24.21	26.47
tables only visits	46.06	45.66	41.91
tables and B1 visits	2.39	2.30	2.13
B1 and e-roulette visits	4.16	3.83	4.23
tables and e-roulette visits	4.42	4.22	3.72
all types visits	0.90	0.80	0.76

Table 3.3. Proportions of *male* visits with different mixes of gambling activities

gambling mode	percent of visits in 2012	percent of visits in 2013	percent of visits in 2014
B1 only visits	11.23	12.82	15.21
e-roulette only visits	24.75	23.78	26.37
tables only visits	52.64	52.71	47.79
tables and B1 visits	2.26	2.17	2.11
B1 and e-roulette visits	3.42	3.16	3.67
tables and e-roulette visits	4.81	4.58	4.08
all types visits	0.90	0.78	0.76

Table 3.4. Proportions of *female* visits with different mixes of gambling activities

gambling mode	percent of visits in 2012	percent of visits in 2013	percent of visits in 2014
B1 only visits	30.80	33.93	37.23
e-roulette only visits	25.57	24.79	26.71
tables only visits	30.31	28.78	23.62
tables and B1 visits	2.79	2.70	2.47
B1 and e-roulette visits	6.04	5.50	5.98
tables and e-roulette visits	3.55	3.43	3.16
all types visits	0.93	0.87	0.84

3.3 <u>Duration of gambling</u>

Tables 3.5, 3.6 and 3.7 summarise data on the length of time spent gambling during casino visits (defined by the time between first and last use of the player card for gambling). The tables refer respectively to proportions of gambling visits, of gambling visits which included B1 play and of visits where B1 play was the only gambling.

- Regardless of type of visit, one half or more of visits in each year featured less than one hour of gambling activity.
- The median visit is always in the range 40 minutes to one hour.
- The mean duration is always much higher because of the influence of significant numbers of 'extreme' observations.
- For example, more than 11% of machine-only visits included more than three hours play and a similar proportion lasted between two and three hours.
- From data in Table 3.6, there were more than 24,000 'B1-only' or 'some-B1' visits in 2014 where gambling was spread over more than five hours.[31]

Table 3.5. Proportions of visits (any gambling) by length of visit

visit length (mins)	percent in 2012	percent in 2013	percent in 2014
less than 30 mins	33.99	34.49	33.47
30 to 59 mins	22.67	22.70	22.12
60 to 89 mins	13.82	13.75	13.70
90 to 119 mins	8.87	8.79	8.99
120 to 179 mins	10.08	9.94	10.46
180 to 240 mins	4.98	4.91	5.24
more than 240	5.59	5.42	6.03
mean visit length	78.01	76.82	80.23
median visit length	49	48	50
N	1,194,892	1,190,445	1,226,251

[31] It is perhaps worth noting that this number relates only to play that was observed because the player chose to use his or her loyalty card.

Table 3.6. Proportions of visits with any B1 play by length of visit

visit length (mins)	percent in 2012	percent in 2013	percent in 2014
less than 30 mins	32.39	32.35	30.51
30 to 59 mins	19.78	20.22	19.88
60 to 89 mins	13.46	13.64	13.76
90 to 119 mins	9.60	9.50	9.86
120 to 179 mins	11.85	11.80	12.42
180 to 240 mins	6.25	6.13	6.51
more than 240	6.68	6.37	7.07
mean visit length	85.18	83.92	88.33
median visit length	56	55	59
N	290,793	308,470	342,113

Table 3.7. Proportions of B1-only visits by length of visit

visit length (mins)	percent in 2012	percent in 2013	percent in 2014
less than 30 mins	40.07	38.81	36.17
30 to 59 mins	18.63	19.33	19.24
60 to 89 mins	11.99	12.39	12.85
90 to 119 mins	8.43	8.52	9.04
120 to 179 mins	10.40	10.49	11.19
180 to 240 mins	5.39	5.37	5.76
more than 240	5.09	5.10	5.74
mean visit length	73.39	74.11	78.74
median visit length	43	45	49
N	201,863	225,917	254,797

Commentary: As often in gambling data, the typical behaviour is observed to be moderate; but, nevertheless, far-from-typical behaviour which may give cause for concern contributes significantly to the overall level of activity at venues. Long duration of play has been noted widely as suggestive of problem gambling and harm (though of course there will be many cases where a long session just reflects consumer preferences without any harm resulting to the player or others). For example, Schelling & Schrans[32] studied 711 video lottery terminal (VLT) players in Nova Scotia, examining a very comprehensive list of behavioural, physiological and emotional indicators for their efficacy in predicting which players were problem gamblers. They

[32] T. Schellinck & T. Schrans, 'Identifying problem gamblers at the gambling venue: Finding combinations of high confidence indicators', *Gambling Research*, 16:1:18-24, 2004.

noted that playing for more than three hours was the strongest among the behavioural indicators as a predictor of the probability that the player was a problem gambler. Combined with the presence of any one of other leading indicators (player feels nauseous, player feels sad, player kicks the machine) allowed a player to be identified as a problem gambler with better than 95% confidence. These sorts of findings are capable of being exploited in the development of tools for detecting problematic play in casino gaming machines but also for use by casino staff charged with applying responsible gambling protocol. For example, lengthy play on a machine could be flagged for staff who could then observe the physical state and behaviour of the player. What would be the burden on staff? Our data identify about 29,000 machine-only visits in 2014 where duration of play exceeded three hours. That would represent about 80 players per day across the Rank estate who would be flagged for assessment after three hours of play.

3.4 Player spend during casino visits

By player spend, we mean the loss incurred by the player from gambling. This, rather than amount bet, measures what the player has left behind after his or her gaming. It is equivalent, for example, to measuring spending on a visit to the cinema by the price of a ticket (which is what the film fan leaves behind after seeing the show).

Tables 3.8 and 3.9 describe the distribution of spending on machine play, first for all visits which included B1 play and then for the subset of visits where play on B1 machines was the only gambling activity.

The summary statistics in Tables 3.8 and 3.9 have the 'visit' as the unit of observation. Table 3.10 presents information on how many *players* accounted for visits where spending on B1 machine play was above various thresholds (Figure 3.1 provides a pictorial representation of these data).

- Sometimes of course players win (negative spending). In just under one quarter of visits, players finish ahead at the end of their machine play.

- On almost the same proportion of visits (though a lower proportion in the final year, 2014, when higher stake and prize limits were in place) the player loses but by less than £20.

- The median spend for machines-only visits was about £20 in 2012 and 2013 but nearly £26 in 2014.

- The mean spend is always much higher because of the influence of significant numbers of 'extreme' observations.

- In 2014, just under 20% of all visits including B1 play and just over 20% of B1-only visits resulted in a player (B1) loss of more than £100.

- In more than 8% of machine-only visits the loss exceeded £200.

- The data for visits involving machine play include more than 11,000 occasions (3.3% of the total) on which a player lost more than £300 in the machines.

- Table 3.10 documents that, across the three years, there were 28,716 such (tracked) visits. Some of these may have represented one-off cases of extravagant or binge behaviour. However, since only 8,604 players contributed to the total, it is clear that a small proportion of the playing population exhibited repeated single-session high spending.

Commentary: the story is the now familiar one of a large proportion of players exhibiting moderate behaviour and a small but emphatically non-trivial number of players playing to levels which may be a cause for concern.

Certainly it is possible for low spenders to experience harm, for example even small losses repeated regularly could take some people beyond a tipping-point where they become financially stressed. However, the typical spend on machine play on a single visit to the casino is in the range £20-£26 and this is not at all out of line with the cost of alternative commonplace entertainments such as restaurant meals, nights at the cinema and professional sports events. With this perspective, there seems little reason to dispute the casino industry's contention that it provides a service which is of social benefit: it allows people with certain preferences to extract more fun from their entertainment budgets than would be possible if their choices did not include the opportunity of gaming at the casino.

But, as the late Bill Eadington long ago remarked, problematic play is the Achilles' heel of legal gambling.[33] Here we have data which show spending in the hundreds of pounds on individual machine visits to the casino, with evidence of repetition of the behaviour by the same players over time. Much of this behaviour may indeed be problematic. Of course, some of these players may be making rational choices on how to spend their high incomes. But the levels of expenditure documented would challenge most budgets given typical household income levels in Great Britain and it is therefore plausible that the greatest harm from unwise gambling behaviour is likely to be found among the atypically heavy players rather than among those whose spending is closer to the median. On the other hand, as Wardle, Parke & Excell[34] note, while high

[33] W.R. Eadington, 'The Economics of casino gambling', *Journal of Economic Perspectives*, 13:3: 173-192, 1999.

[34] For reference, see footnote 26 above.

expenditure is a very plausible marker for harm, prior research provides little evidence concerning the thresholds that might be set such that exceeding the threshold would be a reliable indicator of harm.

While Table 3.10 illustrates that the absolute number of observations of an individual spending hundreds of pounds in the machines during just one visit is large, it is also to be noted that in the great majority of these cases spending is in the *low* hundreds. In particular, spending above £1,000 is very rare and there are no cases of a player losing as much as £1,500.

The explanation is almost certainly that, in contrast to say betting or casino games, gaming machines are regulated in a way which effectively limits the loss a player can incur. It is possible to calculate the *theoretical loss* per hour on a gaming machine. This concept refers to the loss a player with 'average luck' would incur from continuous play over a period if always placing the maximum stake permitted on each spin and if playing at the maximum permitted speed. Currently, regulations specify that the maximum stake on a B1 machine is £5 and there must be a gap of 2.5 seconds between each spin (the 'game cycle'). Assuming a return to player of 96%, the hypothetical player, able to extract the full 1,440 spins allowed, would have an expected loss of £288 per hour. Even at this implausibly frenetic pace of play, with a bet on every spin of £5, it would take more than five hours of non-stop play before the expected session loss reached £1,500. Before Uplift, there would have had to have been more than twelve hours such play. It is therefore not surprising that no instances of a £1,500 loss are observed in the data set.

More detailed analysis of heavy play will be presented in Chapter 5 below.

