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Abstract

Gambling is often regarded as a lower form of pleasure with an elitist perception of gamblers as being either ignorant or exhibiting poor mathematical skills. Gambling also poses a challenge to the notion of rational decision-making because individuals take on wagers which are losing bets by expectation. From the paternalistic perspective, gambling may be attributed to poor decision-taking resulting from cognitive failures and biases. From the liberal perspective, however, it is possible to account for gambling within the framework of rational choice by appealing to risk preferences or by a utility of gambling itself. This paper examines how a person's cognitive ability (IQ) predicts his betting behaviour. We combine three individual-level data sets from Finland, including online horse bets from the betting monopoly, cognitive ability test scores from the Finnish Defence Forces and administrative registry data on Finnish citizens. Our results show that intelligence is a positive predictor of participation, gambling consumption and success in gambling. Moreover, we find that gamblers are unlikely to exhibit poor mathematical skills because mathematical intelligence drives this result. Our results suggest that a one standard deviation increase in mathematical IQ from the mean increases the probability of participation in betting by more than a third, the bettor's annual amount wagered by a half and his annual losses by 40%. Overall, our results are consistent with gambling being consumption of entertainment, which intelligent individuals enjoy. This is consistent with the liberal perspective on gambling.

Keywords: gambling, horse betting, intelligence, mathematical intelligence, consumption, performance

JEL Codes: D12, D91, G41, L83

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Compliance with ethical standards

This study has been approved by the University of Eastern Finland's Committee on Research Ethics.

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1. Introduction

Gambling is a very popular pastime almost everywhere it is permitted. National surveys globally indicate that most people gamble at some point in their life (Caldo and Griffiths, 2016) and indeed in much of Europe the majority of adults are current players. For example, recent official household survey data from Great Britain indicate that 57% of adults (16+) have gambled in the past year, a participation-rate very similar to that estimated for going to bars, pubs and clubs and a little higher than the figure for gardening (Conolly et al., 2018, Department for Digital, Culture, Media and Sports, 2018). Those British adults spent £14.4b on gambling (player losses) in the latest year (Gambling Commission, 2019), about £260 (USD 340) per capita. Per capita spending was similar or rather higher in, for example, Italy (Agenzia Digani Monopoli, 2019) and the United States (https://www.casino.org/gambling-statistics/).

Despite this popular appeal, gambling has been a controversial issue in human societies. Throughout history, gambling has been regarded as morally corrupt because wagering makes it possible to receive gains of labour without engaging in productive effort (Brenner and Brenner, 1990; Sauer, 2001). In particular, religions have condemned gambling on moral grounds (Sauer, 2001). Further, powerful elites have promoted the negative image of gambling though with little evidence to support the view (Brenner and Brenner, 1990; Statman, 2002)[1]. Nowadays the emphasis in anti-gambling rhetoric has shifted from morality to the adverse effects of gambling, specifically to harm experienced by the minority of individuals who develop gambling disorder, an illness recognised by the American Psychiatric Association. Consequently, gambling-related harm is the main reason given now for governments to regulate gambling by restricting supply of gambling opportunities[2].

Sauer (2001) identifies alternating cycles of liberalization and paternalistic restrictions shaping gambling markets. The liberal perspective is more willing to see gambling as a consumer product which yields utility to those who enjoy gambling (e.g. Sauer, 2001). The paternalistic perspective sees gamblers, and especially the poor, as vulnerable to gambling harm, which warrants government intervention to rein in gambling instincts (Statman, 2002). Though not often directly articulated, some of the paternalistic concern appears to stem from a

[1] An example of such attitude towards gambling is the renowned investor Warren Buffet's remark that "gambling is a tax on ignorance" at Berkshire Hathaway's 2007 annual meeting.
[2] National surveys indicate that gambling problem prevalence varies between 0.12% and 5.8% across the world (Calado and Griffiths 2012).

preconception that gambling is a harmful hobby or preoccupation of individuals with low intelligence or a weak understanding of mathematics and probability: people waste their money on gambling rather than spending or investing it in more sensible ways. This is illustrated by the curricula of several educational programs concerning potential hazards of gambling, which teach the concepts of probability and randomness to their target groups (Keen et al., 2017).[3]

Gambling products pose a challenge to the theory of rational consumer behaviour because they have a negative expected value. In the spirit of the paternalistic perspective, purchasing such products may be attributed to poor decision-taking resulting from cognitive failures and biases. Research suggests that a higher cognitive ability predicts less proclivity for taking on harmful risks, such as smoking cigarettes, and a willingness to assume risks that are potentially beneficial to the decision-maker, such as equity investments (Dohmen et al., 2018; Grinblatt et al., 2011). This would reinforce the view of those who identify gamblers as typically of relatively low intelligence because they are willing to put money at risk with a negative expected payoff.

From the liberal perspective, however, it is possible to account for gambling within the framework of rational choice by appealing to risk preferences (Friedman and Savage, 1948)[4] or by admitting a utility or entertainment value to the process of gambling itself (Conlisk 1993). This latter perspective sees gambling, at least in part, as a consumption activity pursued for enjoyment rather than as a set of decisions based only on the assessment of monetary risk and reward. As put by Asch and Quandt (1990, p. 423): “A day at racetrack or casino may be simply a consumption type activity for which one is prepared to pay a price that includes the track ’take’ or the house ‘advantage’.” Within the liberal perspective, any link between gambling and intelligence might then result from differences according to cognitive ability in either risk preferences or tastes in consumption of entertainment rather than ignorance.

[3] Indeed, Keen et al. (2017, p. 321) suggest that these educational programs “should focus primarily on teaching mathematical principles that account for the long-term unprofitability of users, such as expected value.”
[4] While (mostly) risk-seeking behaviour of gamblers is inconsistent with the rational behaviour prescribed by expected utility theory, it is consistent with Friedman and Savage (1948) whose model depicts how decision-makers simultaneously buy insurance for protection against falling out of their current social status and risky prospects with potential to elevate their social status above the current one (Brunk, 1981; Statman, 2002).

However, research into the relationship between cognitive ability and gambling behaviour is scant at the level of the individual[5]. For this reason, it is not clear whether empirical evidence lends support to the paternalistic or the liberal perspective on gambling. To address this gap in the literature, we investigate how participation in gambling, expenditure on gambling and success in gambling correlate with intelligence. Specifically, we use both a composite measure of intelligence (composite IQ) and measures of mathematical intelligence, visuospatial intelligence and verbal intelligence to predict consumers' gambling behaviour in horse betting.

We use a unique large-scale data set from Finland to examine how cognitive ability predicts gambling behaviour in an actual market environment. First, we use horse race betting data to investigate an individual's betting choices. The betting data set contains all horse race bets placed on the Finnish monopoly operator's online platform by each bettor during a year. Second, we use cognitive ability test scores to examine how the individual's intelligence predicts his wagering. The intelligence data set contains scores of cognitive ability tests administered to all conscripts by the Finnish Defence Forces between 1982 and 2010. Finally, we use administrative registry data on the Finnish male population to control for potential influences exerted by the individual's socioeconomic background on his betting choices.

Our results show that intelligence is a positive predictor of participation and the level of consumption in horse betting. Moreover, our findings suggest that mathematical IQ drives the result. That is, persons who score highly in mathematical aptitude tests tend to be more likely to participate in betting and to spend more if they do. We also find that a high mathematical IQ and a high level of education are associated with better performance in betting. This suggests that individuals use their 'human capital' in gambling activity in a similar manner as they do in other situations involving economic decision-making. Generally, our results show that wagering cannot be attributed to poor decision-making skills resulting from cognitive failures as suggested by the paternalistic perspective. We argue that our findings are congruent with the liberal perspective which perceives gambling as a form of consumption some people enjoy.

[5] Using *aggregate* data from a US racetrack, Rosett (1965) examined the pattern of returns to simple and exotic bets and concluded that "sophistication and rationality" drive decision-taking in the market. On the other hand, it is unclear what proportion of market participants bring about this level of efficiency.

Our paper makes two contributions to the literature. First, our paper is among the first to investigate correlations between betting choices and intelligence using real-world data. Second, we contribute to the burgeoning literature on the role of cognitive skills in economic decision-making.

This paper proceeds as follows. In Section 2, we review the empirical literature on the role of intelligence in economic decision-making. Section 3 discusses gambling and horse betting as consumption. Section 4 presents the data and Section 5 the methodology used in this study. Section 6 reports the results. Finally, Section 7 discusses the results in light of the literature and Section 8 concludes the paper.

2. Prior empirical literature

2.1 Empirical research into intelligence

Consumer decision-making involves traits and skills pertaining to an individual consumer as well as social motives and situational factors (Lynch 2011). Research into the contribution of intelligence to decisions taken by individuals has gained traction recently. In psychological theory, intelligence is a set of properties "that make for effectiveness, regardless of the environment a person is in" (Baron 2005, p. 15). Thus, intelligence contributes to a person's ability to execute successfully rational plans in any environment (Baron, 2005). For instance, cognitive skills appear to play a role in who becomes an inventor (Aghion et al. 2018) or in who purchases risky assets (Grinblatt et al. 2011).

There are two main data sources in the empirical research into the nexus of intelligence and economic outcomes. First, experimental studies which use lotteries with (often) monetary payoffs that mimic real-world decisions (e.g. Webb et al. 2014). Second, field studies which apply registry data on individuals' IQ test scores to elicit information on how intelligence is correlated with economic decisions (e.g. Grinblatt et al. 2011). Each stream of research has its upside and downside. Experiments are carried out in controlled environments where they can be designed to elicit causal inference. However, experiments are usually characterised by limited sample sizes and by their artificial nature, which may impair their predictive power (e.g. Webb et al. 2014). Field studies use data extracted from actual decisions in which individuals do not know that an external observer examines their decisions. However, field studies tend to be correlation studies, which does not allow for making strong causal claims. Further, since the IQ tests generating the data have often been administered to conscripts to the military, required to perform national service (e.g. Adams et al. 2017; Aspara et al. 2017; Bratsberg and Rogeberg 2017; Grinblatt et al. 2011), they relate predominantly to males, restricting their generalisability to the whole population.

