ANALYSIS OF PLAY AMONG BRITISH ONLINE GAMBLERS ON SLOTS AND OTHER CASINO-STYLE GAMES

by

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1. Background

The over-arching aim of the National Responsible Gambling Strategy is to minimise gambling-related harm. Pursuance of this goal requires increased understanding of the effects of product characteristics and environment and this constitutes Priority Action 4 of the Strategy document.

In the last few years, operators of land venues, in particular in the bookmaker and casino sectors, have provided data for research commissioned by GambleAware which has enabled analysis of patterns of play on gaming machines. For example, this has brought into the public domain basic information, hitherto unknown, on the proportions of gaming sessions ending in large losses or of long duration. However, the patterns of play in these traditional environments may not be replicated in the online environment where a large (more than 30%) and increasing proportion of gaming by British consumers takes place. As a first step towards filling this gap in knowledge, thirteen operators have provided one month of data to the Gambling Commission to allow analysis of patterns of play on products, slots and non-slots (casino games excluding poker), comparable to those offered in the land-based sectors.

This Report to GambleAware presents descriptive analysis of the data provided to the Gambling Commission and comments on what further data might usefully be obtained from operators to enable further progress on Priority Action 4 of the National Responsible Gambling Strategy.

2. Description of the data

Operators provided data for slots and non-slots gaming activity on its website(s) during January, 2017[1]. Note that the category of "non-slots" comprises casino games such as roulette and blackjack (but excluding poker). The data do not cover other gambling activities such as sports betting and bingo.

The information was under the following headings

(i) At the level of the individual customer, the outcome of the month's gaming in terms of the player's *net expenditure* (player loss) on slots/ non-slots games. This information appeared as a frequency table enumerating the outcomes in 23 bands ranging from "<-£5,000" to ">+£5,000" (where a minus sign signifies a win rather than a loss for the player).

[1] One operator provided data for December 2016.

(ii) At the level of the individual bet (or spin), the number of plays, for slots/ non-slots games where the *stake size* was within each of fifteen bands ranging from “below 25 pence” to “more than £500”.

(iii) At the level of the individual customer, the *frequency* with which slots/ non-slots games were played during the data period. This information was presented in terms of the number of days on which there was play, for example the number of customers who played slots games on exactly five days within the period.

(iv) A contingency table showing the number of customers who played on *n* days and lost an amount in range *j* (for example, the number of customers who played on ten days and lost in total between £100.01 and £200 over the month), where the number is shown for each possible combination of *n* and *t*.

Two of the thirteen operators which supplied data had organised the information on both player losses and stake sizes using different ranges from those suggested by the Gambling Commission. For example, one had merged some of the bands for player loss. Arbitrary assumptions would have had to be made to reorganise these operators’ data to be consistent with those from the other eleven. We have therefore excluded the two operators from our analysis of player losses and stake sizes. This is unlikely to have changed the picture presented by the analysis. We will show below that there was very little difference in patterns across the eleven individual operators. Since we understand that all thirteen were large, mainstream operators (rather than, for example, operators targeting only high spending customers), the omission of two of them should not in any relevant sense make the data unrepresentative of the remote sector serving British players.

Another inconsistency between operators was that seven of them provided data for four weeks and six provided data for the full month (31 days). Strictly, this introduces non-comparability of data as between the two groups of operators and this affects data under all headings. For example, on frequency, nine active days might mean 9 out of 28 or 9 out of 31. However, our judgement was that the resulting loss of precision has to be balanced against the loss of a considerable volume of data were we to choose to exclude one of these groups of operators, so we report merged data. Where the number of active days for any individual player is reported as 29, 30 or 31, we record the number as 28.[2]

Most of the data are from January, 2017. We have no information on whether January is a “typical” month in the remote gaming sector but have no reason to believe that it is unrepresentative in terms of patterns of play (for example the proportion of players recording ‘heavy’ losses).

[2] In the section on number of active days in the month, we were able to reinstate the two operators excluded from analysis of player net expenditure and of stake sizes. This section will therefore be based on returns from all thirteen operators.

3. Limitations of the data

The data are likely to provide a useful starting point for understanding and evaluating the significance of the heterogeneity in the degree of engagement by players in the remote sector. Metrics made available are incapable of identifying how many players experience harm but may still be suggestive of how concerned about harm one should be. For example, a Report from PwC and the Responsible Gambling Council[3], which used a survey (with a problem gambling screen) of British players to analyse characteristics of play which predicted problems with their online play, cited the proportion of days on which bets were placed as a key marker of harm. This is consistent with the finding in the literature review by Gainsbury[4] that "many active gambling days per month" is well-established as an informative marker for harm. Of course, one cannot know from our data whether any particular very frequent player experiences problems but it would be a cause for concern if websites attracted a large proportion of such heavily engaged customers and in turn that would suggest that measures to monitor such players should be particularly emphasised as part of a harm minimisation strategy.

While the data sets provided therefore have value, they do of course have limitations. As with all research employing account-based data, the most obvious weakness is that one does not observe all gambling activity (online or offline) by individual players. In our case, the same individual may play within the month at more than one of the operators and therefore appear in the data twice or multiple times. This is particularly important because problem gamblers are disproportionately likely to use more than one website.[5] If the individual losses of significant numbers of heavy players are each spread across more than one operator, this will lead to misleadingly low estimates of the proportion of online gamblers who experienced large losses over the data period.

While this is an unavoidable problem in the absence of multiple-operator monitoring of player behaviour, the present data have the avoidable problem that those who play both slots and non-slots games are treated as separate customers when playing these respective categories of game. This is potentially important to the extent that 'number of games played' has itself been identified as a marker of harm.[6] It would have been informative had data been additionally provided on player losses and active days in terms of individuals taking part in

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[3] PwC & Responsible Gambling Council, *Remote Gambling Research. Interim Report on Phase 2*, GambleAware, 2017, https://about.gambleaware.org/media/1549/gamble-aware_remote-gambling-research_phase-2_pwc-report_august-2017-final.pdf

[4] S.M. Gainsbury, Online Gambling Addiction: the Relationship Between Internet Gambling and Disordered Gambling, *Current Addiction Reports*, 2015, 2: 185-193, https://doi.org/10.1007/s40429-015-0057-8

[5] The Report by PwC/ Responsible Gambling Council (footnote 2 above) found that 75% of PGSI problem gamblers used more than one website.

[6] See, for example, N. Adami , S. Benini , A. Boschetti , L. Canini , F. Maione & M. Temporin, Markers of unsustainable gambling for early detection of at-risk online gamblers, *International Gambling Studies*, 2013, 13:2: 188-204, DOI: 10.1080/14459795.2012.754919

either slots or non-slots games (i.e combining the two categories as well as reporting them separately). Similarly, on stake sizes, the number of plays at each staking level is presented in the data set but it is not revealed how many players are involved: the number of players who ever gamble at a high stake may, for example, be small even if the number of high stakes plays is high *if* the same players repeatedly engage in high value bets.