Table 3.8. Proportions of visits with different levels of player loss on B1 machines (all visits including B1 play)

visit spend on B1 slots	percent in 2012	percent in 2013	percent in 2014
won	24.44	24.39	24.05
less than £20	27.40	26.16	23.56
£20 to £50	18.66	19.16	18.46
£50 to £75	8.04	8.30	8.65
£75 to £100	5.47	5.57	6.22
£100 to £200	10.00	10.19	11.53
£200 to £300	3.35	3.51	4.21
more than £300	2.64	2.71	3.32
mean spend	31.52	32.59	38.52
median spend	19.25	19.88	22.26
N	290,793	308,470	342,113

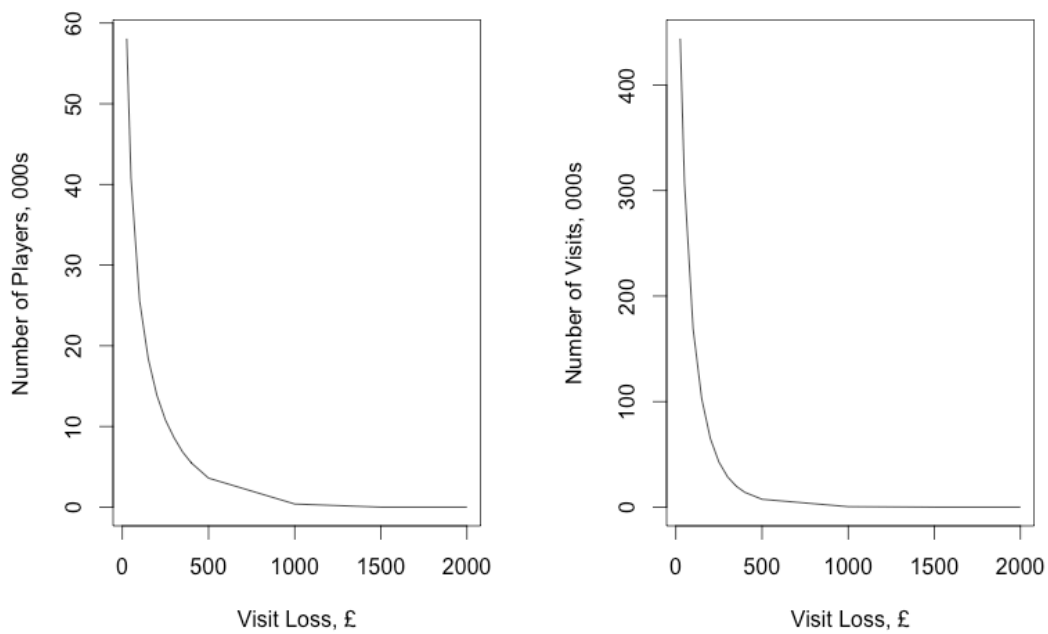
Table 3.9. Proportions of visits with different levels of player loss (B1 machine-only visits)

visit spend on B1 slots	percent in 2012	percent in 2013	percent in 2014
won	24.78	24.69	24.40
less than £20	24.54	23.87	21.14
£20 to £50	18.38	18.91	18.02
£50 to £75	8.41	8.56	8.89
£75 to £100	5.86	5.88	6.59
£100 to £200	11.09	11.08	12.58
£200 to £300	3.86	3.94	4.68
more than £300	3.07	3.06	3.69
mean spend	35.12	35.38	41.59
median spend	20	20.3	25.81
N	201,863	225,917	254,797

Table 3.10. How many players lost more than £x on B1 machines on a single visit? (all visits with B1 play, 2012-2014)

There are	443958	visits in which	58074	players had a visit spend of	£25	or more
There are	306228	visits in which	40776	players had a visit spend of	£50	or more
There are	168815	visits in which	25563	players had a visit spend of	£100	or more
There are	102601	visits in which	18405	players had a visit spend of	£150	or more
There are	65037	visits in which	13877	players had a visit spend of	£200	or more
There are	42644	visits in which	10795	players had a visit spend of	£250	or more
There are	28716	visits in which	8604	players had a visit spend of	£300	or more
There are	19856	visits in which	6827	players had a visit spend of	£350	or more
There are	14049	visits in which	5485	players had a visit spend of	£400	or more
There are	7448	visits in which	3599	players had a visit spend of	£500	or more
There are	446	visits in which	388	players had a visit spend of	£1,000	or more
There are	0	visits in which	0	players had a visit spend of	£1,500	or more
There are	0	visits in which	0	players had a visit spend of	£2,000	or more

Figure 3.1. Levels of B1 losses (over players and over visits)



3.5 <u>The relationship between visit spend and duration of play</u>

Table 3.11 presents information on the mean and median duration of play for different ranges of visit outcome (amount lost). We use here data on B1-only visits during 2012-2014.

- A typical winner has spent about one hour playing when he or she quits
- A spend of less than £20 is typically associated with a very short duration of play
- Beyond that, large losses and lengthy play are closely correlated

Commentary: problematic play is often defined as involving the allocation of excessive time or money to gambling. Naturally, if lengthy duration or high spending are accepted as indicators of potential harm, the two will usually be found together. This follows both from the regulatory constraints on stakes/ time between spins (which require lengthy play if a high loss is to be built up) and from the mathematics of the game (as visit length increases, the house advantage inevitably bites as deviations far from the return-to-player set on the machine become less likely).

All this is obvious. Nevertheless there are points of interest in Table 3.11. From Tables 3.8 and 3.9, about one-quarter of visits end in a player win. From Table 3.11, these wins are typically associated with about one hour of play whereas the player is more likely to be 'ahead' after a short duration of play than after one hour (abstracting from complications such as stake size varying systematically as a session progresses). This is at least suggestive that players who are ahead early tend to persist in playing because they have not gambled long enough to satisfy their thirst for entertainment (or else because they treat gains as 'house money' which they are willing to use more freely than their own money). But, after about an hour, some of those ahead do quit their session. Further research might be recommended concerning the determinants of individuals' decisions over whether or not to quit machine play while ahead.

A recent research paper by Walker and colleagues[35] implicitly questions whether advice on responsible gambling should in fact advise players to 'set a limit and stick to it'. Some of those who continue to play (say, beyond an hour) might be following this advice literally by playing to the point where they exhaust their pre-set budget. But if players who win always return those winnings to the machine, they will never end up with winning sessions to offset the losses they inevitably incur on other visits. This means that, over time, they will make bigger losses and, if they are problem gamblers, the harm they incur from gambling is likely to be magnified.

This line of thinking leads to the conclusion that pre-commitment facilities should extend to allowing (if not encouraging) the player to set a win limit where he would have to take his winnings and play no more. A criticism of this is that some players may be induced to treat the win limit as a target and extend their play. We would add to the debate that players could be nudged towards quitting while ahead by making players pause before reinvestment of winnings. For example, wins could be put into a separate bank within the machine, requiring extra steps before these gains could be used to buy further spins.

Table 3.11. Player spend and visit duration (minutes)

visit spend on B1 slots	mean visit length	median visit length
won	84.3	57
less than £20	26.2	11
£20 to £50	48.5	29
£50 to £75	71.8	51
£75 to £100	88.0	68
£100 to £200	118.5	99
£200 to £300	161.8	145
more than £300	212.4	192

[35] D.M. Walker, S.W. Litvin, R.S. Sobel & R.A. St.-Pierre, 'Setting win-limits: An alternative approach to 'responsible gambling'', *Journal of Gambling Studies*, 31:3:965-986, 2015.

3.6 Time of day and intensity of play

This section presents information on how the volume of machine play in casinos varies across the day and investigates whether intensity of play varies by time. Intensity of play at any point in time is measured by the casino (B1) win per minute divided by the number of people playing the machines.

Figure 3.2 shows how many (loyalty card) customers, on average, are gambling (in the set of casinos we observe) at each time of day. This includes any gambling activity. Figure 3.3 presents similar information but just for people using B1 machines.

Figure 3.4 shows average casino win-per-minute from B1 machines by time of day.

Figure 3.5 shows average B1 casino win-per-minute per B1 user by time of day. This is our measure of spending intensity.

- The busiest time in casinos is around 10 p.m.
- Typically, the number of gamblers has halved by about 2 a.m. but at that time it is still about as busy as at 6 p.m.
- The pattern of use for B1 machines broadly follows that for the casino generally
- Casino revenue from machines is highest in the evening
- Spending intensity increases steadily through the evening hours, reaching a maximum shortly after 2 a.m. but remaining at a high level throughout the early hours

Commentary: Research for The Responsible Gambling Trust[36] on staking patterns on bookmaker machines revealed that, from 10 p.m., there was a striking increase in the propensity of players to stake at the maximum permitted level. It was also noted that the mix of B2/B3 games shifted in a riskier direction. Given these findings, and given that casinos remain open twenty-four hours a day (allowing still 'later' hours to be considered, compared with bookmakers), we examined whether there was evidence that machine play through the night in casinos tended, on average, to

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[36] H. Wardle, E. Ireland, S. Sharman, D. Excell & D. Gonzalez-Ordonez, *Patterns of play: Analysis of data from machines in bookmakers* (London: Responsible Gambling Trust), 2014.

be more ‘risky’ than during the daytime and evening periods. We chose intensity of play as a summary variable because it is the product of both stake size and pace of play, each an indicator of how likely it is that play is poorly controlled and harmful. Our measure of spend intensity used in Figure 3.5 is calculated by spreading the visit spend uniformly over the duration of the visit. For example, for a single visit in which spend is £10 and the visit activity began at 8.01pm and ended at 8.20pm, then the spend intensity for each minute between 8.01pm and 8.20pm is 50p. It is then assumed that there was a 50p loss in the minute beginning, for example, at 8.14pm of this visit. We perform this task for each and every visit which included the minute beginning at 8.14pm and calculate the average spend intensity across all visits which included this minute.

The diurnal trend is very clear in Figure 3.5. Up until shortly after 2.00 a.m., the following holds: **the later the visit finish, the more intense gaming has been (on average)** on that visit. For the rest of the overnight period, playing intensity falls over time but remains at an elevated level. All this is suggestive of a greater propensity for ‘late’ play to be harmful. Reasons may include that a higher proportion of night time customers are vulnerable persons. For example, customers in the casino in the early hours may be less likely than average to enjoy a stable home life. Particularly in city centre casinos, they are likely also to include many workers from the night time economy who have finished shifts as such as waiters, bar tenders or doormen, generally low-paid occupations. We recommend further research on potential harm from gambling which takes place during the night.

Previous research in this area has focused on the possible benefits when jurisdictions have introduced restrictions on hours of operation of gaming machines. However, in their comprehensive survey of the effectiveness of policies designed to mitigate problem gambling, Williams, West & Simpson[37] find the evidence on the effects of such policies to be inconclusive. Our judgement is that policy initiatives in this direction have taken place without being informed by systematic research on the nature and extent of any harm associated with late play. Such research could in any case inform other approaches, for example staff training might take note of distinctive features of night gambling were more understood about it.

[37] R.J. Williams, B.L. West & R.I. Simpson, *Prevention of problem gambling: A comprehensive review of the evidence and identified best practices* (Toronto: Ontario Problem Gambling Research Centre and the Ontario Ministry of Health and Long Term Care), 2012.