Experimental studies indicate that an individual's cognitive skills correlate with consistent behaviour. In a large-scale experiment administered to employees of a trucking company, Burks et al. (2009) find that cognitive skills predict consistent choice patterns in a series of lotteries involving risky and fixed monetary payoffs. Further, they also find that higher cognitive skills are associated with patience in choices. Experiments also suggest that an individual's savings decisions are related to his or her cognitive abilities, which help processing complex information involved in their decision-making (Ballinger et al. 2011).

Theories of behavioural economics, such as prospect theory, give reason to expect that risk-taking behaviour could be related to cognitive abilities and personality traits (Dohmen et al. 2010). For instance, Dohmen et al. (2010) use survey data and report that decision-makers with a higher cognitive ability are significantly more willing to take on risk in lottery experiments. In contrast, Andersson et al. (2016) find, from a large-scale experiment, that any apparent relationship between risk preferences and cognitive ability is likely to be spurious and explained by a tendency for behavioural noise to decrease with cognitive ability Thus, the conclusions drawn in these studies appear to be dependent on the data source and/or methodology (i.e., a particular experiment). However, recent field studies suggest that cognitive ability does predict risk-taking behaviour: individuals with a higher cognitive ability are more willing to take on risks that are beneficial to them (e.g., equity investments) and less willing to take on harmful risks (e.g., smoking) (Dohmen et al. 2018).

2.2 Intelligence and consumption

Recent empirical field studies also show that intelligence is a predictor of consumption choices. Intelligence has been associated with price consciousness, as high-IQ men tend to prefer mutual funds with low management fees (Grinblatt et al. 2016). Faced with increasing inflation expectations, men with high as opposed to low IQ increase their consumption propensity (D'Acunto et al. 2019c). Further, high-IQ men appear to respond more strongly to changes in nominal interest rates by increasing borrowing when the rates go down and by decreasing borrowing when the rates rise, whereas the use of debt by low-IQ men is less sensitive to interest rates (D'Acunto et al. 2019a). High intelligence is also associated with a sensitivity to changes in tax policy: high-IQ males increased their consumption of environmentally friendly cars following a favourable tax treatment to this type of automobile (Aspara et al. 2017).

Research into financial markets shows that IQ plays a key role in determining an individual's decision to invest in risky assets. Using a survey of over-50-year-old respondents in 11 European countries, Christelis et al. (2010) find that cognitive abilities predict direct stock market participation and indirect participation through mutual funds. Further, Grinblatt et al. (2011) use an administrative data set on the Finnish population together with IQ test scores for Finnish males and report that IQ is strongly correlated with stock market participation.

Research into components of IQ points to the importance of mathematical ability in economic contexts. In a study of mortgage defaults, Gerardi et al. (2013) discover that a high numerical ability predicts timely debt repayments and a reduced likelihood of ending up in foreclosure. They also find that higher verbal IQ helps avoiding foreclosure, but its effect appears to be significantly lower than that of numerical ability. Agarwal and Mazumder (2013) report that high IQ is associated with an ability to minimise interest payments in credit card purchases, a skill they attribute to the mathematical component of IQ. Aspara et al. (2017) also use a decomposition of IQ in their study. They find that although the verbal and visuospatial IQ measures are correlated with the purchases of low emission cars following the introduction of a pro-environment tax policy, the effect appears to be most pronounced for mathematical IQ.

2.3 Intelligence and performance

Studies indicate that there is robust evidence for intelligence affecting how decision-makers perform in various tasks involving economic consequences. Experimental studies mimicking real-world financial decision-making suggest that a high IQ is associated with better performance whether children (Li et al. 2017), college students (Demaree et al. 2010), or adults are used as test subjects (Webb et al. 2014).

Likewise, field studies on household finances support the important role intelligence plays in how individuals perform in decisions involving financial products. In the stock market, a high IQ is positively correlated with higher risk-adjusted returns (Grinblatt et al. 2011). High-IQ investors are also better at market timing, finding profitable investments and executing their trades (Grinblatt et al. 2012). In the market for mutual funds, high-IQ investors are more capable of discerning funds' pricing structures and consequently avoiding excess fees

(Grinblatt et al. 2016). Further, cognitive abilities appear to improve the investor's ability to purchase investment products requiring a higher level of information processing skills (Christelis et al. 2010). Also, decisions involving the use of leverage point to a positive association between intelligence and performance. Agarwal and Mazumder (2013) report that high-IQ individuals are less likely to make costly mistakes in mortgage applications. Further, they find that high mathematical IQ, and, to a lesser extent, verbal IQ scores are driving their result. In an investigation into subprime mortgage borrowers, Gerardi et al. (2013) report that high-IQ individuals are less likely to end up in foreclosure, a result they attribute to better strategic skills enabled by cognitive ability.

To a large extent, empirical evidence extracted from other contexts echo the findings established in experimental settings and financial markets. Burks et al. (2009) report that high cognitive skills enable truckers to plan complicated trips, increasing their job retention and pay. D'Acunto et al. (2019c) find that high-IQ men make more accurate inflation forecasts. In a related study, D'Acunto et al. (2019b) note that while mathematical ability matters the most in prediction accuracy, verbal and visuospatial intelligence also are positively correlated with forecast accuracy for inflation. However, in a study of Chief Executive officers in Sweden, Adams et al. found that non-cognitive skills, measured at entry into obligatory military service, were more important than cognitive skills in accounting for reaching the level of a CEO and, among CEOs, cognitive skills did not predict pay. Nevertheless, the median IQ of the leaders of large Swedish firms was in the top 17% of the population by cognitive ability.

2.4 Intelligence and gambling

Research into the influence of intelligence on gambling behaviour is relatively limited in scope. Most gambling researchers have focused on correlations between cognitive ability and problem gambling. However, although problem gambling is an important issue in public health, it affects only a minority of gamblers. For example, 80% of Finnish adults gamble, but the estimated prevalence-rate of problem gambling is 3.3% of the adult population (Salonen and Raisamo 2015). These studies tend to suggest that low cognitive ability predicts pathological gambling whether intelligence is defined by non-verbal reasoning skills (Kaare et al. 2009) or by verbal intelligence (Rai et al. 2014). However, mathematical intelligence may be a somewhat distinct form of cognitive ability in this respect as numerical ability was not a protective factor against pathological gambling in an Australian study comparing pathological players, regular players and infrequent players (Lambos and Delfabbro 2007). Moreover, teaching mathematical skills relevant to gambling does not appear to change their gambling behaviour (Williams and Connoly 2006). However, since studies of problem gambling focus on a subset of gamblers, their findings may not be generalizable to the wider population.

Outside problem gambling, only a few studies have attempted to examine IQ's contribution to gambling. Ceci and Liker (1986) study a small group of active racetrack bettors and find that IQ does not predict forecasting accuracy. Forrest and McHale (2018) analyse survey data from more than 2,000 individuals who were part of a longitudinal cohort of English children tracked from birth to now. At age 20, members of the panel were questioned about their gambling behaviour and a problem gambling screen was also administered. Their study models both an individual's probability of being a regular (weekly-or-more) gambler and his or her probability of being a problem gambler. Scores in national maths and English aptitude tests taken at age 15 are among the regressors in each case. While test scores fail to be significant predictors of problem gambling, maths score is a strongly significant positive predictor of regular participation in the male equation (and a positive and marginally significant predictor in the female equation). Forrest and McHale also explore the relationship between regular play and maths aptitude scores for individual gambling activities and reported that the positive correlation appeared to hold for both skills-based and non-skilled (e.g. scratchcards) games.

3. Gambling as consumption and horse race bets

Commercial gambling involves placing an amount of money at risk in hope of a larger gain in a context where the expected value of the wager is on average negative. This negative return is often represented as the price paid for the entertainment (Eadington 1999; Asch and Quandt 1990). On aggregate or in the long run, this constitutes a viable proxy for the price of gambling, (but this may not be the case in analysis at the individual level or in the short run).

Representing expected loss as the price for entertainment is consistent with recognising that players may enjoy gambling activity (Conlisk 1993). In a recent experimental study, Voichek and Novemsky (2019) report that wagering on a sports event (or even on a coin flip) makes it more enjoyable to watch for the test subjects regardless of whether they win or lose their bets. Further, they report that people under-appreciate the positive effect of gambling on their experience of watching a sports event.

At the same time, gambling is conceptually a peculiar product for which to model consumer behaviour because the total amount spent on gambling is random during each gambling session. This means that when a consumer buys into a certain amount of gambling activity, the final expenditure on the activity reveals itself after the betting session concludes. This is the main difference between gambling products and other consumer products or services, such as alcohol or seeing a play in a theatre.

To illustrate gambling consumption in a single gambling session, assume that a bettor decides before a session a maximum amount of money X, which he or she is ready to spend or lose for enjoyment. There are four possible scenarios of the total loss (expenditure) during the betting session:

a) If the total amount staked (S) is all lost without gains (g), then the expenditure of the session (x) is the total stake, which is also the maximum possible loss ($X = x = S$);

b) If the bettor wins some amount ($g < S$) within a betting session and keeps the gains, then the expenditure of the session is the total stakes minus gains ($x = S - g < X$);

c) If the bettor re-invests all his or her gains, then the expenditure of the session is otherwise the same as in (a) but with gains included in the total volume ($S^* = S + g$);

d) If the gains exceed the total stakes ($g > S$) when the betting session concludes, then the expenditure in the session is negative, i.e., the consumer is paid for betting ($x = X - g < 0$).

We can safely assume that bettors prefer situation (d) to all other situations because they are 'paid' for their enjoyment. Further, bettors in situation (c) are better off than those in situation (a) even if their expenditures were the same because they have had more enjoyment for the same expenditure. Finally, one can assume that bettors who prefer betting more, choose to re-invest their gains (c) rather than keep their gains (b) for purchase of other, alternative products. This, in turn, suggests that although they have lost more than the bettors who did not re-invest, they have wagered more and have had more enjoyment as a result. That is, the total stakes take into account the extra enjoyment following the re-invested gains. Therefore, inspecting only the net loss may waste valuable information on betting preferences.