Following the presentation of our analysis, we will make suggestions as to what further data might usefully be obtained from the operators if richer insights are to be obtained.

4. Player net expenditure

Based on the raw data combining returns from eleven operators, Table 1 presents the number of players in each range of net expenditure (player losses) and Figures 1 and 2 the corresponding percentages of players in each net expenditure band. Negative net expenditure refers to players who made a profit from their activity in the month.

Table 1. Player net expenditure during the month

net expenditure	slots	slots %	non-slots	non-slots %
< -£5000	558	0.04	527	0.07
-£1000.01 to -£5000	4,010	0.32	2,708	0.34
-£500.01 to -£1000	6,451	0.52	3,413	0.43
-£200.01 to -£500	17,161	1.37	8,182	1.04
-£100.01 to -£200	19,715	1.58	9,592	1.22
-£50.01 to -£100	22,985	1.84	13,193	1.68
-£30.01 to -£50	16,660	1.33	12,040	1.53
-£20.01 to -£30	12,372	0.99	10,489	1.33
-£10.01 to -£20	17,504	1.40	19,647	2.50
-£5.01 to -£10	13,849	1.11	20,688	2.63
-£0.01 to -£5	43,900	3.51	60,911	7.75
Even (£0)	18,394	1.47	84,191	10.72
£0.01 to £5	277,329	22.16	190,392	24.23
£5.01 to £10	124,237	9.93	78,014	9.93
£10.01 to £20	134,259	10.73	73,488	9.35
£20.01 to £30	83,487	6.67	38,992	4.96
£30.01 to £50	103,287	8.25	41,375	5.27
£50.01 to £100	123,541	9.87	43,242	5.50
£100.01 to £200	87,291	6.98	29,561	3.76
£200.01 to £500	73,048	5.84	24,485	3.12
£500.01 to £1000	29,333	2.34	10,217	1.30
£1000.01 to £5000	20,279	1.62	8,853	1.13
> £5000	1,801	0.14	1,520	0.19

Figure 1. Player net expenditure (slots)

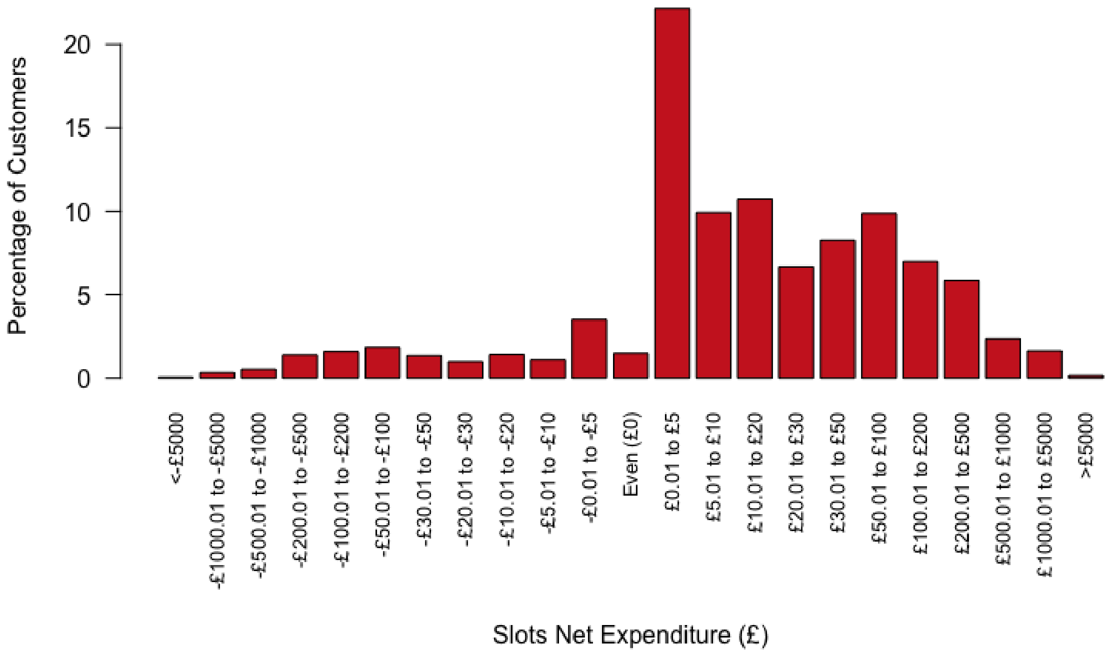


Figure 2. Player net expenditure (non-slots)

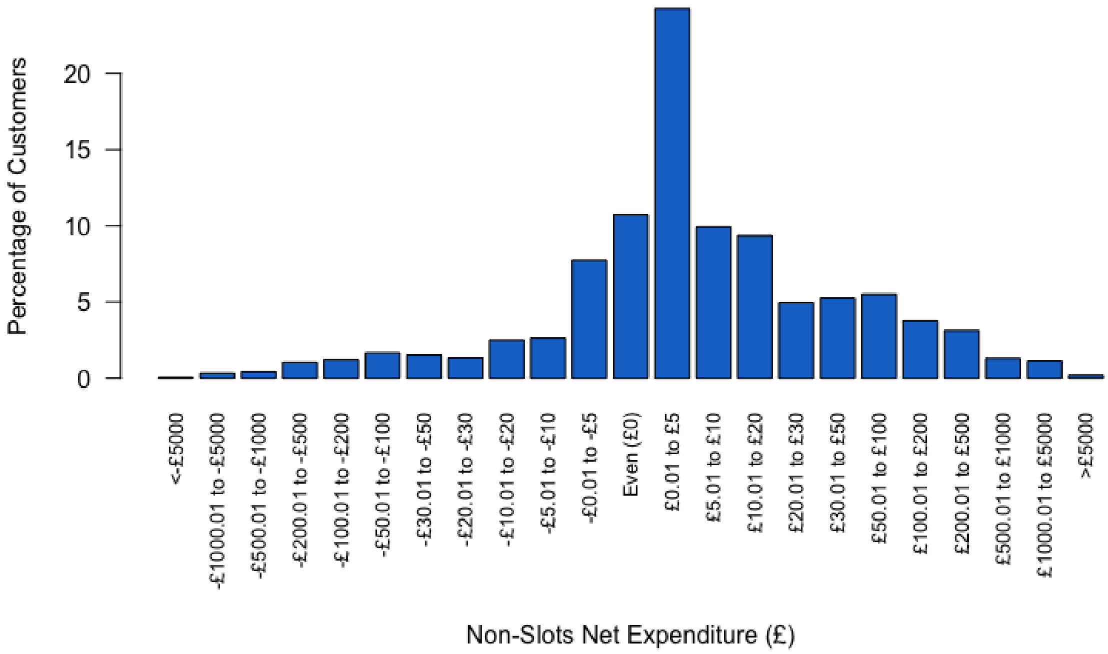
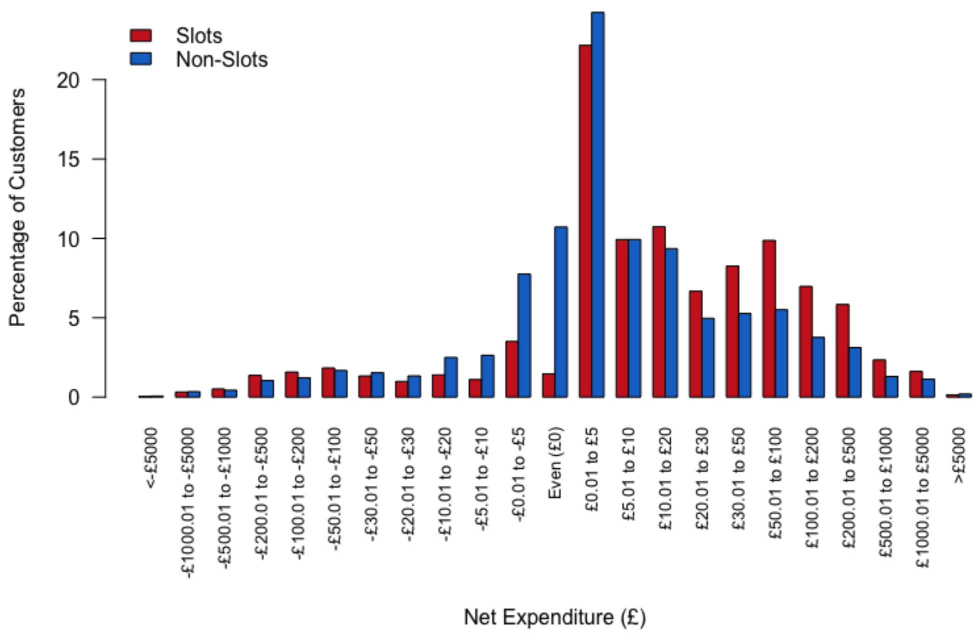