Fig. 3.2. Average numbers of gamblers at different times of day

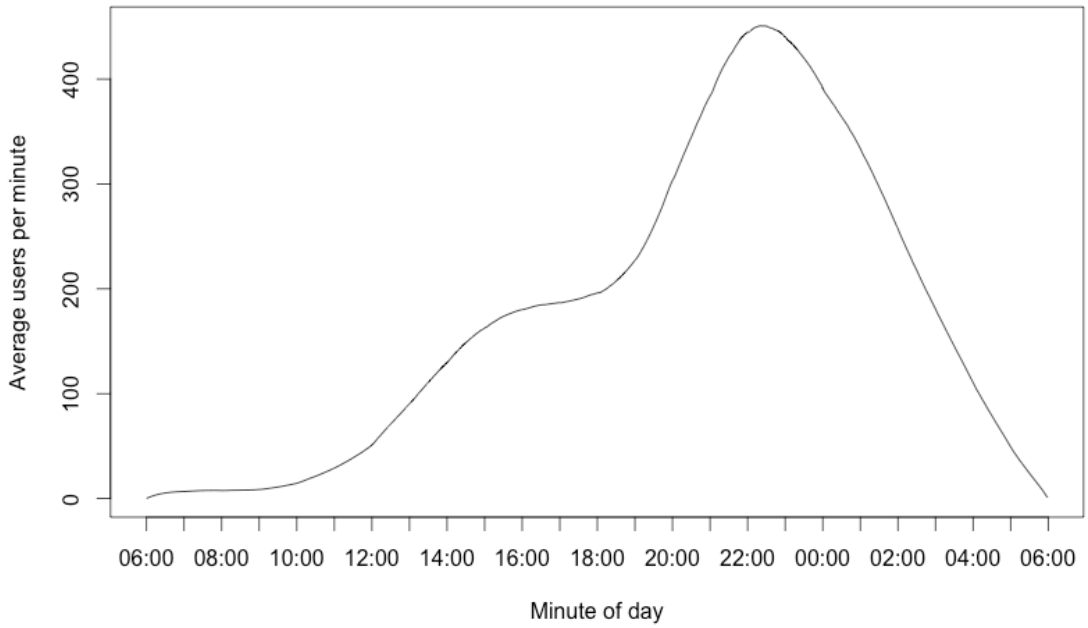


Fig. 3.3. Average number of B1 users at different times of day

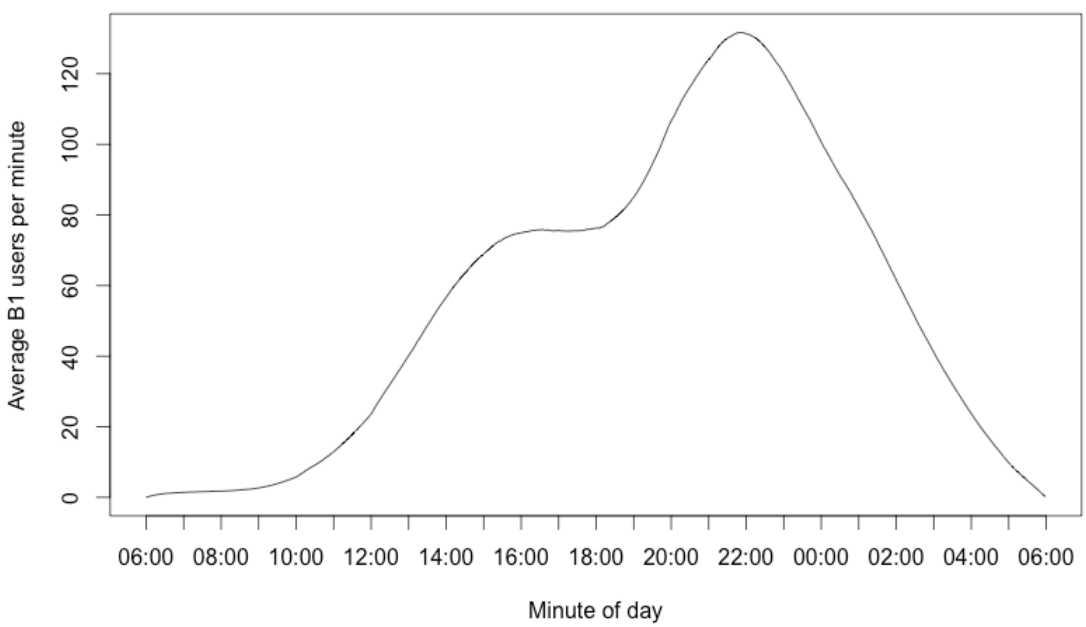


Fig. 3.4. Average B1 casino win per minute at different times of day

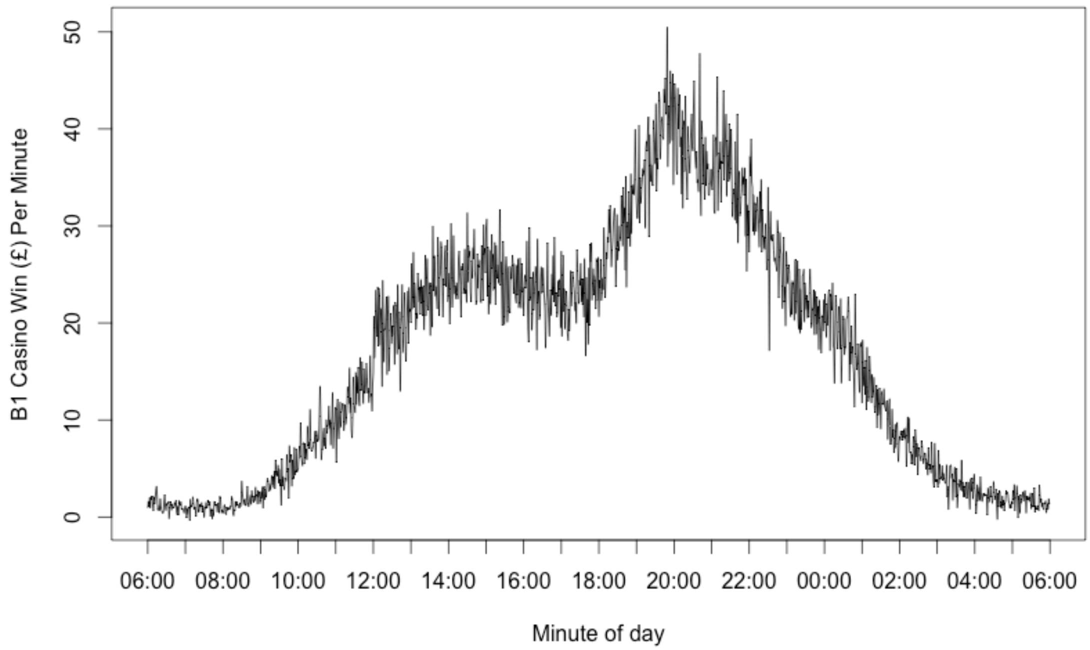
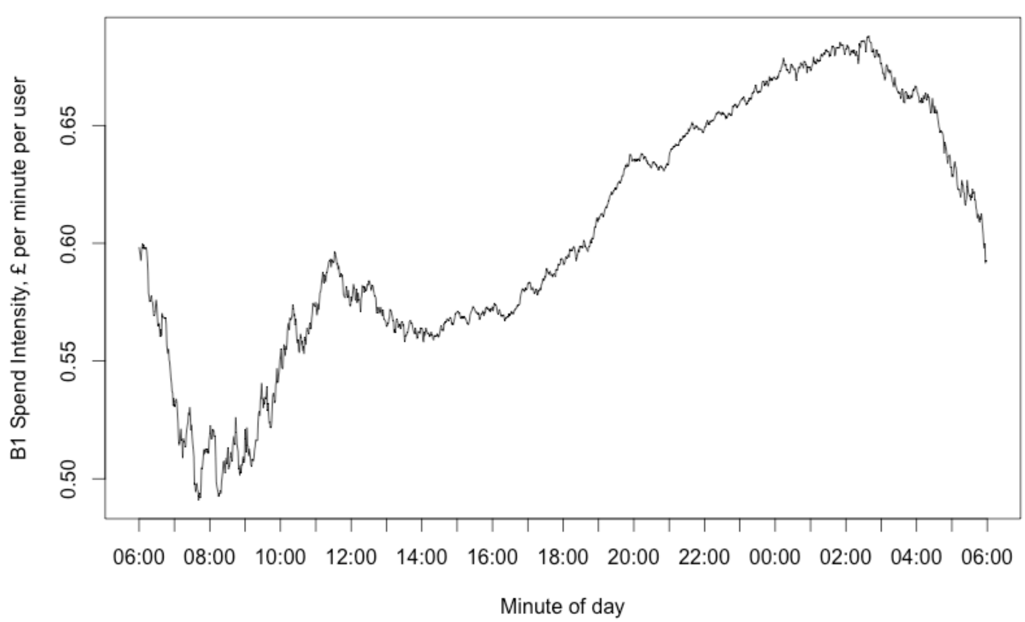


Fig. 3.5. Average spending intensity of B1 users at different times of day



3.7 Closing remarks to Chapter 3

Because such information has not been publically available before, we have presented a picture in numbers of machine gaming in British casinos, painted from data from one operator (which is likely to be representative of the industry) and relating to players who use loyalty cards as they play (who may or may not be representative of the whole population of players).

We have examined measures such as frequency of visit to the casino, time and money spent gambling and intensity of play. The picture if one focuses on the median values for variables (i.e. on typical behaviour) is benign. Typically, customers visit only occasionally, play for only a short time and spend only amounts comparable to what they would spend if their tastes lead them instead to the cinema or to a bar for a round of drinks after work. Such levels of engagement with B1 machines (unless combined with heavy use of other gambling facilities, not observed in the data) are intuitively unlikely to be associated with significant gambling harm.

But a significant minority of customers play to levels (whether measured by time spent or money lost) where it might be suspected that they have problems with their gambling. No single indicator is capable of identifying who is a problem gambler but the number of players flagged as potential problem players is significant on any of the criteria we have examined. All operators might investigate the potential of using tracked data to monitor for potential problems among their customers. In the following two chapters we focus on two particular patterns of behaviour which might be included in such monitoring.