The exposition above illustrates that bettors have a true incentive to place bets in a way that maximises their gains, because they may spend the gains on other products or re-invest their gains in more betting should they enjoy it enough. Loosely speaking, bettors in chance-based gambles cannot influence their gains because they are random. However, in skill-based gambling bettors have an opportunity to use their skills to improve their gains. In fact, with a sufficient level of skills or sufficient investment in acquiring relevant information, they may have a chance to gamble in such a way that they make profit in the long run.

Horse race betting is a skill-based gambling activity. Although some participants may make their choices randomly, many will study factors such as the form of the runners, the quality of the jockeys and the suitability of the distance and conditions for each horse before forming a judgement on whether and how to bet. This gives scope for knowledge and skill to be exercised when evaluating the probability of each possible outcome and the potential for skilled players to earn above-average returns.

As in many jurisdictions, for example the American states with racetracks or France, horse betting in Finland follows the pari-mutuel (or tote) model. In this model, the bets placed on a horse relative to the total pool mechanically produce the horse's market share, which determines the odds of the outcome. That is, the odds are the inverse of the market's estimate of the winning probability, corrected for the take-out rate. The operator collects all bets placed in the pool and redistributes them to the bettors who bet on the correct outcome, excluding the take-out rate (which is the fixed fraction of the pool that covers the operator's expenses and profit). Consequently, pari-mutuel odds represent the market's aggregate probability estimates, which means that bettors wager against each other. More detailed information on the pari-mutuel betting system is available in Appendix A1.

4. Data sources

4.1 Betting data

In Finland, the pari-mutuel betting system is used for all types of bet (such as win bets, trifecta and others described in Appendix A2), with each bet type having its own pool. The operator is Veikkaus Ltd. (formerly Fintoto Ltd.), which has a legal monopoly for offline and online horse race betting in the country. It provided us with a data set consisting of all horse bets made on the company's online betting platform between September 1, 2015 and August 31, 2016. Approximately 60% of horse race bets are placed at the online platform. Their total monetary value was €141 million and the betting company's takeout was €33 million (23% of the stakes). The data include aggregated information on the betting types a bettor has played on each day during a year. Our key variables for analysis are total stakes, and gains made during the one-year observation period. In total, we had information on all 47,324 bettors (of whom 75.5% were male) who participated in on-line horse betting during the observation period. More detailed information on the betting environment and data description are available in Appendix A2.

4.2 Registry data

We draw on Finnish Longitudinal Employer-Employee Data (FLEED) for 2015. The data cover the entire Finnish population between ages 15 and 70 (3.92 milllion) and contain approximately 200 variables measured at the level of the individual. Statistics Finland gathers the information from various administrative registers. Finnish administrative data are of a high quality with little missing data. The main reasons for an individual represented in the betting data set not being included in the administrative register data would be either that he or she was living abroad or that he or she has died recently. In this study, we use the information on the individuals' age, native tongue, place of residence, education, labour market status, income, number of children, family type and whether they pay the non-mandatory Church tax. We use this information to construct control variables to be included in our empirical models.

4.3 IQ data from Finnish Defence Forces

In Finland, military service is mandatory for males and voluntary for females. Conscripts are predominantly male with female volunteers accounting for only about 2% of the total number over the past two decades. The majority of conscripts carry out their service at the age of 19 or 20, usually after they have finished their secondary education. The Finnish Defence Forces (FDF) administer a mandatory cognitive ability test to all conscripts. It is used to screen potential candidates for officer training. The cognitive ability test, also referred to as the intelligence quotient (IQ) test, contains subtests for arithmetic, verbal and visuospatial reasoning. Each subtest has 40 multiple-choice questions (the number of correct answers lies between 0 and 40).

Our data contain all individuals who took their military service between 1982 and 2010. During this period, the test has remained unchanged. Conscripts take the test in standardised group-administered conditions in all FDF units. Our sample of the FDF data contains a large proportion (71%) of Finnish men over the birth cohorts between 1962 and 1990.

The FDF data record the date when a conscript took the cognitive ability test and the number of correct answers in each subtest for each individual. We use measures for cognitive ability derived from the subtests. We refer to the arithmetic ability test score as the “Math IQ”, the verbal ability test score as the “Verbal IQ” and the visuospatial ability test score as the “Visuospatial IQ”. Further, we calculate the arithmetic mean of these three abilities for each individual, which we refer to as “Composite IQ”. We normalised these raw test scores by the test year with the mean at 100 and the standard deviation 15. This normalisation is intended to remove any influence from possible secular trends in cognitive ability (e.g., the Flynn Effect). We use normalised test scores in our analysis. Appendix A3 includes more details about the tests.

One should also acknowledge some limitations of the FDF data. First, as pointed out by Heckman et al. (2019), IQ test results may be biased because they are a function of both the attribute to be measured and the effort input of the subject. Biases may arise if different individuals have different incentives to effort. In our context, however, there seems to be no obvious systematic reason for conscripts to underperform in cognitive ability tests. Moreover, it is improbable that a proclivity for gambling and how much a conscript wants to be an officer are correlated with each other. Second, our sample does not include all males as some are exempt from military service and some opt for non-military service instead. Finally, the sample excludes the female population because there are no IQ data available for them.

4.4 Combined data set

This study uses an individual-level data set which combines data from three sources: 1) online betting data, 2) socioeconomic registry data, and 3) cognitive ability test data. Statistics Finland combined the three data sets using individuals’ encrypted social security numbers. Our sample contains all Finnish males who took the FDF cognitive ability test during their military service between 1982 and 2010. When combined with the registry data from year 2015, the sample of potential bettors contains 705,089 males between the ages of 25 and 53[6]. First, we modelled participation in horse betting (defined by holding an online account which was used at least once in the data period) as a function of cognitive ability scores from the FDF data and several variables retrieved from the registry data. 15,488 individuals in the set of 705,089 males were participants. Next, we modelled level of activity and financial return among the 15,488

[6] The maximum age is relatively low because older men did not take the IQ test during their military service.

participants using cognitive ability scores from the FDF data and several variables retrieved from the registry data.

5. Methodology

5.1 Betting activity

Our main goal is to find whether there is a link between cognitive ability and betting preferences. Thus, our estimation strategy is straightforward. To model betting activity, we use the so-called two-part model. In the first part, we model the decision to spend on betting, i.e., whether a person participates in betting or not. We refer to this model as the participation model. In the second part, we model the amount spent on wagering conditional on participation. We refer to this model as the consumption model. Estimation via a two-part model allows different mechanisms to drive the decision whether to bet and the decision how much to bet. This is appropriate, for example, where there is a hurdle to overcome (such as a fixed cost arising from distaste for or moral doubts about gambling) if an individual is to participate at all.

The first part of the two-part model is a binary outcome equation which models the probability of being a bettor with probit estimation. In this model, participation is unambiguous: if a person has used his betting account for betting purposes during the one-year observation period, we record this person as a horse race bettor.

The second part uses linear regression to model consumption conditional on being a bettor. In this study, we use two measures to model the level of betting activity among active bettors. First, we use the total net spending during the year. The advantage of total loss is that it is analogous to consumer spending on other services since it is the amount of money left to the supplier in exchange for consuming the product. Its disadvantage is that some bettors made a profit over the year, which brings forth the unappealing concept of a negative expenditure on betting. Therefore, when we apply this measure, we drop the winners from our analysis. Second, we use the total stakes during the observation period. It is a wider measure of betting activity because it also takes into account possible re-investment of wins and therefore models a general preference for betting activity. Moreover, all participants have some betting volume, so all bettors are included in the analysis. Each of these measures to be used in the consumption model are highly skewed (non-normal). Hence, we use the natural logarithm of these variables in our analyses.

5.2 Betting success

Success can be variously defined. The most obvious signal of success would be that the bettor made a net profit from the year's betting activity. However, one could also regard a bettor as displaying above-average skill if his rate of return on stakes was lower than the track take-out calculated for his mix of bets (taking into account that different bet types have different take-out rates). If a bettor 'beats the track' in this way, it implies that he has paid part of what is effectively the betting operator commission through winnings from other bettors. For instance, a bettor may have placed €1,000, all of it on win bet (bets that the chosen horse will finish first), during the year and won back €900 (i.e. the total loss is €100). As the take-out rate on win bets is 15%, the expected loss in a mathematical sense is €150. Therefore, the bettor has 'beaten the track'. Some other bettors must have lost above their mathematically expected loss in order that our more successful bettor avoids part of his contribution to the track take. In that sense, the bettor who 'beats the track' is winning money from other bettors.

In either case, making a profit or 'beating the track', what seems to be success may in fact be mere chance. Certainly if one listed winners on a single day, one might be reluctant to regard them as demonstrably skilled rather than as lucky bettors. How substantially is this problem mitigated when, as here, the period of record is extended to one year?

We satisfied ourselves that there is an informative signal if a bettor achieves success over a year under either definition of success. We split the year into two equal sub-periods. We then established that 'success in the first six months' was in each case a statistically significant predictor of 'success in the second six months'. This appears to validate that there are skilled traders in the betting market and they begin to be identified over a period as short as six months. This in turn validates our treating 'success over twelve months' as an informative signal transmitted by the data.

We use binary outcome models to examine success in betting. Probit models are used to estimate the probability of being successful, namely 'being a winner' and 'beating the track'. We refer to these models as the 'success models'.

6. Results

6.1 Descriptive statistics

Table 1 reports descriptive statistics for the dependent and independent variables used in this study. Our sample includes 705,089 males aged between 25 and 53 of whom 15,488 were horse bettors. This means that 2.2 % of males in our sample participated in online horse race betting.

During our observation period, the average total amount wagered was approximately €4,000 per bettor. However, this figure for total stakes should not be equated with expenditure on betting. Expenditure is more naturally represented by bettor losses, i.e. stakes minus amounts claimed back as winnings. On this definition, average spending on betting was €734. If we consider only the bettors who lost money over the period as a whole, average amount lost was about €1,042.