Figure 3 puts the information on slots and non-slots losses together to facilitate comparison. There is a clear tendency for there to be a higher proportion of heavy player losses in slots play than in non-slots play. This may reflect to some extent simply that slots bets are more often at longer odds because of the nature of the games and the way in which they are played.

Figure 3. Percentage of players in each net expenditure band by game type



Information displayed in Table 1 and Figures 1-3 relates to just over 1.25m slots players and just over 785,000 non-slots players. As is familiar from most gambling data sets, the majority of players spend relatively low amounts of money. For example, 73.2% of slots players and 85% of non-slots players either won money over the month or had a loss of £50 or less. While harm can be found among low- as well as high-level gamblers, it would be fair to note that an expenditure of £50 per month is by no means remarkable across leisure pursuits.

On the other hand, while the proportions of big spenders are low, the number of individuals in question is non-trivial. In the course of January, 2017, there were more than 22,000 individuals losing in excess of £1,000 on slots, whilst for non-slots play, there were more than 10,000 customers losing in excess of £1,000. The data tell us nothing about these individuals. Some may be sufficiently wealthy that losses of this magnitude are not important to them. Others might have been returning to the operator large wins earned in the preceding month. But, for large swathes of the population, expenditure of £1,000 per month would be unsustainable and even one month with such a loss could generate harm for some households.[7]

[7] According to the Office for National Statistics data set on income and wealth, median household disposable income (i.e. inclusive of benefits and after deduction of income and council taxes) was £2,194 per month over 2015-16. For a typical household, this level of spending on online games would, then, use up close to half of disposable income (which has to cover housing, utilities, food, clothing and so on).

Because player losses are recorded in bands, it is not possible to calculate precisely what proportions of operator revenue are derived from high spenders. However, *very rough* estimates can be made. We counted a player win or loss of more than £5,000 as exactly £5,000 and took the mid-point of each other band of win or loss as applying to all players in that band. On this basis, the month's gross gaming yield (net house win) for the operators was £117.8m in the case of slots games. 59.2% of this was contributed by the 1.7% of players who spent more than £1,000 in the month. 78% of revenue came from the 4% of players with net expenditure of more than £500 in the month. These figures are suggestive of high dependence on a small proportion of players. However, these estimates should be treated with caution to the extent that the data relate to only one month. Over a longer period, the apparent big spenders may appear less so since some of them will just have had random 'bad luck' in this particular month. To obtain more robust estimates, it would be informative were remote operators routinely to supply the Commission with annual summary statistics illustrating the degree of concentration of spending. Though harder to collect in retail settings, comparable data from the non-remote sector should also be returned where possible. Generally, there would be more concern over gambling sectors which depend on large contributions by a small number of bettors rather than on small contributions from a large number of bettors and such data may therefore guide policy makers on appropriate relative levels of regulatory control across sectors of the industry.

Finally in this section, we present the data (Figures 4 and 5) on the pattern of losses among customers by operator. The purpose of this exhibit is to show whether the eleven operators are similar to each other in the patterns displayed. Clearly they are. This implies that useful data could be obtained in the future even if they were available only from a sub-set of the operators included in the present exercise.

Figure 4. Percentage of customers in net expenditure bands at individual operators (slots)