4 RETURNING TO THE CASINO

4.1 Chasing losses across visits

It appears to be very widely accepted that, if a player returns to the gambling venue another day because he or she wants to try to win back losses, then this is symptomatic of problem gambling and, by implication, of gambling harm. Indeed both problem gambling screens employed in the British Gambling Prevalence Survey inquire about such behaviour. Thus the first question on the Prevalence Survey version of the DSM-IV screen asked: **When you gamble, how often do you go back another day to win back money you lost?** (Every time I lost/ Most of the time I lost/ Some of the time (less than half the time I lost)/ Never). Similarly, Item 3 of the PGSI screen was: **In the past 12 months, how often have you gone back to try to win back the money you'd lost? (**Almost always/ Most of the time/ Some of the time/ Never).[38]

Given very limited overlap of questions between the two screens (which results in limited overlap of the sets of respondents identified as problem gamblers), the almost identical wording in each case underlines that there is a strong consensus that going back after losses (between-sessions chasing) is behaviour particularly characteristic of the problem gambler.[39]

To gain more insight into the association between this sort of loss-chasing behaviour and gambling harm, we examined and analysed raw data for slots players from the 2010 British Gambling Prevalence Survey. We could have examined just data for slots players who had reported casinos as one of their venues for playing. However, participation in casino-based machine gaming in the population and therefore in the sample was low. Such a restricted sample would have yielded (literally) only a handful of problem gamblers available for study. Broadening the sample to include all slots players[40] allowed us to work with a sample of 357 monthly-or-more players of whom 28 (7.8%) were PGSI problem gamblers and 38 (10.6%) were moderate-risk gamblers, defined by scores of 8 or more for problem gamblers and 3-7 for moderate-risk gamblers. For each item, including of course, item 3 as quoted above, "most of the time" scores 2 points and "almost always" scores 3 points. There are nine items altogether.

[38] The questions on each screen are listed on pp. 182-3 of the Survey Report (for full reference, see footnote 2 above).

[39] The South Oaks Gambling Screen, used in prevalence surveys in many countries, also has an almost identical question on going back to win back losses.

[40] In the Prevalence Survey, FOB-T machines, found in licensed betting offices, are defined as a separate gambling activity- 'slots' play here therefore refers to all other gaming machines.

Of the 66 individuals whose gambling we regarded as problematic (classified as either problem gamblers or moderate-risk), only 19 answered “almost always” or “most of the time” to the loss-chasing question. On the basis of these self-report data, chasing losses across visits appears therefore to have quite low sensitivity[41] as an indicator of problem gambling if used alone (though this is not to say that it would not be efficacious if used in combination with other markers).

Specificity[42], on the other hand, proved to be high. In the sample of 357 regular slots players, 20 (5.6%) endorsed Item 3 to the extent of at least “most of the time”. Of these 20, nineteen were indeed classified as PGSI moderate-risk or problem gamblers.

A claim for high specificity could however be regarded as almost tautological. Answering “most of the time” scores two points on the screen and therefore any respondent giving this answer is already close to the threshold of three points for classification as a moderate-risk gambler. And anyone answering “almost always” is *ipso facto* at least a moderate-risk gambler on the PGSI screen because he or she ‘earns’ three points from that response alone. It would therefore be more informative to attempt to evaluate the specificity of between-session loss as a predictor of harm rather than of problem gambler status.

It is certainly possible to imagine an individual who self-reported chasing losses (and was a moderate-risk gambler as a result) but who experienced no consequential harm. For example, he or she goes back quickly after losses but does not spend enough overall to cause financial embarrassment. We therefore sought to answer the question of whether endorsement of Item 3 predicts harm as opposed to problem gambling status.

As with other screens, the PGSI includes a mix of questions, some of which refer to behaviour patterns thought to be associated with problem gambling and some of which refer to potential harmful consequences from gambling. Three items in the PGSI unambiguously involve consequences as opposed to capturing signs of ‘addictive’ behaviour: Items 1 (bet more than could afford to lose), 4 (borrowed money/ sold items to fund gambling) and 8 (gambling caused

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41 Sensitivity refers to the ability of a screen to flag a large proportion of the true cases in the group studied.

42 Specificity refers to the ability of a screen to avoid ‘false positives’, i.e a screen has high specificity if a large proportion of cases which are flagged are true cases.

financial problems). We defined an individual as having experienced harm from gambling if he or she answered anything from "sometimes" upwards to any of these questions.[43]

Of the twenty respondents who endorsed the loss-chasing item, nineteen reported having experienced harm in their responses to Items 1, 4 and 8. We are working here with small numbers; but this is still highly suggestive that self-report of between-session loss-chasing by regular slots players has high specificity as a marker for harm. Since this is one of the few self-reported behaviours, captured in the screens and potential markers for harm, which has an empirical counterpart in tracked gambling data, between-session loss-chasing is an obvious candidate for inclusion in any algorithmic design for detecting problematic gambling that might be developed by the casino industry in the future. This chapter lays the ground by modelling behaviour of players in terms of how quickly they return for further play following losses.[44] We apply our model first to the generality of players to find what the typical response to losses is. We then apply the model player-by-player to investigate the extent of *atypical* response to losses. Finally, we assess how often alerts for loss-chasing might be generated from monthly screening of players for loss-chasing based on their observed behaviour in the preceding six months.[45]

4.2 Modelling time between visits: Typical behaviour

We employ a statistical model the output of which is an equation where the variable to be explained is the time (measured in days) between B1-visits to the casino (where a B1 visit was defined as any visit in which B1 games were played- such a visit may or may not have included table games). We estimate the model over data from 2012-2014, restricting the set of players

[43] Of the sample of 357 regular slots players, 104 (29.1%) had experienced harm on this definition. They may in addition have experienced harm in dimensions not covered in the PGSI.

[44] Returning more quickly to play after heavier than usual losses is consistent with loss-chasing as defined in the problem gambling screens. However, we have no access to players to ascertain the reason for their behaviour and so, strictly, it cannot be assumed that they made a conscious decision to try to win their money back. In our commentary below we nevertheless refer to the behaviour as 'loss chasing', consistent with usage of the term in prior literature (see Narayanan & Manchanda, footnote 6 above).

[45] In a study of the behaviour of internet gamblers which focused on players who closed their accounts because of problem gambling, Xuan & Shaffer noted that chasing losses could take different forms, for example, a player might go back to try to win back losses but behave either cautiously or conservatively in their style of betting (players can choose different gambles distinguished by stake size and volatility of return). These distinctions are likely to be informative but our data were insufficiently granular for this to be investigated here. Reference: Z. Xuan & H. Shaffer, 'How do gamblers end gambling: Longitudinal analysis of Internet gambling behaviors prior to account closure due to gambling related problems', *Journal of Gambling Studies*, 25:239-252, 2009.

included to those who had at least 100 machine visits observed over the whole data set (i.e. not just 2012-2014).[46]

We use a survival regression model. Survival models seek to analyse the determinants of 'time to next event'. As the name might imply, they were developed for and have been widely used in the field of medicine. Here the word 'survival' is often literally descriptive of the focus of interest because the time to event refers to the time to death following an intervention. For example, one might model the number of months to death following a transplant and predictor variables might include time-invariant variables such as the gender of the patient and time-varying variables such as whether the patient is experiencing a particular symptom. In this example, there is only one occurrence of the event, death. But models are equally capable of being employed to predict time to next event where multiple occurrences of an event are possible, for example in medicine researchers might model relapses or hospital re-admissions.

Over time, the tools developed for application in medicine have also come to be employed regularly in the social sciences (as well as in engineering where time to equipment failure is a common subject for study). For example, many people who experience unemployment in fact experience repeated spells of unemployment. Just as medical researchers are interested to model how long a patient is able to stay at home before having to be readmitted to hospital, so social scientists would wish to gain insight into what determines how long an individual can hold down a job before re-entering unemployment. They use survival regression.

Here we have a similar situation to model: for each individual, we observe repeated cases of the event over the data period and we are interested in modelling time to next occurrence of the event. In our case gambling at the casino is the event. Survival models are the natural tool of choice for analysis.

A complication in survival analysis in any field is that there is likely to be some point in time when the data period ends. At the end of the data period, some patients in the study may be well and will in fact never be readmitted to hospital again; some employees in the study may be settled in secure jobs and will never become unemployed again; some machine players will have quit the habit and will not go to the casino ever again. On the other hand, *some* patients would be observed to be readmitted, *some* people in jobs would be observed to lose their jobs, and *some* gamblers would be observed to visit the casino again, if only the data period could have been extended.

[46] The results were remarkably stable when we varied the qualification threshold to 50 and 150 visits observed over the six years.

Survival analysis has to incorporate some conventions for dealing with issues surrounding *censored data*. Our data are censored in the sense that if (on the final day included in the data) a subject has been observed to have already gone *t* days without visiting the casino, it is known only that the time between the last visit and the next one is greater than *t*. The duration of the final spell is therefore recorded as *t* ('censored to *t*') whatever the true duration. The true duration may in fact be indeterminate because the subject will never go to the casino again and is therefore 'cured'.[47]

In our case, we treat a player as 'cured' (has stopped using the casino) if the time between his or her final recorded visit and the end of the data period is longer than the maximum gap between visits observed for that player earlier in the data set. This assumption was used in the estimation reported below. However, we carried out a series of sensitivity tests on our results for alternative assumptions, such as a player is cured if the duration of abstinence recorded at the end of the data period has already reached three times/ twice/ 1.5 times the maximum gap recorded for that player in the data up to the date of the final recorded visit. Results proved remarkably robust to changing the assumption about when a player is to be regarded as cured: findings reported below are therefore not to be regarded as sensitive to our choice at this stage in building the model.

The model seeks to explain the time between visits. After the equation has been estimated, it can then be used to calculate a predicted time between visits for any given set of values of the predictor variables. These predictor variables capture details of the individual and his previous behaviour and experiences at the casino.

Our focus is on the impact on 'time to next visit' of the player's profit or loss on his or her preceding visit. The outcome of the player's previous visit must, however, be put in context. A particular player may be a free spender at the machines on every visit and if the loss from the latest visit were high compared to other players, this in itself would not be expected to affect his or her decision on when to visit if it had been just a 'normal' night for that player. Rather we look for an effect from losses which are untypically high for the *particular* player.

Consequently we introduced the concept of *normalised* wins and losses. Our variable *losses on last visit* is measured in such a way that, if the player spent (lost) exactly his or her 'normal' amount, then *losses on last visit* is recorded as equal to 1. And, for example, having lost twice as much as normal would result in *losses on last visit* taking the value 2.

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[47] The word 'cured' here is used here because the accepted terminology in the statistical literature reflects that the origins of the techniques lie in medicine (rather than because we think of casino visiting as an illness!).

But what is 'normal' for a particular player at a particular time in the data set? Normal spend is calculated as a weighted average of previous observations of spend for that player with more recent observations given greater weight in the calculation. The details of the weighting scheme and notes on other technical details of the modelling exercise are presented as boxed text below. This boxed text may be skipped by the general reader without loss of continuity.