Both measures of gambling activity, total stakes and bettor loss, are highly skewed (the median is substantially lower than the mean), which suggests that the volume of betting is modest for most gamblers but that a minority are heavily engaged. 9% of bettors are winners, which means that their gains exceed their losses. On the other hand, 23% of bettors would have been winners without the track's takeout, which means that they lost less than would have been 'mathematically expected' given track take-out rates. Comparing descriptive statistics for bettors and non-bettors, there is little difference in make-up in respect of several socio-economic and demographic variables. However, on average, bettors appear to be less educated and to have a lower status in the job market than the rest of the sample male population.

All IQ variables are normalised to have a mean of 100 and a standard deviation of 15. As expected, the IQ variables are positively correlated with each other (e.g. Gerardi et al., 2013; Aspara et al., 2017; Young et al. 2018). Correlation between mathematical and verbal IQ is 0.69, between mathematical and visuospatial IQ 0.64, and between visuospatial and verbal IQ 0.59. These figures suggest that various cognitive abilities are not independent from each other. On the contrary, a person exhibiting a high mathematical aptitude is also likely to perform well in tasks involving verbal and visuospatial reasoning. As a consequence, high correlations between the IQ measures limit their simultaneous use in reasoning which involves the ceteris paribus assumption: the assumption that a single dimension of IQ can be increased while holding other dimensions constant would not be valid.

Regarding the IQ variables, median visuospatial and verbal IQs are slightly lower among bettors but the median mathematical IQ is more than three points higher than in the total sample. Appendix B1 presents variable definitions and summary statistics for all variables, including the reference categories for socio-economic background variables, in more detail.

Table 1. Summary statistics of dependent and independent variables.

Summary statistics						
- Dependent variables -						
	N	Mean	sd	p50	p10	p90
Participant	705,089	0.02	0.15	0	0	1
Total stakes (€)	15,488	3,980.56	25,888.60	230.85	13.60	7,702.55
Net spending (all bettors) (€)	15,488	734.47	7,985.75	78.90	0.60	2,153.65
Net spending (only losers) (€)	14,067	1,041.60	4,796.25	107.90	9.40	2,409.61
'Being a winner'	15,488	0.09	0.29	0	0	0
'Beating the track'	15,488	0.23	0.42	0	0	1
- Independent variables -						
	All males N=705,089			Male bettors N=15,488		
	Mean	sd	p50	Mean	sd	p50
Age	39.94	8.46	40	40.95	8.06	42
Blue-collar	0.30	0.46	0	0.35	0.48	0
White-collar	0.38	0.49	0	0.34	0.47	0
Basic	0.12	0.32	0	0.14	0.35	0
College	0.23	0.42	0	0.22	0.42	0
Post-graduate	0.13	0.33	0	0.08	0.26	0
Pays the church tax	0.65	0.48	1	0.67	0.47	1
Income	31,179	67,455	27,724	30,936	50,964	27,866
Has one child	0.19	0.39	0	0.20	0.40	0
Has two or more children	0.38	0.48	0	0.35	0.48	0
Married or cohabiting	0.68	0.47	1	0.69	0.46	1
Divorced or widowed	0.13	0.34	0	0.12	0.33	0
Urban residence	0.87	0.33	1	0.86	0.35	1
Swedish-speaker	0.04	0.20	0	0.01	0.12	0
Composite IQ	100	15.00	100.87	100.82	14.33	101.53
Visuospatial IQ	100.01	14.98	101.47	99.07	14.41	100.71
Verbal IQ	100.01	14.98	100.15	100.04	14.22	100.15
Maths IQ	100.02	14.99	100.54	103.10	14.88	103.58

Figure 1 illustrates how the measures of IQ are correlated with the probability of being a bettor when the bettor's socioeconomic background is not controlled for. The points in the plots show the proportion of individuals who participated in online horse betting at least once during the observation period in a respective IQ decile. In the case of the composite IQ measure, the gradient is slightly positive indicating a low but positive correlation between IQ and the propensity to be a horse race bettor. Inspecting the separate dimensions of IQ, the plots suggest that mathematical IQ and visuospatial IQ are respectively positive and negative predictors of participation in horse betting. However, there appears to be no relationship between verbal IQ and betting participation.

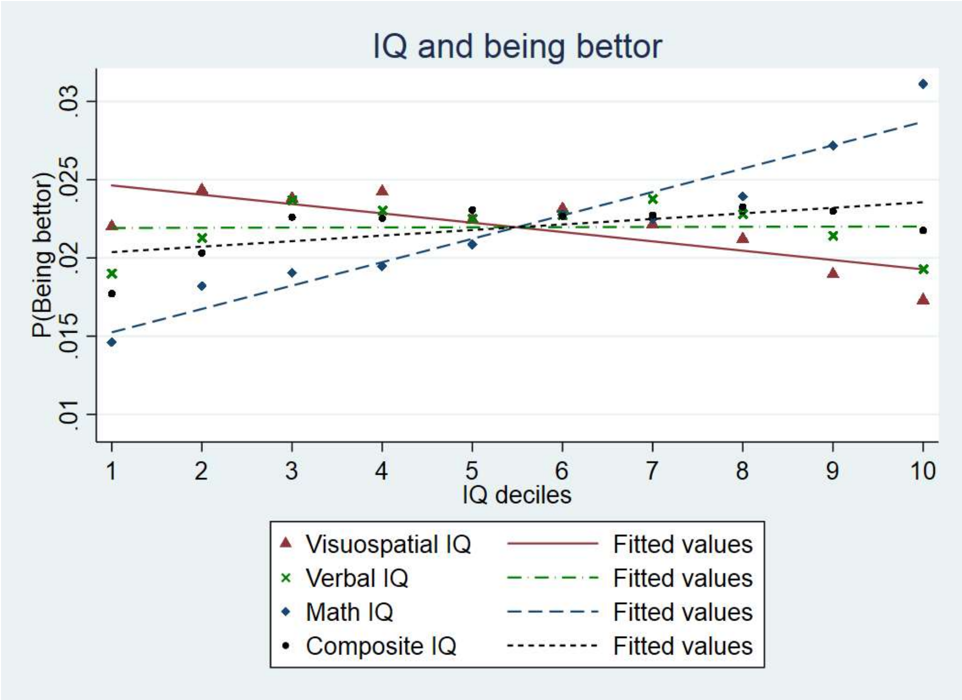

Figure 1. IQ and betting participation.

Figure 2 illustrates the correlations between IQ scores and net expenditure on betting among those who participated at all. The composite IQ score has a positive slope indicating that net expenditure is positively correlated with IQ. Decomposed scores suggest that only the visuospatial IQ does not predict a higher level of spending. However, both verbal and in particular maths IQ strongly predict higher net expenditure on betting.

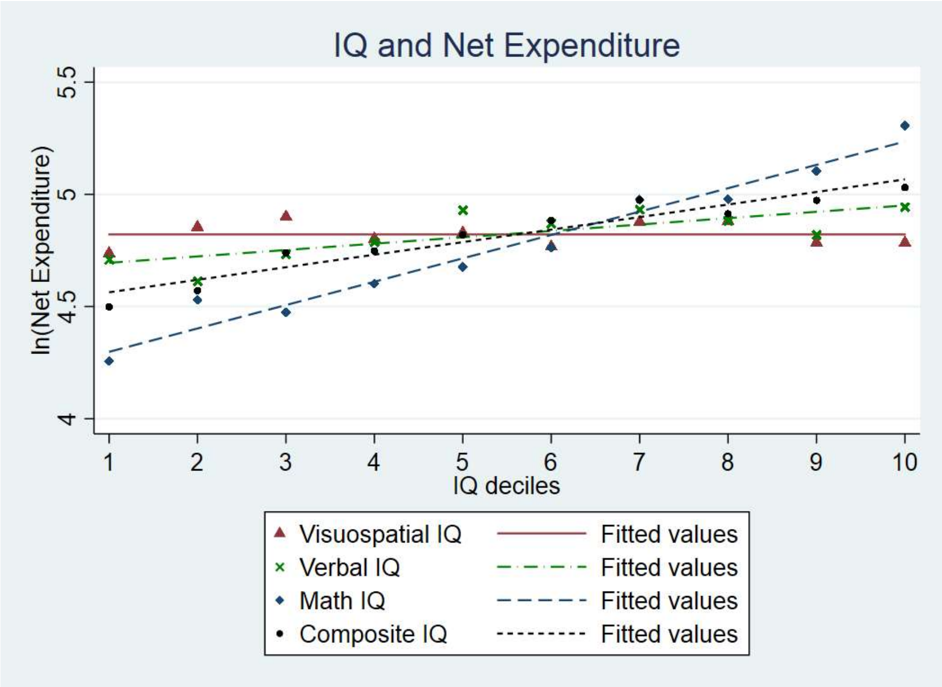

Figure 2. IQ and net spending on betting.

Figure 3 depicts how the measures of IQ are correlated with successful betting. All measures have positive slopes which indicates that a higher IQ predicts being more likely to be profitable. The effect is strongest for the maths IQ and the composite measures and weakest for visuospatial IQ.

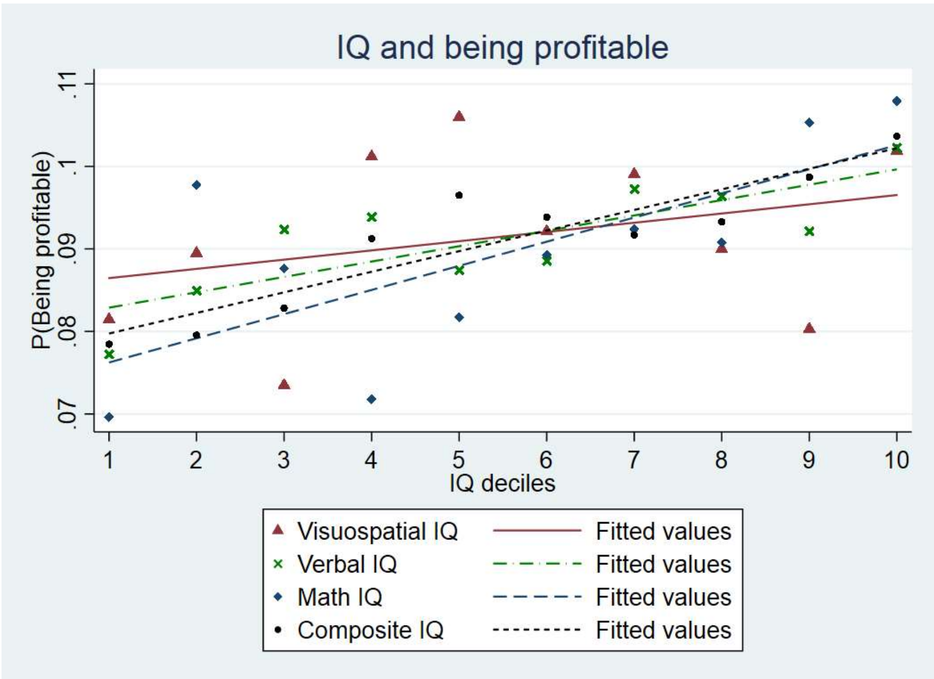

Figure 3. IQ and success in betting.