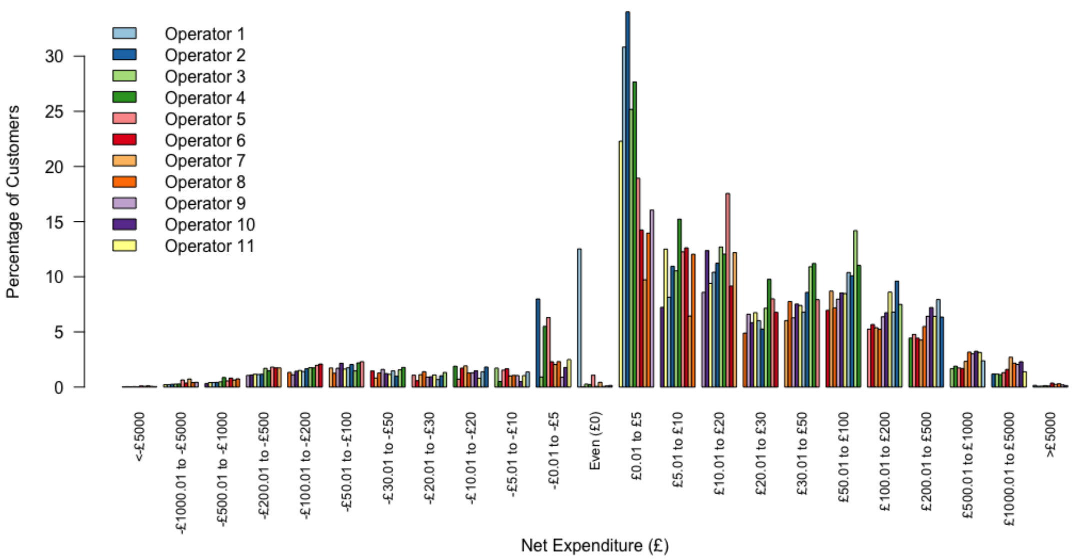
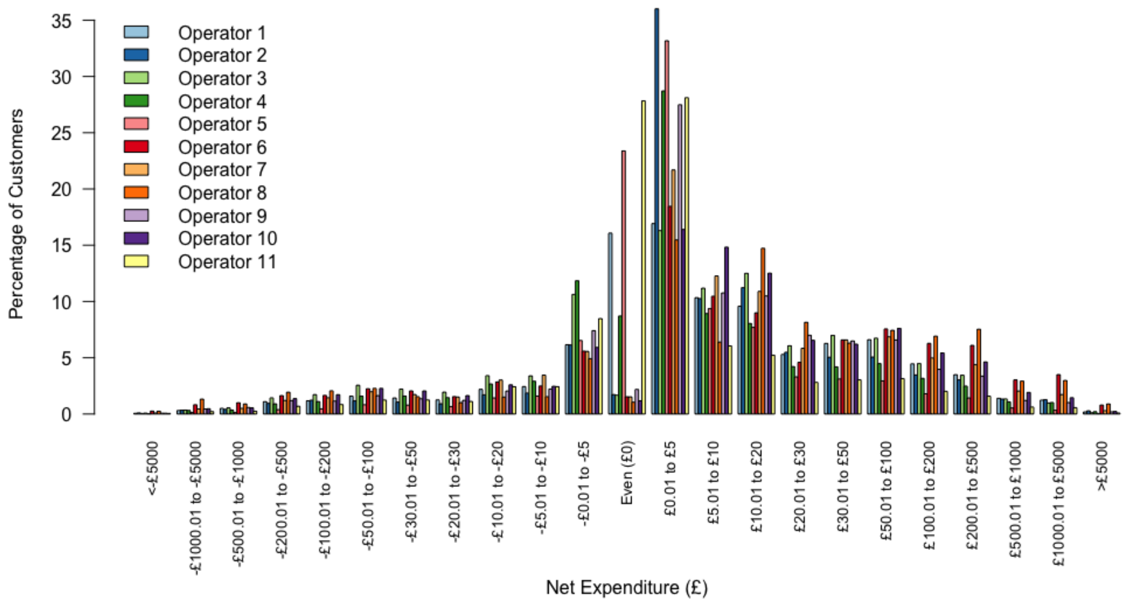


Figure 5. Percentage of customers in net expenditure bands at individual operators (non-slots)



5. Stake size

Here the data set had the individual play as the unit of analysis. For slots and non-slots separately, Table 2 shows the number of plays, across eleven operators combined, in each of fifteen ranges of stake from "below 25 pence" to "more than £5,000". Figures 6 and 7 present the same information in terms of percentages of plays in each band.

For both product categories, the majority of plays are at relatively small stakes. For example, for slots, 82.8% of spins are at stakes of £1 or less and for non-slots the corresponding figure is 57%. Both statistics are broadly in line with those for comparable products offered in an offline environment (B1 slot machines in casinos and FOB-T machines, primarily played for roulette, in betting shops are perhaps appropriate comparators for remote slots and non-slots respectively). For example, 50% of spins on FOB-T machines in 2013-14 were at a stake of £1 or less.[8]

[8] H. Wardle, E. Ireland, S. Sharman, D. Excell & D. Gonzalez-Ordonez, Patterns of play: *analysis of data from machines in bookmakers*, NatCen Social Research for The Responsible Gambling Trust, 2015, https://about.gambleaware.org/media/1328/patterns-of-play-report-june-2015.pdf

Table 2. Distribution of individual plays by stake size

stake size	slots	slots %	non-slots	non-slots %
25p or less	607,561,253	33.29	33,731,960	24.56
26p to 50p	524,299,150	28.73	21,889,687	15.94
51p to £1	380,003,656	20.82	22,751,217	16.56
£1.01 to £2	181,498,702	9.95	13,468,906	9.81
£2.01 to £5	100,684,189	5.52	17,305,341	12.60
£5.01 to £10	20,010,207	1.10	10,470,480	7.62
£10.01 to £20	6,672,109	0.37	7,034,251	5.12
£20.01 to £30	2,019,201	0.11	3,346,100	2.44
£30.01 to £40	503,269	0.03	1,676,227	1.22
£40.01 to £50	794,377	0.04	1,391,228	1.01
£50.01 to £75	192,340	0.01	1,335,639	0.97
£75.01 to £100	321,834	0.02	1,003,284	0.73
£100.01 to £250	292,509	0.02	1,309,353	0.95
£250.01 to £500	24,260	0.00	406,828	0.30
£500.01+	4,477	0.00	227,756	0.17

Figure 6. Percentages of play with various levels of stake (slots)

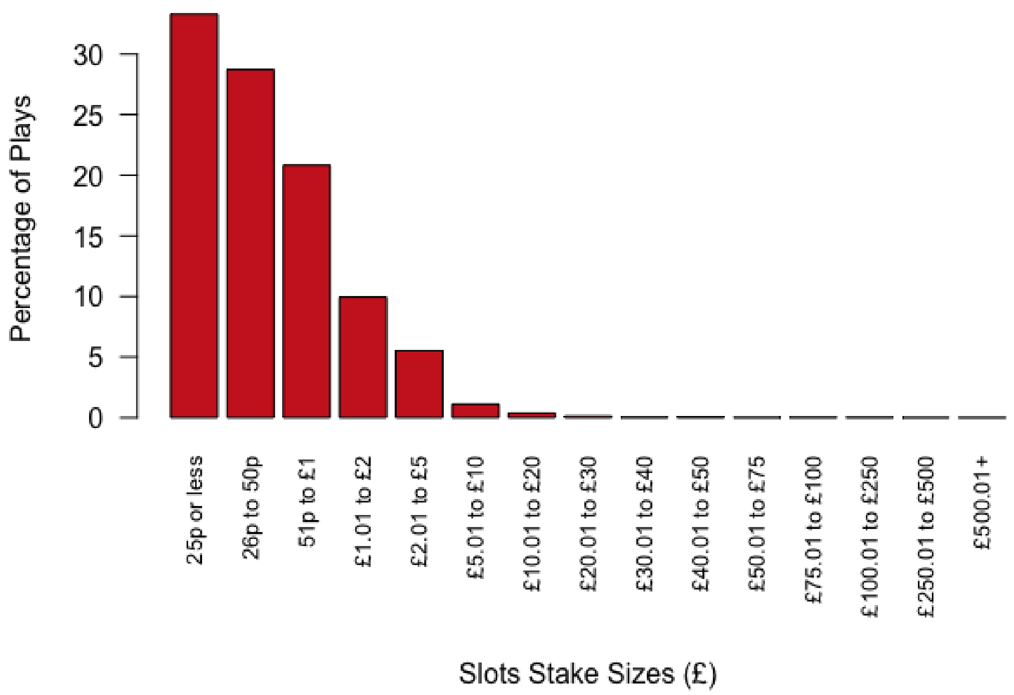


Figure 7. Percentages of play with various levels of stake (non-slots)