Further controls for the past experience of the player include a measure of his or her 'normal' frequency of visit, captured by *past frequency* (which again is based on a weighted average across previous quarters for which the player is observed). This is included because we are then able to interpret the estimated effect of the *losses on last visit* as capturing whether the timing of the next visit is shifted forward or back compared with when the player would normally have been expected to return to action. Similarly we control for *duration of last visit* made (where again we normalise so that the length of time spent playing on the last visit is measured relative to the player's typical visit length in previous observations).

Box 4.1. Technical notes on the survival model

All analysis and data processing was done in R.[48] *The survival model was estimated using functions from the survival package written by Therneau*[49].

We first estimated a Cox regression, which is a common framework to adopt in survival modelling. However, it assumes proportional hazards (for example, the effect of losing on the previous visit would always, say, double the expected time between visits, regardless of the values of the other covariates and the baseline time between visits) and this assumption was rejected when tested, i.e. hazards were not found to be proportional.

Here, it was assumed that the response followed a log-logistic distribution. We experimented with using the Weibull, log-normal and exponential distributions; but the choice of log-logistic gave the best fit.

To account for unobserved heterogeneity across individuals, a frailty term was included in the model specification. The frailty term in a survival model is analogous to a random effect term in a regression.

loss on previous visit *and* winnings on previous visit *were calculated relative to a weighted average of a player's mean losses over all previous quarters where there had been a visit.*

For N observations (e.g. a player is observed in 4 quarters (N=4 "observations")), the weights in the weighted mean are given by
for (i in 1:N) (2^(i-1))/(2^N -1)

For these values of N we get weights:
N=2: w1 = 2/3, w2 = 1/3
N=3: w1 = 4/7, w2 = 2/7, w3 = 1/7
N=4: w1 = 8/15, w2 = 4/15, w3 = 2/15, w4 = 1/15
and so on. The principle is that weights halve every observed quarter and sum to one.

A similar weighting procedure was adopted to capture past quarterly number of visits and when normalising duration of immediately preceding visit.

We experimented with normalising player loss with respect to previous amounts staked instead of previous amounts lost; but results were barely changed and so we do not report them.

[48] R Core Team (2015). *R: A language and environment for statistical computing* (Vienna: R Foundation for Statistical Computing), 2015, https://www.R-project.org/.

[49] T. Therneau, *A Package for Survival Analysis in S_. version 2.38*, 2015, http://CRAN.R-project.org/package=survival.

Finally, control variables were added to the model to allow for any influence from the player's age, the player's gender and whether the player lives in a deprived area (the variable *deprivation* defined in Section 2.2 above).

To return to our focus variables, we have explained how we derived the variable *losses on last visit*. The specification of the equation must also acknowledge that some visits end in wins. Thus we define a variable, *winnings on last visit*, which is defined symmetrically with the loss variable. When it is equal to (for example) 1, this means that the player won an amount equal to the loss he 'normally' incurs. If it were equal to 0.5, it would mean that, instead of his 'normal' loss of £x, he actually ended up ahead by £0.5x.

It is also possible that, regardless of amount, the player's decision on when to return is affected by the dichotomous outcome: did the player win or did the player lose? The indicator variable *loser on last visit* allows for adjusting the predicted time to next visit if the player had been a loser rather than a winner.

Table 4.1 presents the results from modelling. All predictor variables (except *female*) are statistically significant at the 1% level, which is to say that we can be very confident that each of them has an impact in the set of players' decisions on how long to wait before playing again.

The direction of impact is revealed by the sign of the coefficient estimate on the relevant variable. A positive sign for a variable indicates that its influence tends to increase the duration of time to next event. A negative sign indicates a tendency for the variable to act towards shortening the time to next event.

The coefficient estimates on *loser on last visit* and on *losses on last visit* are each positive. This implies that average behaviour is such that **being a loser (as opposed to a winner) tends to lengthen the period to next gaming; and the larger the loss, the greater the impact in delaying a return to the casino.**

Conversely, the coefficient estimate on *winnings on last visit* is negative. **Experiencing a profit on a machine visit decreases the time to next visit and the bigger the winnings, the faster the player tends to return to play.**

Because the model is non-linear, the magnitudes of these effects vary according to the characteristics of the situation as described by the values of all the predictor variables. The predicted impact of a change in a predictor variable may be calculated using the coefficient estimates in Table 4.1, imposing values corresponding to the particular situation.

As an illustration, consider a 30 year old male, not from a deprived area. Losses on his last visit and the time he spent were exactly ‘normal’ for him (loser on last visit=1, losses on last visit=1, duration of last visit=1). His previous visit frequency was every 23.25 days. The model predicts that this time his return will be after 24.3 days.

Suppose he had had a very unfavourable outcome on his last visit: he lost four times his ‘normal amount’. Now, predicted time to next visit increases to 27.1 days.

Table 4.1. Survival regression analysis: time to next B1-visit

	coefficient	standard error	p-value
loser on last visit	0.2355	0.0026	<.001
losses on last visit	0.0379	0.0029	<.001
winnings on last visit	-0.0428	0.0055	<.001
Age	0.0010	0.0015	.004
female	0.0054	0.0181	.765
deprivation	-0.0967	0.0167	<.001
past frequency	-0.3844	0.0001	<.001
duration of last visit	0.0026	0.0007	<.001
Intercept	2.1155	0.0255	<.001
number of observations	1,537,748		

What if he had been ‘lucky’? Had he *won* double the amount of his ‘normal’ loss (loser on last visit=0, losses on last visit=0, winnings on last visit=2), the model reduces predicted time to next visit to 17.5 days: he is expected to make an appreciably faster return to the casino.[50]

[50] Gender proves to have little influence in the model and the illustrative figures here were barely different when we changed ‘he’ to ‘she’.

These patterns of response are derived from modelling across all players. They therefore reveal 'average' responses. In fact, some players are likely to behave differently because they are loss-chasers (instead of being deterred from going when there are prior losses, they return earlier than they would usually). Others will follow their regular habits such that visit decisions are in fact independent of past outcomes. That the 'average' behaviour is still to be quite strongly deterred from playing by prior losses (and to be quite strongly attracted back by prior winnings) suggests that there must indeed be players whose responses to previous outcomes are stronger than these illustrative figures suggest.

Our findings on 'average' behaviour are not surprising. There are various perspectives which would have lead one to expect the pattern of results shown in Table 4.1 for the focus variables:

(i) Traditional economic analysis would propose a 'wealth effect: losing (winning) makes people poorer (richer) and less (more) able and inclined to revisit the casino.

(ii) Behavioural economics embraces the notion of 'mental accounting'[51]: in their minds, some individuals may have allocated certain funds to gaming and, if they have spent them before the end of their mental accounting period because they have lost heavily on the most recent visit, they believe they cannot afford another session on the machines. Winners, by contrast, are underspent and may make an extra visit to the casino because they do not think of the possibility of using their gains to enjoy a visit to the opera (arts spending belonging to another account). This is related to the 'house money' effect which proposes that gamblers treat winnings not as their own money but as free money from the house to be reinvested in further bets. This may lead to winners lengthening visit duration to dispose of the free money but, if there is a time constraint, they may return another day to get rid of it.

(iii) Individuals may exhibit another cognitive flaw, namely belief in the phenomenon of the 'hot hand'.[52] For example, winners may believe they are on a winning streak and hasten back to win again.

(iv) Probably the simplest explanation is that their most recent experience may shift individuals' perceptions of how enjoyable playing machines in a casino really is. For example, heavy losses may cause disillusion and the subject may even be 'cured' and never go again.

This discussion of what underlies 'average' behaviour is necessarily highly speculative. But our interest actually lies elsewhere. Harm from gambling follows not from typical but from atypical behaviour. If players return to the casino faster because they are driven to try to recoup losses,

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[51] R.H. Thaler, 'Mental accounting matters', *Journal of Behavioral Decision Taking*, 12:183-206, 1999.

[52] J. Sundali & R. Croson, 'Biases in casino betting: The hot hand and the gambler's fallacy', *Judgement and Decision Taking*, 1:1: 1-12, 2006.

this is a highly specific marker of gambling harm. To try to assess how many players behave in this atypical way, our next step was to estimate the survival model at the level of each individual player. We were looking for players where the sign on the *losses on last visit* variable was reversed compared with the result from the general case.

4.3 Modelling time between visits: Individual-level modelling

We estimated the survival regression model on the 14,545 individuals for whom we had at least 50 observations. The model is more spartan than before. Age, gender and deprivation are no longer included because these tend to stay the same across each individual player over observations (without variation, no effects can be inferred). We also drop the *loser last time* variable because this is also time-invariant in most cases (i.e. most players lost on each visit they made). The predictors in the model now are therefore: *losses on last visit*, *duration of last visit*, and *past frequency* (with the same weighting procedures applied as before to capture what is normal for a player).

Figure 4.1 summarises the findings in the form of a histogram displaying the number of players for whom the size of the coefficient estimate on *losses on last visit* was in each range as displayed on the horizontal axis. This figure includes all coefficient estimates regardless of whether or not they were statistically significant whereas Figure 4.2 charts only those which were statistically significant.