6.2 Empirical models

6.2.1 First part: Participation model

We estimate four probit models in which we estimate how the probability of being a bettor is associated with a person's IQ. In Model 1, we use composite IQ as the focus variable. In Models 2, 3 and 4, we carry out similar (separate) estimation for visuospatial, verbal and mathematical IQ. All models use the same set of control variables. We do not include all IQ variables in the same model due to high positive correlations between the variables, which may cause problematic multicollinearity (see Aspara et al., 2017). Furthermore, we interpret our results using the ceteris paribus assumption and thus it is not reasonable to assume that other cognitive abilities remain constant as one of them changes.

Table 2 reports the estimated marginal effects for Participation Model 1. The estimated coefficient on composite IQ implies that a higher IQ predicts an increased probability of being a bettor: a one standard deviation increase from the mean in composite IQ increases the predicted probability of participating in online horse betting by 0.35 percentage points (against the sample population participation rate of 2.2%)[7].

Among the control variables, a white-collar job, higher education level, urban residence, belonging to the Swedish-speaking minority and number of children are negative predictors of betting participation. In contrast, a blue-collar job, lower education level, paying the church tax, being in a cohabiting relationship and higher income are positively correlated with being a bettor. The probability of participation increases up to the age of 44.

[7] The effect size is calculated as follows $e^{\beta \times std} = e^{0.0002326 \times 15} \approx 1.0035$, in which β is the coefficient estimate and *std* is the standard deviation of the variable of interest.

Table 2. Regression results of participation model 1.

	Participation Model 1	
	Probit: participant = 1	
Focus variable	Marg. Effect	Standard error
Composite IQ	0.0002***	0.10×10^{-4}
Controls		
Age	0.0034***	0.0002
Age^2	0.39×10^{-4}***	$<0.10\times10^{-5}$
Blue-collar	0.0026***	0.0005
White-collar	-0.0016***	0.0005
Basic	0.0040***	0.0006
College	-0.0025***	0.0005
Post-graduate	-0.0114***	0.0005
Pays the church tax	0.0031***	0.0004
Log(Income)	0.0006***	0.0002
Has one child	-0.0004	0.0005
Has two or more children	-0.0041***	0.0004
Married or cohabiting	0.0014***	0.0005
Divorced or widowed	0.0002	0.0007
Urban residence	-0.0026***	0.0005
Swedish-speaker	-0.0144***	0.0005
Pseudo R^2	0.012	
Log likelihood	-73,531.076	
No. obs.	705,089	

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.
Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.

Table 3 reports the results for Participation Models 2 to 4 in which each dimension of IQ is analysed separately from the others. The estimated coefficients suggest that mathematical IQ, which is positive and significant, is the driver of the positive correlation between composite IQ and betting participation. Although verbal IQ is also positive and significant, the magnitude of the estimated coefficient on mathematical IQ is almost five time larger than the corresponding estimate on verbal IQ. Moreover, the sign of the estimated coefficient on visuospatial IQ is negative, which indicates an opposite direction for participation in betting though its impact is neither large nor statistically significant (p = 0.187). Further, the effect size of mathematical IQ in Model 3 is relatively high when compared with the effect size of composite IQ in Model 1. A standard deviation increase from the mean in mathematical IQ increases the predicted probability of participating in online horse betting by 0.74 percentage points. Thus, if a composite, hypothetical individual had the same mean characteristics as the population, there would be a 2.2% predicted probability of participation; but this would increase by about a third, to 2.9%, if he had a mathematical IQ one standard deviation above the mean.

Table 3. Regression results of participation models 2-4 on betting.

	Participation Model		
	2	3	4
	Probit: participant = 1		
	Marg. effects	Marg. effects	Marg. effects
Focus variables	(standard error)	(standard error)	(standard error)
Visuospatial IQ	-0.16×10^{-4} (0.1×10^{-4})	-	-
Verbal IQ	-	0.10×10^{-3}*** (0.1×10^{-4})	-
Maths IQ	-	-	0.49×10^{-3}*** (0.1×10^{-4})
Controls	Yes	Yes	Yes
Pseudo R^2	0.01	0.01	0.02
Log likelihood	-73,690.974	-73,658.366	-72,917.427
No. obs.	705,089	705,089	705,089

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.
Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.
Appendix B2 presents tabulated coefficient estimates on the control variables.

6.2.2 Part two: Consumption Model

In the second part, we model level of consumption of horse betting conditional on participation. Consumption is defined by either the log of total stakes or the log of net spending over the data period. As before, we run models which include either composite IQ or one of the separate components of IQ. Consequently, we estimate eight models for the level of consumption. The sample sizes used in the models differ from each other though. The models that use total stakes as the dependent variable use all bettors in the data set. However, the models that use the bettor's total loss as the dependent variable exclude (the minority of) bettors who made a net profit over the observation period.

Table 4 reports the results for consumption models 1 and 2. Composite IQ predicts a higher level of consumption whichever measure of consumption is used. First, let us consider a link between composite IQ and betting consumption quantitatively in terms of net spending. It is a more intuitive measure because it relates to real money spent on betting. Increasing the value of composite IQ by one standard deviation from the mean raises spending by 16%[8]. In monetary terms, this is equivalent to an additional €167 spent on horse betting in a year. In terms of

[8] The effect size is calculated by $e^{\beta\times std} = e^{0.0098189\times15} \approx 1.159$.

betting volume, a one standard deviation increase from the mean in composite IQ raises predicted betting volume by 21.5%, which implies a €857 increase in the amount staked.

Patterns revealed by results on control variables suggest that level of consumption among horse bettors increases with age. Elasticity with respect to income is positive but low. Membership of the lowest educational group is associated with elevated spending but differences between other educational groups are small. Blue-collar workers who bet on horses tend to spend more than white-collar workers. While urban residence was a negative predictor of participation, it predicts spending elevated by 20% compared with non-urban bettors.

Table 4. Regression results: log(Total stakes) and log(Net spending) with composite IQ.

	Consumption Model 1		**Consumption Model 2**	
	OLS			
	log(Total stakes)		log(Net spending)	
Focus variable	Coefficient	Standard error	Coefficient	Standard error
Composite IQ	0.013**	0.002	0.010**	0.001
Controls				
Age	0.168***	0.027	0.138***	0.025
Age^2	-0.002***	0.000	-0.001***	0.000
Blue-collar	-0.042	0.050	-0.035	0.046
White-collar	-0.133**	0.055	-0.116**	0.051
Basic	0.129**	0.060	0.135**	0.055
College	0.048	0.056	0.063	0.052
Post-graduate	0.073	0.085	0.045	0.080
Pays the church tax	0.094**	0.043	0.100**	0.040
Log(Income)	0.056***	0.020	0.061***	0.019
Has one child	-0.055	0.058	-0.045	0.054
Has two or more children	0.002	0.052	0.014	0.048
Married or cohabiting	-0.203***	0.061	-0.182***	0.056
Divorced or widowed	0.013	0.080	0.014	0.074
Urban residence	0.199***	0.057	0.221***	0.052
Swedish-speaker	-0.234	0.171	-0.106	0.157
Constant	-0.471	0.575	-0.310	0.532
R^2	0.03		0.03	
No. obs.	15,448		14,067	

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.
Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.

Table 5 reports other consumption models in which cognitive abilities are estimated separately. The estimations yield results that are qualitatively similar to those of the participation models. Whereas mathematical IQ is a strong positive predictor of spending, verbal IQ is only mildly positive and visuospatial IQ is negatively but not significantly associated with the level of spending. Increasing the value of the mathematical IQ score by one standard deviation from the mean increases total stakes (net spending) by 47.7% (37.7%), which is equal to approximately €1,900 (€393).

Table 5. Regression results: log(Total stakes) and log(Net spending) with the separate measures of IQ.

	Consumption Model					
	3	4	5	6	7	8
	OLS					
	log(Total stakes)			log(Net spending)		
Focus variables	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)
Visuospatial IQ	-0.001 (0.001)	-	-	-0.001 (0.001)	-	-
Verbal IQ	-	0.006*** (0.002)	-	-	0.004*** (0.001)	-
Maths IQ	-	-	0.026*** (0.001)	-	-	0.021*** (0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.025	0.026	0.046	0.025	0.025	0.042
No. obs.	15,488	15,488	15,488	14,067	14,067	14,067

Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Appendix B3 presents tabulated coefficient estimates on the control variables.

In Table 6, we report a variance decomposition of total stakes to investigate the relative contribution of each separate component of IQ in Models 1, 3-5. Although the values of R-squared are relatively low, it obtains the highest value in Model 5 in which mathematical IQ is the explanatory variable. Mathematical IQ explains almost half of the total explained variation of betting volume. Compared to this, the contributions of composite, visuospatial IQ and verbal IQ are modest at 15%, 0.20% and 3.4%, respectively. The figures add further evidence to a conclusion that mathematical IQ drives our results.

Table 6. Variance decompositions of the consumption models of betting volume.

	Variance decomposition in Models 1,3-5				
	Sum of Squares (SS)				
Specification: log(Total stakes)	Model	Residual	Total	Partial SS	Fraction of Partial SS (%)
Model 1: Composite IQ	2828.83	93005.12	95833.96	422.266	14.93
Model 3: Visuospatial IQ	2411.31	93422.65	95833.96	4.739	0.20
Model 4: Verbal IQ	2490.88	93343.08	95833.96	84.309	3.38
Model 5: Maths IQ	4396.93	91437.02	95833.96	1990.365	45.27

Note: Models included all control variables presented in Table 4.