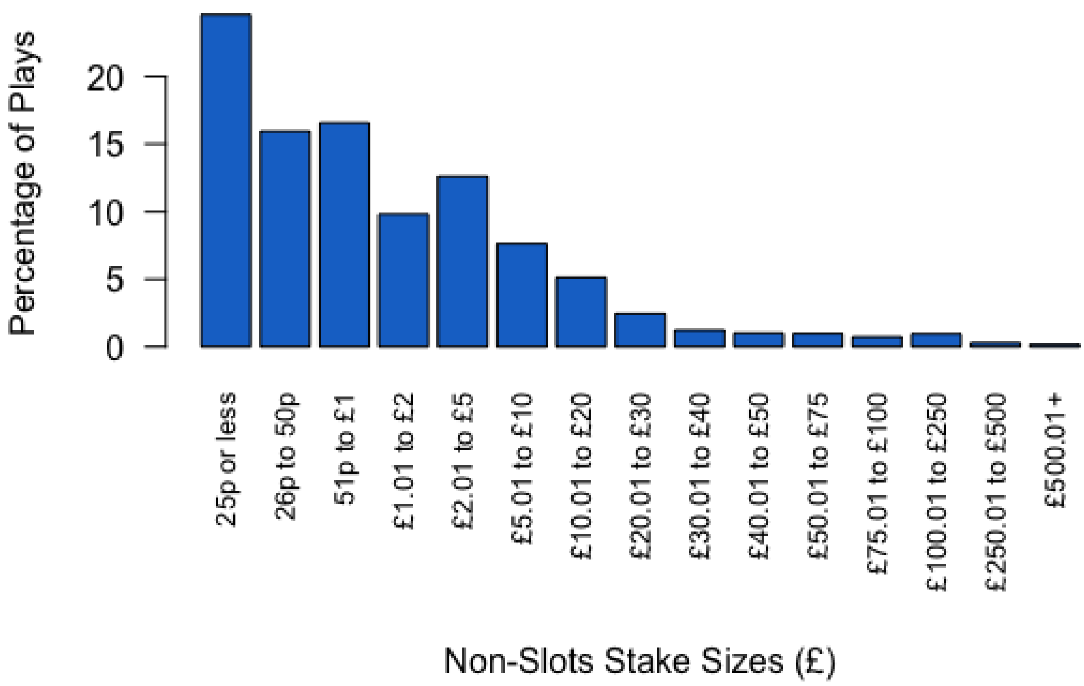
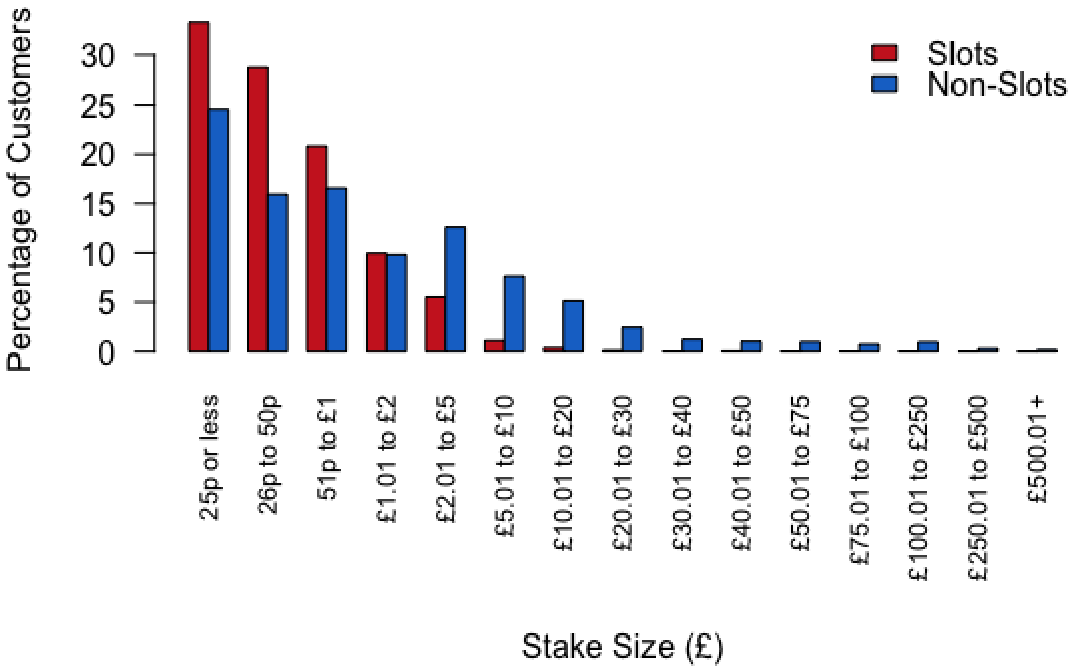


Figure 8. Percentage of plays in each staking band by game type



While most plays for both product categories are at what might be regarded as modest stakes, there is divergence as higher staking levels are considered, as illustrated in Figure 8, which shows the two sets of data on one diagram. It is clear that staking at a high level is much more common for the non-slots product. This is to be expected from the nature of the games and the ways in which they are played. A tendency for casino-style games to be played much more often at high stakes is evident in the offline world as well. For example, a study of FOB-T staking levels found a mean stake more than sixteen times as high when they were played as B2 machines (mostly casino games) as opposed to as B3 machines (only slots games)[9] though part of the reason is likely to be different regulatory limits on stakes.

In the offline environment, the highest permitted stake on slots games in casinos is £5. Here, in the online environment, there is no regulatory limit but, still, the threshold of £5 is crossed in only 1.7% of spins. However, 20.5% of plays on remote casino games (non-slots) involve a stake of more than £5. At a threshold of £50, the corresponding proportions are 0.035% and 2.1% respectively

If we consider more than £100 as a very large stake, then this is very rare (0.018% of all spins) in the case of slots games; but such a stake is placed in 1.4% of non-slots plays. We

[9] See p. 2 of the reference cited in footnote 6 above.

know of no data in the public domain which allows a comparison with the incidence of similarly large stakes in casino games played at tables or as electronic roulette in land-based casinos. However, some comparison may be made with roulette play on FOB-Ts where 5.8% of all plays over a period in 2014-16 had a stake above £50[10], rather higher than for the data studied here though the orders of magnitude might be affected by the different regulatory rules (for example, FOB-T users are unable to bet £200 on one spin, so may make 2 × £100 spins instead).