Figure 4.1. Coefficient estimates across 14,545 players

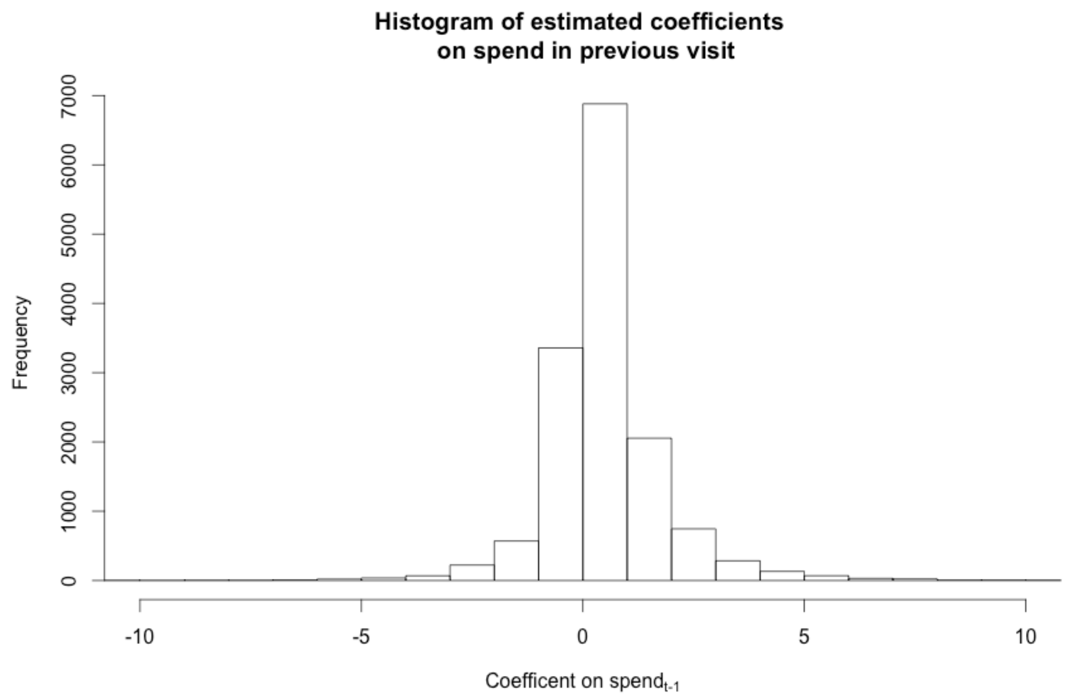
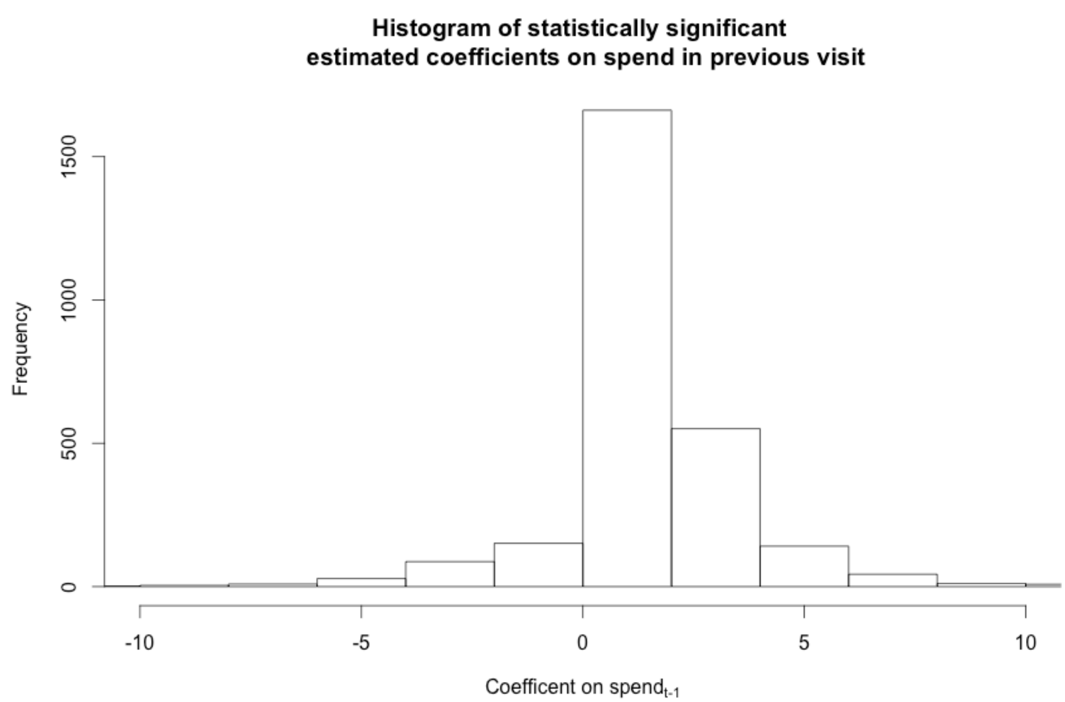


Figure 4.2. Statistically significant coefficient estimates across 14,545 players



The *most common* case is that where the coefficient estimate is not significantly different from zero. This implies that most players' decisions on when to go to the casino again are in fact unaffected by their outcome last time. However, as shown clearly in Figure 4.2, where players *are* influenced by the size of loss they experienced last time, there is a preponderance of positive signs (losses deter return) over negative signs (loss-chasers). It is this preponderance which drove the principal result from the aggregate model where *average* behaviour was to stay away longer, the higher prior losses.

But, of the 14,545 players, 281 (2%) display a statistically significant negative coefficient. These are players who (evaluated over the whole data period) appear systematically to shorten the time between visits when their losses last time are higher than normal. Statistics from the British Gambling Prevalence Survey based on self-report of 'most of the time' or 'always' going back to recoup losses (see section 4.1 above) imply rather higher prevalence of loss-chasing. On the other hand, the PGSI screen refers only to behaviour in the past year. Risky behaviour may often be self-correcting and, when we look at a longer data period than one year for an individual, there may be spells of more 'rational' behaviour such that no systematic tendency to chase losses is detected. Those whom we identify as loss-chasers could be said to be 'chronic loss takers' because their status is established with respect to a long period of time.

Of course loss-chasing does not have to be chronic for harm to be incurred (and indeed it may become non-sustainable and therefore not chronic just because it has resulted in great harm). For practical purposes, we therefore wanted to investigate the performance of the model when used over shorter periods. If a version of the model were to be used to identify loss-chasers with a view to interventions to prevent harm, it would need to be applied over relatively short periods (though there would be a limit to how short because a propensity to chase losses between visits by definition requires a number of visits before it can be identified).

Since the number of observations on an individual becomes more limited over a shorter duration, the statistical degrees of freedom become relatively low. It would then be desirable to reduce the number of predictor variables. We therefore re-estimated the survival regression model as presented above with just one predictor variable, *losses on last visit*. Our purpose was to assess whether this would produce a radically different estimate of the number of chronic loss-chasers. If it did, this would show that dropping variables gave potentially unreliable results and it might then be problematic to apply the stripped-down model to shorter runs of data.

In fact, we were reassured. The number of players identified as chronic loss-chasers went up just a little, to 311 (2.2% instead of 2%). Therefore we will use the stripped-down model in the following section to investigate the frequency with which shorter-run testing identifies loss-chasing behaviour.

But, before we left the 'chronic loss chasers', we were curious to know something about their profile. Table 4.2 presents a profile of 311 players identified as loss-chasers over the period as a whole. Table 4.3 presents a profile of all the players in the analysis who did not exhibit (statistically significant) loss-chasing.

Table 4.2. Profile of players identified as loss-chasers

	age	female	distance to casino	deprived	total visits	spend per visit
mean	41.97	0.19	11.57	0.48	142.34	131.28
lower quartile	27	0	1	0	67	36.43
50th	39	0	4	0	94	77.7
upper quartile	55	0	10	1	160.5	155.02

Table 4.3. Profile of players not identified as loss-chasers

	age	female	distance to casino	deprivation	total visits	spend per visit
mean	49.99	0.32	12.55	0.39	148.96	99.25
lower quartile	36	0	1	0	71	19.8
50th	51	0	3	0	100	45.2
upper quartile	63	1	10	1	165.75	101.26

Comparing the two groups, the representation of females is one of the more striking differences. Amongst the generality of players, females make up 32% of the total whereas only 19% of the loss-chasing players are women. It is clear also that, while they have similar numbers of visits per person, loss-chasers tend to lose much more money than the rest.

To investigate more formally we estimated a logistic regression where the variable to be explained was the probability that a player from this group (players for whom there are fifty machine visits observed in the data set, i.e. more-than-very-occasional players) is classified as a loss-chaser. Predictor variables were: *age*, *female*, *distance* and *deprivation*.[53] We also included additional indicator variables to designate individuals who ever *played table games* and individuals who ever made *late visits*.[54]

Results are in Table 4.4. Age and gender are statistically significant predictors of a loss-chasing pattern of play but the other predictors are not.

Table 4.4. Logistic regression (probability that an individual is a loss-chaser)

	coefficient	standard error	p-value
age	-0.0023	0.0004	<.001
female	-0.0385	0.0169	<.001
distance	0.00004	0.0018	.979
deprivation	0.0363	0.1326	.784
played table games	-0.0132	0.0133	.320
late visits	-0.0201	0.0353	.955
Intercept	-2.821	0.0425	<.001
number of observations	14,455		

Combining the results from the logistic regression with conclusions drawn from the profile tables, it appears that **loss-chasing is more prevalent among males, among younger players and among those whose overall level of spend on machines is higher.**

[53] Definitions for *distance* and *deprivation* are provided in section 2.2 above.

[54] From Tables 4.2 and 4.3, amount spent also seems likely to be a predictor of loss-chasing. However, it could not be included in the regression because the variable to be explained (loss-chasing) is itself generated using data on past spending.

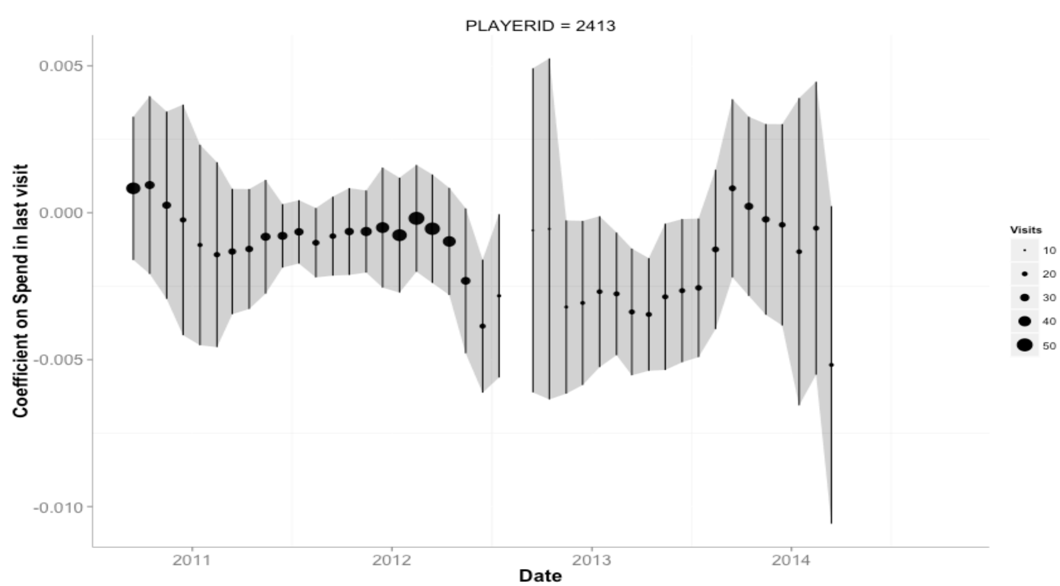
4.4 Individual modelling with a six months time horizon

We fitted a survival model for time between visits on rolling six months windows of data, one person at a time. For example, we recorded whether or not the individual was to be classified as a loss-chaser at month *t* by fitting the model for his or her data in the six months up to month *t* and testing for a significant negative sign on *losses on last visit*. We then moved on to month *t+1* and recorded 'loss-chaser' status according to the model fitted to data for the six months up to month *t+1* (and so on). In this way we could trace the evolution of each player's behaviour over time and identify any period when he or she may have exhibited loss-chasing behaviour.[55]

Figure 4.3 is a graph for just one sample player. The vertical axis shows the point estimate of the coefficient on *losses on last visit*. Where this is less than zero, this is indicative of loss-chasing but often it can still be statistically insignificant (i.e. the pattern is not distinct enough for us to reject with high confidence the hypothesis that the true value is zero).