6.2.3 Success Model

Next, we model the bettor's success in wagering using two measures for success. These measures are 'being a winner' and 'beating the track', which means that successful bettors have outperformed their peers in a mathematical sense as explained in Section 5. As was the case with the participation and consumption models, we estimate separate models for composite IQ and its three components resulting in eight 'success' models.

To validate that a one-year period is sufficiently long in separating successful bettors from the rest, we test how being a successful bettor in the first half (six months) of our observation period predicts being successful in the latter half of the observation period. The results suggest that 'being a winner' in the first half increases the probability of 'being a winner' in the second half by five percentage points, which is statistically significant. Similarly, 'beating the track' in the first half increases the probability of 'beating the track' in the latter half by 11 percentage points[9].

Regarding the entire observation period, 9% of the bettors were winners and 23% of them were able to 'beat the track'. The left-hand panel of Table 7 reports the estimates for the probability of a bettor making a profit in the one-year period. In Model 1, the coefficient estimate on composite IQ is not statistically significant. The right-hand panel of Table 7 reports the estimates for 'beating the track'. Although the results are comparable to the 'being a winner' model, they suggest that composite IQ slightly increases the probability of 'beating the track'.

The results for background variables suggest that some of them are associated with being profitable. First, the probability of profitability increases with age up to the age of 45. Second, urban residents are more likely to make a profit. Third, a higher level of education is a predictor of being profitable. More precisely, a bachelor's and postgraduate degree as the highest level of education increases the probability by 2 and 3 percentage points, respectively. These figures are relatively high compared with the consumption models in which a higher education level did not play a significant role.

[9] The results of the probit estimations are presented in Appendix B4.

Table 7. Regression results: success models with composite IQ.

	Success Model 1		Success Model 2	
	Probit			
	'Being a winner'		'Beating the track'	
Focus variable	Marginal effect	Standard error	Marginal effect	Standard error
Composite IQ	0.0002	0.0002	0.0008***	0.0003
Controls				
Age	0.0089***	0.0032	0.0185***	0.0047
Age^2	-0.0001***	0.4×10^{-4}	-0.0002***	0.0001
Blue-collar	-0.0009	0.0060	0.0041	0.0087
White-collar	0.0002	0.0064	-0.0021	0.0094
Basic	-0.0059	0.0070	-0.0160	0.0102
College	0.0195***	0.0069	0.0271***	0.0097
Post-graduate	0.0307***	0.0114	0.0661***	0.0158
Pays the church tax	-0.0043	0.0050	-0.0019	0.0073
Log(Income)	0.0025	0.0025	0.0024	0.0035
Has one child	0.0030	0.0069	-0.0052	0.0099
Has two or more children	-0.0038	0.0061	-0.0078	0.0088
Married or cohabiting	-0.0025	0.0072	-0.0160	0.0105
Divorced or widowed	0.0128	0.0099	0.0154	0.0138
Urban residence	0.0159**	0.0063	0.0129	0.0096
Swedish-speaker	-0.0145	0.0185	-0.0350	0.0273
Pseudo R^2	0.006		0.007	
Log likelihood	-4,706.6639		-8,210.7527	
No. obs.	15,488		15,488	

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.
Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.

Results of the success models 3 to 8, in which the components of IQ are estimated separately are presented in Table 8. They suggest that mathematical IQ is a positive predictor of being a winner as well as of 'beating the track'. Increasing the value of mathematical IQ by one standard deviation from the mean increases the probability of being a winner by less than half a percentage point and the probability of beating the track by less than three percentage points, respectively. The estimated coefficients on visuospatial and verbal IQ are not significant, however.

Table 8. Regression results: success models with the separate measures of IQ.

	Success Model					
	3	**4**	**5**	**6**	**7**	**8**
	Probit					
	'Being a winner'			'Beating the track'		
Focus variables	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)
Visuospatial IQ	0.12×10^{-5} (0.0002)	-	-	-0.0001 (0.0003)	-	-
Verbal IQ	-	-0.65×10^{-4} (0.18×10^{-3})	-	-	-0.0004 (0.0003)	-
Maths IQ	-	-	0.0002* (0.0001)	-	-	0.0017*** (0.0003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.006	0.006	0.006	0.006	0.006	0.009
Log likelihood	-4,707.0844	-4,707.0191	-4,705.2859	-8,215.7661	-8,214.6133	-8,191.661
No. obs.	15,488	15,488	15,488	15,488	15,488	15,488

Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Appendix B5 presents the tabulated coefficient estimates on the control variables.

6.2.4 Links between success and consumption

While the tendency of higher IQ to be associated with greater participation in, and volume of, betting undermines the claim that 'gambling is a tax on stupidity', it might be tempting to argue that, *within* the betting population, the pari-mutuel system generates a redistribution of wealth from a group of lower-IQ individuals to a group of higher-IQ individuals. Certainly our results suggest that higher IQ-individuals are more likely than others to be winners over the year (and they are also more likely at least to 'beat the track'). On the other hand, they are also likely to stake much more than the average participant and hence their losses tend actually to be substantially greater in absolute terms notwithstanding their superior 'performance'. For example, results in Section 6.2.2 above predict that increasing mathematical IQ by a one standard deviation from the mean increases annual amount wagered by 47.7% and annual loss (net spending) by 37.7%. The gap between these two estimates reflects superior performance by higher mathematical IQ individuals but, nevertheless, each on average loses substantially more in absolute terms than a bettor with mean mathematical IQ. Therefore a high-mathematical IQ participant is likely to make a greater contribution to prize payouts, operating costs and operator profit compared with a player with average mathematical IQ. Again there is no obvious ground in the data for representing the betting product as effectively a tax on those with lower cognitive ability.

6.2.5 Robustness checks: regular bettors

To ensure that random players who wager only occasionally are not driving our results, we run a robustness check by estimating the consumption model on a sample of regular bettors. We define a bettor as regular if he wagers at least 50 times during the year, i.e., approximately once a week or more often. The subsample includes 4,573 bettors. This analysis removes much of the randomness from the sample. Further, it is possible that motivation is a key factor in success in betting. If high-IQ individuals are disproportionately likely to be motivated to bet regularly, any success they achieve as a group may be explained by motivation rather than skill alone. However, since motivation cannot be directly observed in our data, we run a robustness check by estimating the success models for a sample of regular bettors to check whether our results are congruent in this context as well. The detailed results of estimations are presented in Appendix B6 and B7.

In the consumption model, the results reveal a pattern that is similar to the baseline results in terms of math IQ and verbal IQ, namely a positive relation between consumption and IQ. However, they also indicate that visuospatial IQ is positively correlated with consumption, which was negative though insignificant in the baseline results. In other words, our findings constitute evidence that all components of IQ are positive predictors of consumption when only the most active players are considered. This, in turn, may indicate that when a player is a motivated gambler, neither mathematical IQ nor visuospatial IQ acts as a deterrent for consumption.

In the success model, the results are in line with the baseline results except for the fact that along with math IQ, composite IQ and verbal IQ also predict success. In the baseline models, the estimates on composite IQ and verbal IQ were positive but not statistically significant. These findings points to IQ being a more relevant ability in this subgroup of players: bettors are motivated to use their 'human capital' to achieve a higher performance in horse race betting.

7. Discussion

This paper examines whether participation in betting, expenditure on betting and success in betting are correlated with measures of cognitive ability. We use a unique individual-level real-world dataset from three data sources: actual gambling consumption data from the betting monopoly company, cognitive ability test score data from the Finnish Defence Forces and socio-economic administrative registry data from Statistics Finland. We find that a person's general intelligence is positively associated with his betting consumption. Our findings also indicate that for the most part, this result can be attributed to mathematical intelligence. That is, persons who score highly in mathematical aptitude tests exhibit a higher probability of participating in horse betting and they also tend to spend more on betting. Our results are economically significant as they suggest that a one standard deviation increase in mathematical IQ increases the probability of having a betting account by more than a third and the bettor's annual amount staked (net spending) by a half (40%). We also find that mathematical IQ and a higher education level are positively associated with performance in betting. To a large extent, our results are robust to alternative model specifications.

Our results can be viewed as consistent with other studies which examine correlations between an individual's cognitive ability and economic decisions. Our results are consistent with Grinblatt et al. (2011) who find that intelligence is positively correlated with an individual's decision to invest in the stock market. To some extent, our results are also consistent with Grinblatt et al. (2012) who report high-IQ investors earning higher returns on their investments. One could surmise that investing in stocks and betting on horses share qualities, such as gathering relevant information on assets in the market, which appeal to or alternatively benefit high-IQ individuals. In other words, horse betting is a skill-based form of gambling akin to placing bets in the stock market, which manifests itself in the observed higher expenditure on betting by high-IQ men in our data.

An additional contribution in our paper compared with Grinblatt et al. (2011; 2012) is that our results are able to point to mathematical intelligence as the driver behind this behaviour. Our findings, which suggest that a high mathematical IQ improves performance in betting are consistent with those of Agarwal and Mazumder (2013), Gerardi et al. (2013) and Aspara et al. (2017), all of which report a positive correlation between numerical ability and performance in economic decisions. Furthermore, our findings are also, to some extent, in line with D'Acuno et al. (2019b) and (2019c) who report high-IQ individuals being superior in their inflation forecasts.

Our findings lend support to the theories which regard gambling as a rational choice as illustrated by Friedman and Savage (1948) and by Conlisk (1993), who argues that gambling has an intrinsic utility or entertainment value. In this respect, our results can be interpreted against the paternalistic and liberal perspectives on gambling markets. If the gambler's cognitive ability is considered a proxy for the need for consumer protection, our results are congruent with the liberal perspective: high-IQ individuals, especially those with a high math ability, can evaluate whether gambling is 'valuable' to them as they appear to prefer engaging in it. Hence, concerns over gamblers' cognitive ability may not warrant excessive market intervention, barring negative externalities of gambling problems to individuals and society. That is, some level of market regulation is necessary to mitigate the social cost of problem gambling. However, gambling in general cannot be regarded as a harmful hobby because it is possible that mathematically intelligent persons are hard-wired to engage in activities that involve "crunching numbers" and assessing probabilistic events.