The placing of high stakes is not a very 'sensitive' indicator of problem gambling since many problem gamblers stake at only modest to low levels. However, it is likely to have high 'specificity' (i.e there is a high chance that any individual placing large stakes is a problem gambler).[11] There is therefore some reason for legitimate concern over relatively common high staking behaviour on non-slots games in the remote sector. However, it is difficult to know how concerned one should be in the absence of further data. We do not know from the data provided how many players placed high stakes on how many occasions. Nor do we know anything about these high staking players (for example, do they tend to be from postcodes in deprived areas?) or when they play (for example, late at night?) even though such data, representing risk factors, could probably be extracted from operators' data for future research.

Finally, in this section, we present (in Figures 9 and 10) the staking patterns of each operator included in the study. Generally, the pattern is similar at each operator. However, the business of operator 11 is untypical in that it is noticeably more focused on low stakes play than is the case for the other operators.

[10] D. Forrest & I.G. McHale, FOB-Ts in British betting shops: Further analysis of machine data to examine the impact of the £50 Regulations, GambleAware, 2017, https://about.gambleaware.org/media/1435/fob-t-report-3-2-17.pdf

[11] See, for example, Table 4.2 in H. Wardle, *People who Play Machines in Bookmakers: Secondary Analysis of Loyalty Card Survey Data*, NatCen Social Research for the Responsible Gambling Trust, 2016, https://about.gambleaware.org/media/1259/natcen-secondary-analysis-of-loyalty-card-survey-final.pdf

Figure 9. Staking patterns at individual operators (slots)

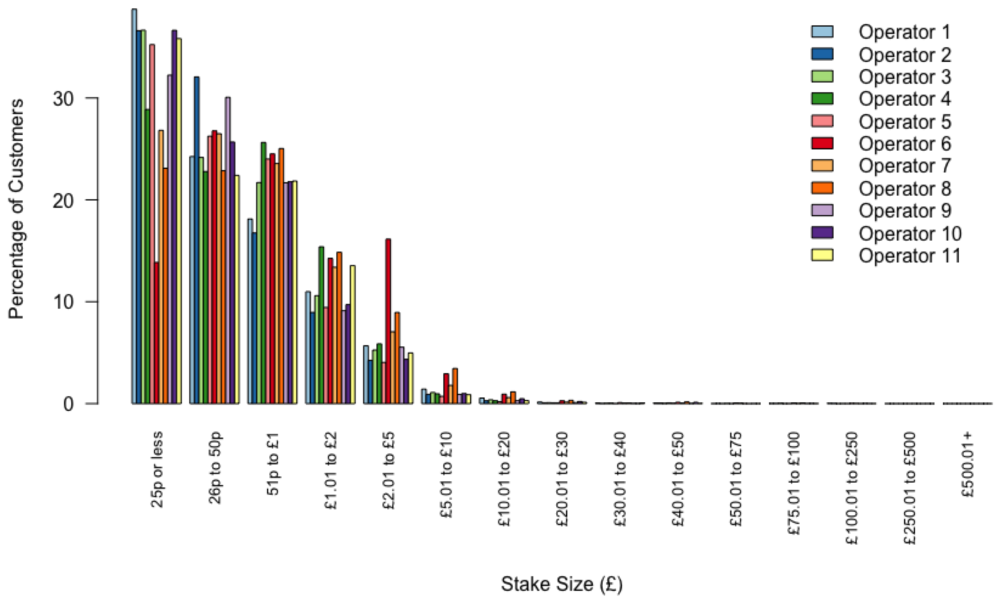
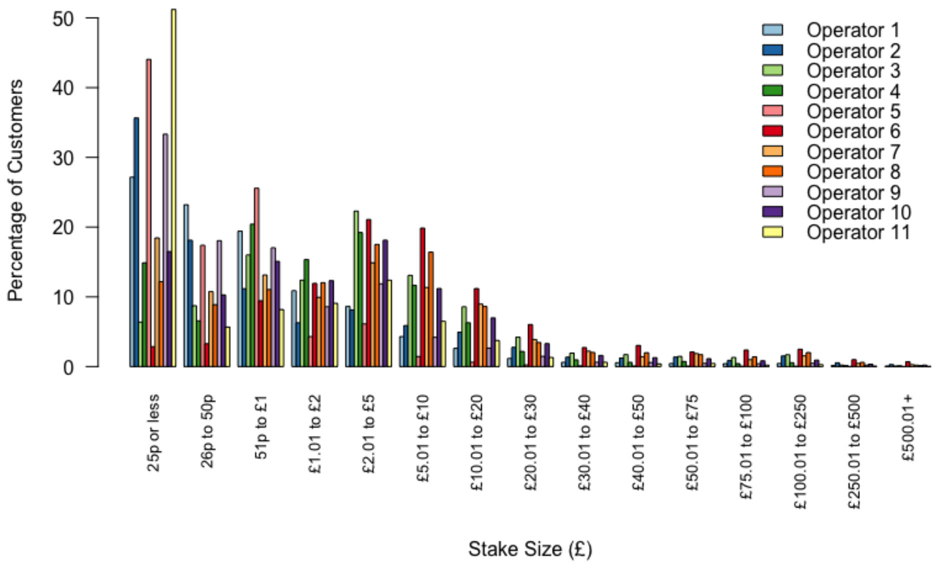


Figure 10. Staking patterns at individual operators (non-slots)