The vertical bar through each point shows the 95% confidence interval on the size of the coefficient. Only if this bar lies entirely in the negative range of the vertical axis can one say that the coefficient estimate is 'statistically significant' (at the 5% level).

Figure 4.3. Loss-chasing over time: an example player



[55] A model was fitted only where a six months window included at least ten machine visits for the particular individual. In this analysis, we used each player's whole history, 2010- January, 2015. Players are typically present only for part of the period.

This particular player was not initially a loss-chaser but showed signs of becoming one roughly a year after first being observed. The size of the dots which indicate the coefficient estimates reflect frequency of visits in the relevant six month window. There is a period of heavy activity (>50 visits per six months) around 2012 and for some time afterwards there is repeated evidence of statistically significant loss-chasing behaviour, even when average frequency of visit has dropped off. Towards the end of the data period, the player still has a preponderance of negative coefficients but there is insufficient evidence to indicate ‘statistically significant’ loss-chasing. This could be because the player is making relatively few visits by that stage and thus it becomes harder for the model to detect clear patterns of behaviour.

We obtained graphs like this one for 16,729 players. It was not uncommon for a player to meet our criterion for loss-chasing for one or more sub-periods within the player’s history. These players would not necessarily have been ‘chronic loss chasers’ in our earlier analysis which measured behaviour as a whole over the full period. But they would have been flagged at some point had they been monitored monthly for loss-chasing based on their play in the preceding six months.

In fact, 3,561 players- 27% of the total- had at least one occurrence of a statistically significant coefficient. To be included in the sample, players had to have recorded at least fifty visits altogether. Therefore this sample does not include very occasional players. But, amongst this sample, **27% exhibited between-session chasing behaviour at at least some point in their player history.** It follows that any future screening for loss-chasing would be likely to flag up significant numbers of players for further investigation.

5 PERSISTENCE OF ATYPICAL BEHAVIOUR

5.1 Introduction

As promised earlier in the Report, we now present further analysis of 'heavy play'. Since problem gamblers tend to account for a disproportionately large share of industry revenue[56], high spending is a plausible marker for harm. Likewise duration of play: Schellinck & Schrans found duration of play in a single session to be a particularly strong predictor of problem gambling among Canadian machine players.[57]

The particular manifestation of heavy play we investigate first is an atypically high level of spending on a single visit to the casino. We then look at play of unusually long duration. Of course these are just two dimensions of behaviour which may identify a player's gambling as atypical relative to the generality of casino customers. But we focus on them to illustrate a more general issue: how persistent is atypical play (a marker for harm) likely to be? If, in a number of periods, we observe how many players exhibit the particular atypical behaviour, and if this number is roughly constant over time, are they likely to be mostly the same people or is there substantial churn in the set of people identified? The answer has implications on a number of fronts. For example, an intervention may seem to correct the behaviour of many subjects but perhaps most people would change their behaviour anyway.

5.2 High spending visits

From Table 3.9 above, it may be calculated that about two-thirds of B1-visits end with the player either winning or in losing less than £50. Even amongst our sub-sample of players for whom we had fifty or more observations (ruling out occasional players), the median spend was below £50 (Table 4.3). We therefore take a spend of more than £100 as unusual (and one of £200 as highly unusual). Is there anything different about the profile of players who engage in such costly visits compared with those whose outlay is more modest?

Table 5.1 is based on 7,416,661 machine visits observed in the data. It shows shares in the number of visits observed in different ranges of player loss by player characteristics. Females and those who live in deprived areas account for similar proportions of visits regardless of the level of spending involved. Those who play table games as well as machines are less likely than

[56] See, for example, J. Orford, H. Wardle & M. Griffiths, 'What proportion of gambling is problem gambling? Estimates from the 2010 British Gambling Prevalence Survey', *International Gambling Studies*, 13:1:4-18, 2013.

[57] See footnote 32 above.

average to incur the most modest level of loss on machines. Age offers the most striking contrasts across spending ranges. The under-thirties account for 38.1% of "less than £20" visits but only 11.1% of visits with a "more than £200" loss. The full set of numbers in the row for under-thirties shows that **a machine visit to the casino by a young person is appreciably less likely to result in a large loss compared with a visit by an older person.**

Table 5.1. Profile of players making different sizes of loss on machines in single visits

	<£20	£20-49	£50-99	£100-199	>=£200
female %	40.3	41.3	42.3	43.4	42.0
deprived %	38.1	38.6	38.7	38.2	37.3
under 30 %	38.1	27.7	19.5	14.4	11.1
play tables %	35.6	40.6	42.4	44.0	46.3

5.3 High spend and repeat behaviour

The data set offers an unusual opportunity to assess the extent to which individuals observed exhibiting potentially risky behaviour repeat that behaviour in subsequent periods. For example, the suite of research studies on gaming machines in licensed betting offices, published by The Responsible Gambling Trust in December, 2014, was based on transactional data (which was able to reveal the distribution of player expenditure in a session but with visits anonymous) and on loyalty card data (which linked sessions to players but only for a short period as bookmakers had only recently introduced loyalty cards). By contrast, we could observe visits by identified players over a period of years. This allows us to present analysis that is, so far as we know, entirely novel.

We focused on players who visited a casino and lost more than £100 at least once in a single visit in a given quarter. We then tracked those players through subsequent quarters to see how many repeated their behaviour.

In Table 5.2, each row represents a particular 'starting' quarter. The first column shows how many players visited a casino and spent more than £100 during that quarter. Each subsequent column shows how many of them repeated the 'offence' in the relevant subsequent quarter. For example, in quarter 2 of 2012, 4,811 players indulged in at least one visit where the net amount left with the machines exceeded £100. Of these 4,811 high spenders, 2,148 did the same thing in the following quarter. One year later, in quarter 2 of 2013, 1,780 of the original 4,811 did it again.

Table 5.3 conveys the same information but in proportionate terms. Thus, of those observed to engage in high spending in quarter 2 of 2012, 44.6% ‘re-offended’ in the following quarter but only 36.1% in the corresponding quarter one year later.

Tables 5.4 and 5.5 are to be interpreted similarly. But this time the figures show how many/ what proportion of the original high spenders had exhibited the behaviour in every quarter in between. For example, for Table 5.5, consider the figure of 0.188 in the row marked 2012, Q2 and the column for 2013, Q2. This tells us that, of all those who had a big-spend visit in 2012, Q2, 18.8% repeated the behaviour in each of the following four quarters, up to and including 2013, Q2.

Table 5.2. Repeat behaviour by players who spent more than £100 in a single visit (numbers of players)

		2012				2013				2014			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
2012	Q1	4428	2133	1795	1700	1562	1525	1472	1380	1432	1318	1329	1291
	Q2		4811	2148	1941	1780	1737	1675	1548	1584	1481	1448	1458
	Q3			4671	2166	1871	1823	1743	1624	1662	1548	1562	1518
	Q4				4780	2210	2081	1983	1843	1859	1713	1684	1694
2013	Q1					4797	2327	2107	1923	1962	1812	1754	1726
	Q2						5021	2416	2148	2132	2009	1947	1873
	Q3							5049	2402	2314	2131	2108	2020
	Q4								5018	2545	2267	2147	2143
2014	Q1									5393	2649	2477	2340
	Q2										5216	2724	2549
	Q3											5838	3032
	Q4												6739

Table 5.3. Repeat behaviour by players who spent more than £100 in a single visit (proportions of players)

		2012				2013				2014			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
2012	Q1	1	0.482	0.405	0.384	0.353	0.344	0.332	0.312	0.323	0.298	0.300	0.292
	Q2		1	0.446	0.403	0.370	0.361	0.348	0.322	0.329	0.308	0.301	0.303
	Q3			1	0.464	0.401	0.390	0.373	0.348	0.356	0.331	0.334	0.325
	Q4				1	0.462	0.435	0.415	0.386	0.389	0.358	0.352	0.354
2013	Q1					1	0.485	0.439	0.401	0.409	0.378	0.366	0.360
	Q2						1	0.481	0.428	0.425	0.400	0.388	0.373
	Q3							1	0.476	0.458	0.422	0.418	0.400
	Q4								1	0.507	0.452	0.428	0.427
2014	Q1									1	0.491	0.459	0.434
	Q2										1	0.522	0.489
	Q3											1	0.519
	Q4												1

Table 5.4 Persistent repeat behaviour by players who spent more than £100 in a single visit (numbers of players)

		2012				2013				2014			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
2012	Q1	4428	2133	1421	1109	893	747	644	570	525	474	437	405
	Q2		4811	2148	1473	1125	905	774	671	612	545	495	457
	Q3			4671	2166	1459	1134	937	804	725	642	577	528
	Q4				4780	2210	1566	1227	1014	901	788	695	633
2013	Q1					4797	2327	1615	1255	1080	927	814	736
	Q2						5021	2416	1676	1369	1138	983	876
	Q3							5049	2402	1768	1393	1175	1024
	Q4								5018	2545	1806	1445	1225
2014	Q1									5393	2649	1906	1525
	Q2										5216	2724	1994
	Q3											5838	3032
	Q4												6739

Table 5.5. Persistent repeat behaviour by players who spent more than £100 in a single visit (proportions of players)

		2012				2013				2014			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
2012	Q1	1	0.482	0.321	0.250	0.202	0.169	0.145	0.129	0.119	0.107	0.099	0.091
	Q2		1	0.446	0.306	0.234	0.188	0.161	0.139	0.127	0.113	0.103	0.095
	Q3			1	0.464	0.312	0.243	0.201	0.172	0.155	0.137	0.124	0.113
	Q4				1	0.462	0.328	0.257	0.212	0.188	0.165	0.145	0.132
2013	Q1					1	0.485	0.337	0.262	0.225	0.193	0.170	0.153
	Q2						1	0.481	0.334	0.273	0.227	0.196	0.174
	Q3							1	0.476	0.350	0.276	0.233	0.203
	Q4								1	0.507	0.360	0.288	0.244
2014	Q1									1	0.491	0.353	0.283
	Q2										1	0.522	0.382
	Q3											1	0.519
	Q4												1