This paper has limitations which should be taken into account when interpreting results. Foremost, our data set includes only online horse race betting data, which is a skill-based form of gambling. Consequently, we lack data on chance-based forms of gambling (and on off-line horse race bets). Although we cannot be certain whether our results are generalizable to other forms of gambling, recent findings of Forrest and McHale (2018) support the claim that mathematical intelligence predicts more general engagement in gambling. In particular, they report that individuals with a high numerical ability are more likely to participate in games of pure chance as well as in skill-based games than individuals with a low mathematical ability. Further support can be found in the Finnish Gambling Prevalence Survey (2015) which shows that 97% of horse bettors also participate in other games of chance (e.g., lotteries, scratch cards etc.)[10]. Similar findings have been reported in the US market in which horse bettors also buy lotteries and gamble in casinos (Walker and Jackson 2008). At the minimum, they indicate that the relatively high-IQ horse betting population is not shy of participating also in games of pure chance. A limitation of the FDF data set is that it only concerns the Finnish male population. Hence, our conclusions should be treated with caution because we do not have IQ test scores for females. Finally, the data is from a limited time interval and from a limited geographical area. Thus, data spanning longer time periods and data from other countries could yield different results.

Our research implies that rather than examining only a general measure of IQ, future studies should focus on the separate components of intelligence and investigate how they predict

[10] A rudimentary analysis of the Finnish Gambling Prevalence Survey data is available from the authors upon request.

economic decision-making. Most notably, since wagering on horses is traditionally regarded as akin to investing in financial assets, future studies could investigate whether mathematical intelligence is also a driver behind retail investors' asset purchases and performance in the financial markets. This line of research could be extended to other domains of economic research as well, because mathematical reasoning could be instrumental in decisions relating to consumption and investment. Regarding betting behaviour and our data set, our aim for future studies is to investigate how intelligence and its subcomponents are correlated with a person's risk preferences in general. This information may also shed light on gambling consumption in a more detailed manner.

8. Concluding remarks

It is common to regard gambling as a lower form of pleasure with an elitist perception of gamblers as either ignorant or exhibiting poor mathematical skills. However, the results presented in this study point in another direction. We find that intelligence is positively correlated with expenditure on horse betting. Moreover, our results suggest that high mathematical intelligence predicts participation in, expenditure on and success in horse betting. Hence, rather than being misguided individuals in need of a paternalistic intervention, our results are consistent with gambling, or at least horse betting, being consumption of entertainment, which intelligent individuals enjoy. As the winner of the second Nobel Prize in Economics, Paul Samuelson (1952) remarked: "When I go to a casino, I go to not alone for the dollar prizes but also for the pleasures of gaming – for the soft lights and the sweet music."

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Appendix A1.

Pari-mutuel betting system

To illustrate how the pari-mutuel betting system works, consider a horse race with $i = 1 \ldots n$ horses (outcomes) with bettors wagering on the winner of the race (Win bet). The odds for the horse i winning the race, O_i, are derived from the wagers placed on the horse i relative to the bets placed on all $i = 1 \ldots n$ horses running in the race. Thus, O_i can be written as

$$O_i = \left(\frac{b_i}{\sum_{i=1}^{n} b_i} \right)^{-1} (1 - \tau_0), \qquad \text{(A.1)}$$

where b_i denotes all wagers placed on the horse i, $\sum_{i=1}^{n} b_i$ is the sum of all bets placed on all n horses, and τ_0 is the operator's take-out rate. In other words, the proportion of bets placed on each outcome relative to the total pool of bets in the race reflects the market information on the winning probabilities of the horses. More complex betting types are similar in principle.

Appendix A2.

Betting environment

Our data set has information on all bets placed at the monopoly operator's online betting platform between September 1, 2015 and August 31, 2016. Given that 2016 was a leap year, the data period was 366 days. Betting was available on all of the days except Christmas Eve and Christmas Day, so we observe each player's bets on each of 364 days.

Online horse race bettors have a wide variety of race meetings available to wager on. In addition to horse race meetings in Finland, a bettor may wager on races in nine other countries. The races are mainly harness trot racing, but thoroughbred racing and Monte racing are also featured. The main betting days in Finland are Wednesdays and Saturdays. On each day, betting typically starts in the morning with foreign thoroughbred races. During the afternoon trotting races in the Nordic countries are available. The main domestic trotting race meetings are held in the evening. After this, there are night trotting events mainly from Sweden. Recently, the supply of foreign horse races has been increasing (e.g. gallop events). While their share of total turnover has increased from 15% in 2015 to 22% in 2016, the main volume still originates from domestic race meetings. Finnish races are not offered widely on international markets, so betting on Finnish races takes place within a somewhat closed betting environment.

Types of bet. The data include full information on all fifteen betting types available in horse race betting in Finland. These can be divided into types of bet that relate to a single race and those which relate to multiple races.

Table A2.1. Definitions of bet types, their share of total turnover and takeout rate.

Bet type	Definition of bet type	Portion of total turnover (%)	Takeout rate (%)
Quinella	The first two horses of a race in the finishing order regardless of their order.	28.06	15
Pick 4	The winners of four consecutive races. No consolidation wins.	13.34	35
Trifecta	The first three horses of a race in correct order.	13.32	30
Win	The winner horse of a race.	7.53	15
Pick 76	The winners of seven consecutive races, a consolation win for 6 correct picks.	6.57	35
Pick 64	The winners of six consecutive races, consolation wins for 5 and 4 correct picks.	6.56	35
Pick 75	The winners of seven consecutive races, consolation wins for 6 and 5 correct picks.	6.12	35
Pick 65	The winners of six consecutive races, a consolation win for 5 correct picks.	5.55	35
Place	Pick a horse that finish in the first three of a race.	3.96	15
Pick 5	The winners of five consecutive races. No consolation wins.	3.48	35
Duo	The winners of two consecutive races.	3.34	25
Each Way	Consisting of two separate sub-bets: Win and a Place	1.21	15
Exacta	The first two horses of a race in correct order.	0.50	25
Pick 86	The winners of eight consecutive races, consolation wins for 7 and 6 correct picks.	0.40	35
Swinger	Two horses that both finish either as the first, second or third in a race.	0.03	25

Appendix A3.

FDF IQ test scores

FDF has administered a cognitive ability test to all conscripts since 1955. It is a multiple-choice test to be completed in two hours using pencil and paper. The conscripts usually take the test during their second week of military service. The raw data exclude the test scores for the non-conscript FDF personnel as well as for the soldiers serving with the Finnish Border Guard. We dropped female conscripts from our analysis because the IQ data and the betting data contain a limited number of females and few of them will have served in the military.

The questionnaire used in the FDF cognitive ability test is classified. Thus, we are unable to provide its details to the reader. However, the contents of its subtests are described in more detail in Tiihonen et al. (2005). According to them, the verbal reasoning subtest contains four types of questions in which a subject: 1) chooses synonyms or antonyms for a word, 2) selects a word belonging to the same category as a given word pair, 3) infers which word in a list of words does not belong to the list, and 4) assigns relationships between two word pairs. The subtest for arithmetic reasoning comprises four types of problem. The subject has to complete a series of numbers that have been arranged to follow a certain rule, to solve verbally expressed short problems, to compute simple arithmetic operations, and to assign relationships between two pairs of numbers. The visuospatial reasoning task is a set of matrices containing a pattern problem with one part removed. The subject is asked to decide which one of the given figures completes the matrix. The visuospatial reasoning test is a standard "culture-free" intelligence test based on Raven's progressive matrices, and therefore its results should be less affected by pretest schooling (Pekkala et al., 2013).

A3. References

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Appendix B1

Variable definitions

Table B1.1. Variable definitions.

Variable name	Time period	Definition
- Dependent variables -		
Participant	1st Sep 2015-31st of Aug 2016	=1 if individual participates at least once in online horse race betting, 0 otherwise
Total stakes	1st Sep 2015-31st of Aug 2016	= ln(Total stakes)
Net spending	1st Sep 2015-31st of Aug 2016	= ln (Net spending), not defined for bettors who won over the year
'Beating the track'	1st Sep 2015-31st of Aug 2016	= 1 if individual has lost less than expected according to the track take-out, 0 otherwise
'Being a winner'	1st Sep 2015-31st of Aug 2016	= 1 if individual has made a profit from betting over the year, 0 otherwise
- Independent variables -		
Age	31st of Dec 2015	= person's age in full years
Age^2	31st of Dec 2015	= square of age
Blue-collar	31st of Dec 2015	= 1 if person's socio-economic status is manual worker, 0 otherwise
White-collar	31st of Dec 2015	= 1 if person's socio-economic status is clerical worker, professional or executive, 0 otherwise
Entrepreneur	31st of Dec 2015	= 1 if person's socio-economic status is entrepreneur, 0 otherwise
Pensioner	31st of Dec 2015	= 1 if person's socio-economic status is pensioner, 0 otherwise
Student	31st of Dec 2015	= 1 if person's socio-economic status is student, 0 otherwise
Unemployed	31st of Dec 2015	= 1 if person's socio-economic status is unemployed, 0 otherwise= 1
Other	31st of Dec 2015	= 1 if person's socio-economic status is unknown, 0 otherwise
Basic	31st of Dec 2015	= 1 if person's highest education qualification is basic education, 0 otherwise
Secondary	31st of Dec 2015	= 1 if person's highest education qualification is secondary education (e.g. vocational school, special vocational school, commercial school etc.), 0 otherwise
College	31st of Dec 2015	= 1 if person's highest education qualification is college education (e.g. Bachelor degree in Science or Engineering etc.), 0 otherwise
Post-graduate	31st of Dec 2015	= 1 if person's highest education qualification is master's degree or doctoral thesis, 0 otherwise
Pays the church tax	31st of Dec 2015	= 1 if individual pays Church taxes, 0 otherwise.
Log(Income)	31st of Dec 2015	= ln(disposable income of individual +1€).