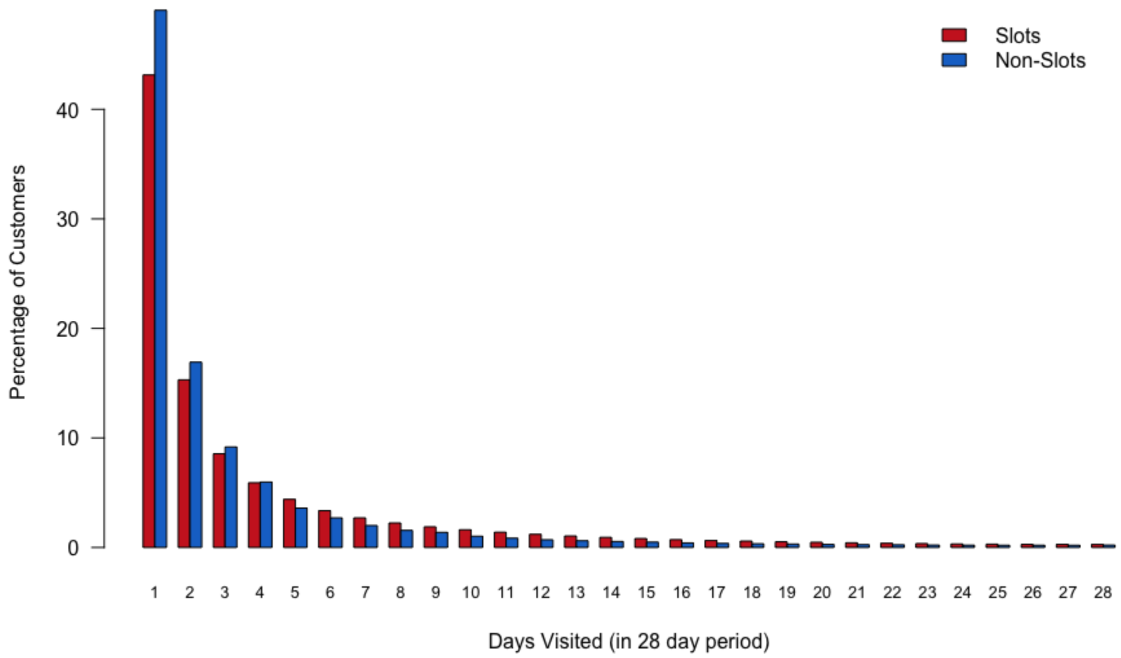
6. Number of active days

Table 3 and Figure 11 present details of how many customers played (at thirteen operators) with different degrees of frequency, as captured by number of days in the month when they played. As noted in Section 2 above, there is some imprecision here, unavoidable because some operators took a month as four weeks and some as the calendar month. But the pattern is so clear that it is very unlikely that different conclusions would have been reached from consistent data.

Table 3. Number of days played by customers in January, 2017 (number of customers)

Days	Slots (%)	Non-Slots (%)
1	536,362 (43.1%)	381,543 (49%)
2	190,294 (15.3%)	131,602 (16.9%)
3	106,320 (8.6%)	71,377 (9.2%)
4	73,415 (5.9%)	46,450 (6%)
5	54,652 (4.4%)	27,961 (3.6%)
6	41,723 (3.4%)	21,011 (2.7%)
7	33,598 (2.7%)	15,570 (2%)
8	27,788 (2.2%)	12,132 (1.6%)
9	23,436 (1.9%)	10,705 (1.4%)
10	20,097 (1.6%)	7,957 (1%)
11	17,287 (1.4%)	6,578 (0.8%)
12	14,935 (1.2%)	5,466 (0.7%)
13	13,024 (1%)	4,780 (0.6%)
14	11,440 (0.9%)	4,209 (0.5%)
15	10,123 (0.8%)	3,780 (0.5%)
16	8,848 (0.7%)	3,239 (0.4%)
17	7,869 (0.6%)	2,868 (0.4%)
18	7,222 (0.6%)	2,618 (0.3%)
19	6,455 (0.5%)	2,414 (0.3%)
20	5,847 (0.5%)	2,161 (0.3%)
21	5,307 (0.4%)	2,018 (0.3%)
22	4,742 (0.4%)	1,903 (0.2%)
23	4,392 (0.4%)	1,691 (0.2%)
24	3,953 (0.3%)	1,607 (0.2%)
25	3,734 (0.3%)	1,545 (0.2%)
26	3,530 (0.3%)	1,557 (0.2%)
27	3,499 (0.3%)	1,539 (0.2%)
28	3,414 (0.3%)	1,684 (0.2%)

Figure 11. Number of days played by customers in January, 2017 (number of customers)



Whether for slots or non-slots, most customers appear to be only occasional users (though we cannot correct for the possibility that some may be new clients whose frequency of play has not yet been revealed because they are recruited part-way into the month). More than half are recorded as having played on only one or two days.

However, there are significant numbers of regular players.[12] More than 27,000 slots customers and more than 11,000 non-slots customers were active on at least 22 days, making them daily- or almost daily-players.[13] These are players about whom operators should be very curious because number of active days is recognised as a key marker of harm from

[12] No precise comparison with frequency of play in other sectors is possible. However, using loyalty card data, Forrest & McHale found that 0.1% of casino players visited on 150 or more days per year and Astbury & Wardle reported that about 1% of FOB-T players had activity on more than 100 days per year. In our data set, about 12% of slots and 7.5% of non-slots players were active on at least 10 days in one particular month. If they repeated their behaviour every month, these players would use the website on at least 120 days per year. On the face of it, this makes remote players much more likely to be frequent users than offline players. But extreme behaviour often reverts towards the mean and many 'frequent' players as measured over one month would become 'infrequent' players observed over a longer period. References: D. Forrest & I.G. Mchale, *Tracked Play on B1 Gaming machines in British Casinos*, The Responsible Gambling Trust, 2016, https://about.gambleaware.org/media/1368/tracked-play-revision-14-12-16.pdf; G. Astbury & H. Wardle, *Secondary Analysis of Machines Data: Examining the effect of proximity and concentration of B2 machines to gambling play*, Geofutures for The Responsible Gambling Trust, 2016, https://about.gambleaware.org/media/1260/geofutures-secondary-analysis-of-machines-data-final.pdf

[13] Some may be double-counted in the sense that they appear frequent players of both types of game.

gambling.[14] Operators should be examining data on, for example, whether these individual customers are from vulnerable demographics and whether they engage in unusually long sessions, because these would be additional indicators of high risk.

We do not have the data to provide additional analysis on factors such as these. However, operators each provided a contingency table showing numbers of customers categorised by level of net expenditure and number of active days. The Project Brief invited us to consider whether there was a relationship between net expenditure and frequency of play.

We merged the information on slots and non-slots players. Operator 11 provided information only on slots players and was omitted from the analysis because its product mix would be different from the other operators. We also omitted operator 9 which had left the £50.01-£100 net expenditure out of the table it supplied to the Gambling Commission.