Regardless of the choice of starting quarter, the pattern is strikingly consistent. About one-half or less of players who have a high spend visit in one quarter repeat the behaviour in the following quarter. After that, 'reoffending' rates fall off slowly but steadily. The longest run of quarters documented in the tables began in 2012, Q1. In Q4 of 2014, less than one-third of the original number had a high-spend visit and less than one-tenth had repeatedly engaged in high spend visits throughout the three years. Clearly many high-spend players are in the high-spend statistics for a long time (and others re-enter), which is why relatively few players account for a high proportion of all the high-spend visits observed in the data set. Thus high-spend visits are far from invariably occasions of 'one-off' behaviour. But equally, there is a strong tendency for this particular example of extreme behaviour to be self-correcting. Most of those who spend heavily in one period do not in fact go on to repeat the behaviour into future periods and after a couple of years it is evident that only a little over 10% are 'stuck' in that pattern of behaviour.[58]

5.4 Lengthy duration of play

Table 5.6 sets out basic information on how many visits and players were involved in various lengths of time spent on machines in single visits. Although the median machine visit in any year tends to be below one hour in length (Tables 3.6 and 3.7 above), this new table illustrates that there is still a non-trivial number of visits which could be regarded as extremely long, for

[58] We do note the hint in the data that fall-off in high-spend behaviour shows signs of being a little slower in quarters beginning in 2014. This was when regulations allowing higher stakes took effect.

example well over 2,000 (loyalty card) visits per year involved more than seven hours of play on machines.

Table 5.6. How many players lost more than £x on B1 machines on a single visit? (all visits with B1 play, 2012-2014)

There are	367065	visits in which	34305	players spent more than	60	minutes on B1 slots
There are	179647	visits in which	18753	players spent more than	120	minutes on B1 slots
There are	43392	visits in which	7345	players spent more than	240	minutes on B1 slots
There are	21055	visits in which	4665	players spent more than	300	minutes on B1 slots
There are	10192	visits in which	2960	players spent more than	360	minutes on B1 slots
There are	4988	visits in which	1821	players spent more than	420	minutes on B1 slots
There are	2445	visits in which	1123	players spent more than	480	minutes on B1 slots

Our cut-off for defining atypical behaviour is set at five hours. Tables 5.7 to 5.10 correspond to Tables 5.2 to 5.5 in the preceding section and are to be interpreted similarly. For example, from Table 5.7, we know that, in 2012, Q1, 759 players took part in at least one long duration (>5 hours) machines visit. From Table 5.8, 21.1% of these had at least one such visit in 2014, Q4. But, from Table 5.10, only 3.4% of the original group had made a long duration visit in every quarter up to and including then.

The pattern is similar to that found in the tables on high spend, which is not surprising given correlation between length of play and player loss. However, there is a somewhat lower propensity to ‘reoffend’. For example, the proportion of players with a long visit in any one quarter who repeat the behaviour in the following quarter tends to be closer to 40% than to 50% and is indeed sometimes lower than 40%. The proportion of players with long duration in the first quarter of the data who persist throughout three years is also noted to be particularly low. However, these differences may just reflect that we set the bar ‘higher’ in our definition of extreme duration in the sense that spend>£100 occurs more frequently than duration>5 hours. In each case the exercise is purely illustrative that there is likely to be substantial churn in players who appear to exhibit potentially worrying behaviour.

That most ‘extreme’ players appear to self-correct their behaviour does not imply that the behaviour should not be addressed by regulators and the industry. Considerable harm may result from relatively short periods of ‘extreme’ gambling. Indeed, while many of the majority who pull back from their behaviour may simply become bored or experience a change of life circumstances, others may do so precisely because the harm they incur compels them to do so, for example they spend all their wealth.

Considerable experimentation is in progress in the bookmaking sector in monitoring machine players for signs of potential harm. One might anticipate that the casino sector will also consider automated systems where algorithms are employed to detect problematic play, triggering interventions such as on-screen messaging designed to nudge the player towards reassessment of his or her actions. It is important that the efficacy of such interventions is properly evaluated. Our demonstration of how common it is for players to show a sign of a potential problem in one period but not in the next suggests that every evaluation should compare the subsequent change in behaviour by targeting players with the behaviour of a control group with similar baseline patterns of behaviour. Further, exit from a group of players showing problematic behaviour continues for the three years in our examples. Players for whom an intervention has been made therefore need several follow-ups where their gambling trajectory is compared with other players who began in a similar situation.

Table 5.7. Repeat behaviour by players who played for more than 5 hours in a single visit (numbers of players)

		2012				2013				2014			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
2012	Q1	759	307	242	220	219	184	184	182	183	165	165	160
	Q2		785	281	242	233	211	213	193	211	188	186	187
	Q3			701	290	236	205	226	203	216	192	192	183
	Q4				755	311	252	249	239	239	215	205	210
2013	Q1					787	325	276	261	272	222	231	212
	Q2						772	313	267	278	238	235	215
	Q3							810	339	315	268	282	241
	Q4								850	362	280	287	294
2014	Q1									891	346	334	299
	Q2										822	375	348
	Q3											968	418
	Q4												1184

Table 5.8. Repeat behaviour by players who played for more than 5 hours in a single visit (proportions of players)

		2012				2013				2014			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
2012	Q1	1	0.404	0.319	0.290	0.289	0.242	0.242	0.240	0.241	0.217	0.217	0.211
	Q2		1	0.358	0.308	0.297	0.269	0.271	0.246	0.269	0.239	0.237	0.238
	Q3			1	0.414	0.337	0.292	0.322	0.290	0.308	0.274	0.274	0.261
	Q4				1	0.412	0.334	0.330	0.317	0.317	0.285	0.272	0.278
2013	Q1					1	0.413	0.351	0.332	0.346	0.282	0.294	0.269
	Q2						1	0.405	0.346	0.360	0.308	0.304	0.278
	Q3							1	0.419	0.389	0.331	0.348	0.298
	Q4								1	0.426	0.329	0.338	0.346
2014	Q1									1	0.388	0.375	0.336
	Q2										1	0.456	0.423
	Q3											1	0.432
	Q4												1

Table 5.9. Persistent repeat behaviour by players who played for more than 5 hours in a single visit (numbers of players)

		2012				2013				2014			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
2012	Q1	759	307	174	118	89	64	54	42	35	33	30	26
	Q2		785	281	168	112	80	66	52	43	41	36	32
	Q3			701	290	171	113	88	72	60	53	46	38
	Q4				755	311	178	123	96	78	64	54	44
2013	Q1					787	325	183	127	103	81	69	55
	Q2						772	313	185	135	97	80	62
	Q3							810	339	205	137	111	87
	Q4								850	362	194	142	110
2014	Q1									891	346	222	158
	Q2										822	375	239
	Q3											968	418
	Q4												1184

Table 5.10. Persistent repeat behaviour by players who played for more than 5 hours in a single visit (proportions of players)

		2012				2013				2014			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
2012	Q1	1	0.404	0.229	0.155	0.117	0.084	0.071	0.055	0.046	0.043	0.040	0.034
	Q2		1	0.358	0.214	0.143	0.102	0.084	0.066	0.055	0.052	0.046	0.041
	Q3			1	0.414	0.244	0.161	0.126	0.103	0.086	0.076	0.066	0.054
	Q4				1	0.412	0.236	0.163	0.127	0.103	0.085	0.072	0.058
2013	Q1					1	0.413	0.233	0.161	0.131	0.103	0.088	0.070
	Q2						1	0.405	0.240	0.175	0.126	0.104	0.080
	Q3							1	0.419	0.253	0.169	0.137	0.107
	Q4								1	0.426	0.228	0.167	0.129
2014	Q1									1	0.388	0.249	0.177
	Q2										1	0.456	0.291
	Q3											1	0.432
	Q4												1

6 REFLECTIONS

Rank Group plc supplied us with a rich and very large data set which has allowed us to present a picture of how machine players behave in British casinos. The broad picture is what one would expect in that typical users play to a modest scale, visits typically lasting about an hour and incurring a loss of the order of magnitude of £25. Those whose behaviour is typical are likely unconstrained by regulatory rules on stakes and pace of play. In earlier research looking at the impact of the Uplift, it was reported that median stake was considerably below £1 against a maximum permitted stake of £5. Even with this sort of stake, the mean loss from an hour of play at maximum pace would be about £50, so typical play also seems unconstrained by the regulatory limit on the length of the game cycle on B1 machines.

Regulation, then, appears to impinge little if at all on typical players.[59] And in fact there is likely little need for regulators to be greatly concerned about them. To be sure, low level play is likely to be harmful for *some* players; but, given that typical expenditure of time and money is no more than is usually swallowed up in other leisure pursuits, it is doubtful whether there is a lot of harm.

It is plausible that most harm is in fact incurred by those whose play is atypical rather than typical. Only a small proportion of all visits featured extreme expenditure of time and money but the absolute number of such visits was still large. Moreover there was a tendency for such visits to be by relatively frequent visitors, as evidenced by the sharp increase in mean spend per visit when we narrowed the sample by setting a qualification rule of fifty observed visits. While some players who play heavily might not experience harm, levels of expenditure of money and time are at levels where it is intuitively plausible that gaming will compromise many individuals' financial wellbeing and their other activities.

It is therefore attractive to think that technology might allow potentially at-risk players to be identified and that non-coercive interventions might be effective in persuading them to pull back from harm. But much work remains to be done before the approach can be confirmed to have worthwhile pay-offs.

Our analysis reveals a number of features relevant to this approach to policy. The study of between-session loss-chasing, which we argued to be a strong marker for harm, showed that a significant proportion of players, particularly of high spending players, experience episodes of loss-chasing, such that the extent of loss-chasing estimated from self-report data, understates the problem. This underlines the need for regular monitoring.

[59] We refer to regulation on the specification of the machine, not on the number of machines.

Heavy spending and long duration of gambling sessions were also shown often to be episodic. This is challenging for future evaluation of monitoring and intervention programmes since one would be looking for differences in the rate of change of the propensity to 'bad behaviour' between treated and non-treated groups where the rate of change would be likely to be high even among the latter. This might make the benefits of intervention seem rather weak.

A limitation of this study is that it focuses on the visit as the primary unit of observation. It is possible that much more of relevance would be revealed by study of within-visit patterns of play. Technology which tracks player behaviour is fully capable of providing details of patterns of play, including styles of play (degree of volatility of returns chosen by players), and no doubt future research will emerge along these lines and be applied in the casino sector.