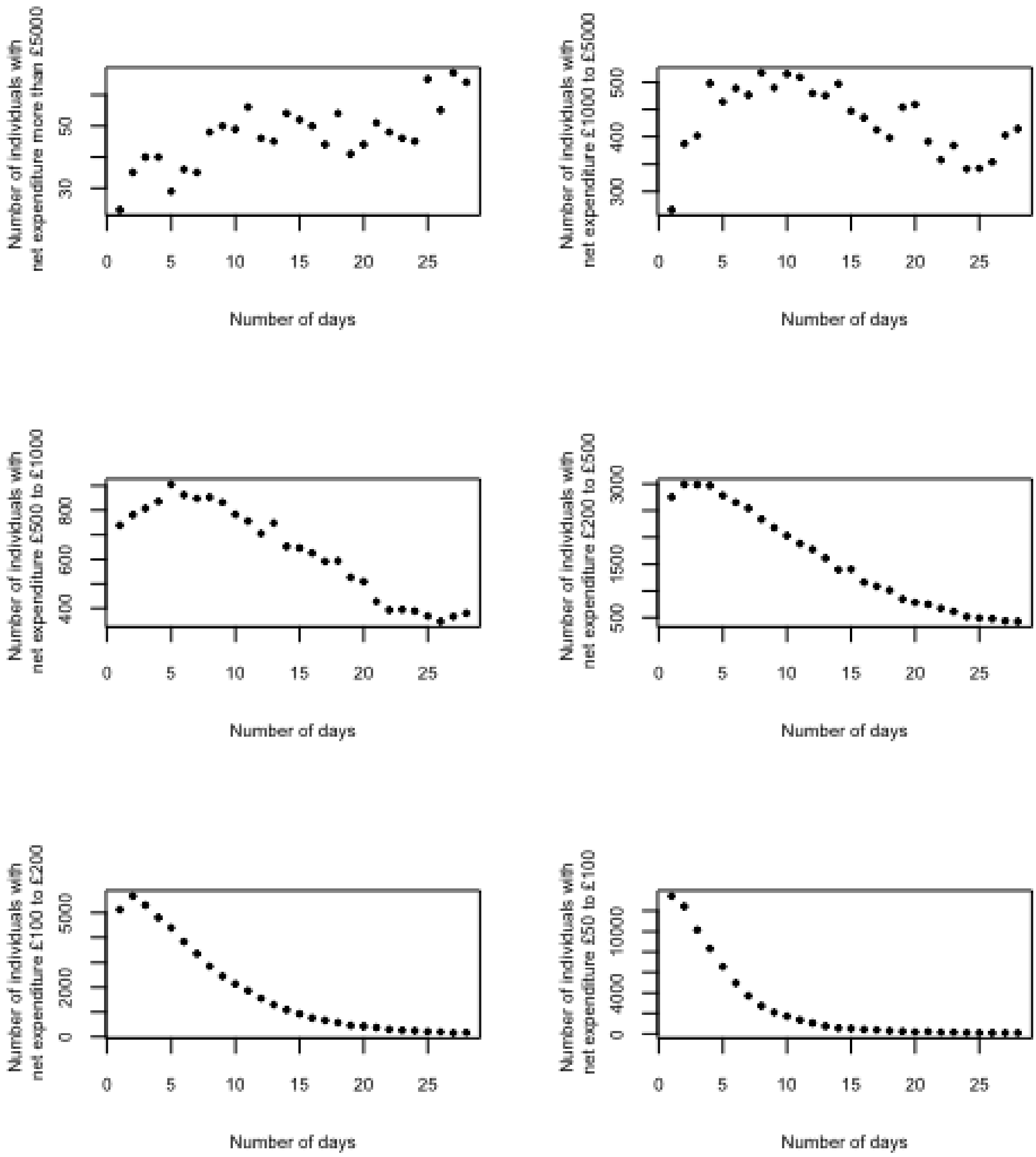
We employed a chi-square test of association to establish that there was a very highly statistically significant relationship between net expenditure in the month and number of active days in the month. Unsurprisingly, players who lost more tended to have played more often.

Perhaps more surprising insight is to be obtained from Figure 12, which looks at sub-sets of players grouped according to the size of their losses over the month. The bottom right panel relates to players with losses in the £50.01-£100 range. Among players with such limited expenditure, the largest number had played on just one day and only a very small minority had played on as many as half the days. As one moves on in ascending order of losses, the peak number of days played increases. For example, among players who lost between £200.01 and £500, the largest numbers had played on either 2, 3 or 4 days in the month and non-trivial numbers had gambled on more than half the days. But for these two groups and the two intermediate groups, the overall pattern appears smooth in every case. By contrast, the groups with the heaviest losses (top two panels) present a somewhat chaotic-looking graph in each case. What does this signify? It shows that there is (unexpected) heterogeneity in how players reach very heavy levels of loss in the month. The top-left panel in Figure 12 focuses on those with the most extreme losses (more than £5,000 in the month). It is true that there are many who reach this outcome after playing on a high proportion of days. But there are also significant numbers of players whose losses are accumulated over only 1-5 days. The explanation may well be that some players are constrained in the number of days they can play because, early in the month, they reach levels of expenditure which are non-sustainable. Simply, they have to stop because they have exhausted their resources.[15] In any event,

[14] See references at footnotes 2 and 3 above.

[15] Some who play on most days in the month may of course have reached unsustainability only late in the month and, if they then change to abstention, it will not be recorded in our one month data period.

Figure 12. Net expenditure and active days during the month



operators should note the presence of these features in the data and act accordingly in design of methods for detecting harm. For example, an indicator for ‘gaps in betting days’ could be employed[16] since this would pick-up cases where frequent players showed episodic periods of abstinence (potentially brought on by their resources being exhausted).

[16] This is a key recommendation in the PwC/ Responsible Gambling Council Report (Footnote 2 above).

7. The need for further data

The thirteen operators which supplied data to the Gambling Commission are to be congratulated on granting permission for these to be shared with external researchers for independent analysis. It has enabled, for the first time, a description of how players in the remote sector behave in terms of levels of spending, stakes and frequency of play. But gaps in knowledge remain.

Were the Gambling Commission to make a second call for data, we would recommend for example

- inclusion of information on session duration: lengthy play is both an indicator and itself a direct cause of harm
- inclusion of information on daily losses as well as losses across a longer period: this would facilitate comparison with data from tracked play on B1 machines in casinos analysed in a study for the Responsible Gambling Trust[17]
- inclusion of information on time-of-day of play: in other sectors, players have been found to stake higher and lose more very late at night and the PwC Report[18] indicates that there may be a high concentration of problem gamblers among users active in the early hours; it would be of interest to know what proportion of player losses are incurred at such ‘risky’ hours
- presentation of data by individual which shows activity across all categories of game as well as for slots/ non-slots separately: problem gamblers tend disproportionately often to play multiple games

Of course provision of anonymised records of individuals’ daily behaviour over a (lengthy) period would allow much richer analysis than is possible with highly aggregated data such as those provided on this occasion. It would permit studies of patterns of trajectories in play and of loss chasing, to take just two examples. This would increase understanding of *how* gamblers play as well as how often and to what level they play. Naturally, data on individual bettors betting on horses and sports would be equally as valuable as data on the online casino products covered in the present Report.

Operators might baulk at the cost of extracting such micro level data though they must be generated in the first place before the aggregated data are assembled. However, it is a reasonable expectation that operators should have data organised in a form which enables them to identify potentially harmful play. Indeed the Licence Conditions and Codes of Practice requires operators to make provisions to identify at-risk customers.[19] Compliance then implies that data sets should be in place. In anonymised form, they could be the basis for valuable analysis by the research community.

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[17] D. Forrest & I.G. McHale, Tracked Play on B1 Gaming Machines in British Casinos, London: Responsible Gambling Trust, 2017.

[18] See footnote 2, above.

[19] Social responsibility code provision 3.4.1. Further, provision 3.9.1, for remote operators, there is a requirement that all of an individual customer’s accounts should be monitored for behaviour that might trigger an interaction with the customer (http://www.gamblingcommission.gov.uk/PDF/LCCP/Licence-conditions-and-codes-of-practice.pdf)