Has no children	31st of Dec 2015	= 1 if individual has no children, 0 otherwise
Has one child	31st of Dec 2015	= 1 if individual has one child, 0 otherwise
Has two or more children	31st of Dec 2015	= 1 if individual has at least two children, 0 otherwise
Single	31st of Dec 2015	= 1 if person lives alone and has never married. 0 otherwise
Married or cohabiting	31st of Dec 2015	= 1 if person lives in a relationship (cohabiting or married), 0 otherwise
Divorced or widowed	31st of Dec 2015	= 1 if persons is divorced or widowed and does not live in a relationship (cohabiting or married), 0 otherwise
Urban residence	31st of Dec 2015	= 1 if individual's municipality of domicile is an urban or semi-urban municipality, 0 otherwise.
Finnish-speaker	31st of Dec 2015	=1 if 1 if individual's native language is Finnish, 0 otherwise.
Swedish-speaker	31st of Dec 2015	= 1 if individual's native language is Swedish, 0 otherwise.
Composite IQ	1982-2010	Arithmetic average of Visuospatial, Verbal and Maths IQ test scores that is yearly normalised (with mean 100 and SD 15). The composite IQ is available for conscripts who performed their military service between 1982 and 2010.
Visuospatial IQ	1982-2010	Yearly normalised (with mean 100 and SD 15) visuospatial IQ test scores for conscripts who undertook their military service between 1982 and 2010.
Verbal IQ	1982-2010	Yearly normalised (with mean 100 and SD 15) IQ test scores for conscripts who undertook their military service between 1982 and 2010.
Maths IQ	1982-2010	Yearly normalised (with mean 100 and SD 15) maths IQ test scores for conscripts who undertook their military service between 1982 and 2010.

Summary statistics

Table B1.2. Summary statistics for males with IQ measures.

	N	Mean	sd	p50	p10	p90
- Dependent variables -						
Participant	705,089	.02	.15	0	0	0
- Independent variables -						
Age	705,089	39.94	8.46	40	28	51
Blue-collar	705,089	0.30	0.46	0	0	1
White-collar	705,089	0.38	0.49	0	0	1
Pensioner	705,089	0.03	0.16	0	0	0
Unemployed	705,089	0.11	0.31	0	0	1
Student	705,089	0.03	0.17	0	0	0
Entrepreneur	705,089	0.11	0.32	0	0	1
Other	705,089	0.04	0.19	0	0	0
Basic	705,089	0.12	0.32	0	0	1
Secondary	705,089	0.53	0.50	1	0	1
College	705,089	0.23	0.42	0	0	1
Post-graduate	705,089	0.13	0.33	0	0	1
Pays the church tax	705,089	0.65	0.48	1	0	1
Income	705,089	31,178.80	67,455.42	27,724	12,134	47,672
Has no children	705,089	0.43	0.50	0	0	1
Has one child	705,089	0.19	0.39	0	0	1
Has two or more children	705,089	0.38	0.48	0	0	1
Single	705,089	0.19	0.39	0	0	1
Married or cohabiting	705,089	0.68	0.47	1	0	1
Divorced or widowed	705,089	0.13	0.34	0	0	1
Urban residence	705,089	0.87	0.33	1	0	1
Finnish-speaker	705,089	0.95	0.21	1	1	1
Swedish-speaker	705,089	0.04	0.20	0	0	0
Other first language	705,089	0.49×10^{-2}	0.07	0	0	0
Composite IQ	705,089	100	15	100.87	79.94	118.84
Visuospatial IQ	705,089	100.01	14.98	101.47	80.02	117.66
Verbal IQ	705,089	100.01	14.98	100.15	80.34	119.51
Maths IQ	705,089	100.02	14.99	100.54	79.51	119.06

Table B1.3. Summary statistics for male horse race bettors with IQ measures.

	N	Mean	sd	p50	p10	p90
- Dependent variables -						
Bet volume	15,488	3,980.56	25,888.60	230.85	13.6	7,702.55
Log(Bet volume)	15,488	5.5.57	2.49	5.44	2.61	8.95
Net spending	14,067	734.47	7,985.75	78.90	0.60	2,153.65
Log(Net spending)	14,067	4.82	2.19	4.68	2.24	7.79
‘Being a winner’	15,488	0.09	0.29	0	0	0
‘Beating the track’	15,488	0.23	0.42	0	0	1
- Independent variables -						
Age	15,488	40.95	8.06	42	29	51
Blue-collar	15,488	0.35	0.48	0	0	1
White-collar	15,488	0.34	0.47	0	0	1
Pensioner	15,488	0.02	0.16	0	0	0
Unemployed	15,488	0.12	0.33	0	0	1
Student	15,488	0.02	0.14	0	0	0
Entrepreneur	15,488	0.12	0.32	0	0	1
Other	15,488	0.03	0.18	0	0	0
Basic	15,488	0.14	0.35	0	0	1
Secondary	15,488	0.56	0.50	1	0	1
College	15,488	0.22	0.42	0	0	1
Post-graduate	15,488	0.08	0.26	0	0	0
Pays the church tax	15,488	0.67	0.47	1	0	1
Income	15,488	30,936.04	50,964.18	27,865.50	13,332	45,077
Has no children	15,488	0.45	0.50	0	0	1
Has one child	15,488	0.20	0.40	0	0	1
Has two or more children	15,488	0.35	0.48	0	0	1
Single	15,488	0.19	0.39	0	0	1
Married or cohabiting	15,488	0.69	0.46	1	0	1
Divorced or widowed	15,488	0.12	0.33	0	0	1
Urban residence	15,488	0.86	0.35	1	0	1
Finnish-speaker	15,488	0.99	0.12	1	1	1
Swedish-speaker	15,488	0.01	0.12	0	0	0
Other first language	15,488	0.10×10^{-2}	0.04	0	0	0
Composite IQ	15,488	100.82	14.33	101.53	81.79	118.80
Visuospatial IQ	15,488	99.07	14.41	100.71	80.02	116.71
Verbal IQ	15,488	100.04	14.22	100.15	81.80	118.68
Maths IQ	15,488	103.1	14.88	103.58	82.91	122.00

Appendix B2

Table B2. Regression results of betting participation models 2-4.

	Participation Model 2	**Participation Model 3**	**Participation Model 4**
	Probit: participant = 1		
	Marg. effects	Marg. effects	Marg. effects
Focus variables	(standard error)	(standard error)	(standard error)
Visuospatial IQ	-0.16×10^{-4} (0.1×10^{-4})	-	-
Verbal IQ	-	0.0001*** (0.1×10^{-4})	-
Maths IQ	-	-	0.0005*** (0.1×10^{-4})
Controls			
Age	0.0031*** (0.0002)	0.0032** (0.0002)	0.0035*** (0.0002)
Age^2	-0.35×10^{-4}*** ($<0.10\times10^{-5}$)	-0.37×10^{-4}*** ($<0.10\times10^{-5}$)	-0.41×10^{-4}*** ($<0.10\times10^{-5}$)
Blue-collar	0.0023*** (0.0005)	0.0024*** (0.0005)	0.0031*** (0.0005)
White-collar	-0.0007 (0.0005)	-0.0011** (0.0005)	-0.0022*** (0.0005)
Basic	0.0024*** (0.0006)	0.0030*** (0.0006)	0.0054*** (0.0006)
College	-0.0009* (0.0005)	-0.0016*** (0.0005)	-0.0039*** (0.0004)
Post-graduate	-0.0092*** (0.0005)	-0.010*** (0.0005)	-0.0132*** (0.0004)
Pays the church tax	0.0025*** (0.0004)	0.0028*** (0.0004)	0.0034*** (0.0003)
Log(Income)	0.0006*** (0.0002)	0.0006*** (0.0002)	0.0005*** (0.0002)
Has one child	-0.0005 (0.0005)	-0.0004 (0.0041)	-0.0004 (0.0005)
Has two or more children	-0.0041*** (0.0004)	-0.0041*** (0.0004)	-0.0041*** 0.0004
Married or cohabiting	0.0018*** (0.0005)	0.0016*** (0.0005)	0.0015*** (0.0005)
Divorced or widowed	0.0002 (0.0007)	0.0002 (0.0007)	0.0004 (0.0007)
Urban residence	-0.0020*** (0.0005)	-0.0022*** (0.0005)	-0.0031*** (0.0005)
Swedish-speaker	-0.0152*** (0.0005)	-0.0147*** (0.0005)	-0.0136*** (0.0005)
Pseudo R^2	0.010	0.011	0.021
Log likelihood	-73,690.974	-73,658.366	-72,917.427
No. obs.	705,089	705,089	705,089

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.

Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.

Appendix B3

Table B3.1. Regression results: log(Total stakes) and log(Net spending) with the separate measures of IQ.

	Consumption Model 3	Consumption Model 4	Consumption Model 5	Consumption Model 6	Consumption Model 7	Consumption Model 8
	OLS					
	log(Total stakes)			log(Net spending)		
Focus variables	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)
Visuospatial IQ	-0.001 (0.001)	-	-	-0.0013 (0.0013)	-	-
Verbal IQ	-	0.006*** (0.002)	-	-	0.004*** (0.001)	-
Maths IQ	-	-	0.026*** (0.001)	-	-	0.021*** (0.001)
Controls						
Age	0.158*** (0.027)	0.165*** (0.027)	0.169*** (0.027)	0.130*** (0.025)	0.134*** (0.025)	0.139*** (0.025)
Age^2	-0.001*** ($<0.10\times10^{-4}$)	-0.002*** ($<0.10\times10^{-4}$)	-0.002*** ($<0.10\times10^{-4}$)	-0.001*** ($<0.10\times10^{-4}$)	-0.001*** ($<0.10\times10^{-4}$)	-0.001*** ($<0.10\times10^{-4}$)
Blue-collar	-0.053 (0.050)	-0.049 (0.050)	-0.018 (0.050)	-0.043 (0.047)	-0.040 (0.047)	-0.015*** (0.046)
White-collar	-0.085 (0.055)	-0.107* (0.055)	-0.175*** (0.055)	-0.078 (0.051)	-0.094* (0.0505)	-0.151** (0.051)
Basic	0.057 (0.060)	0.090 (0.060)	0.185*** (0.059)	0.079 (0.055)	0.103* (0.055)	0.183*** (0.055)
College	0.134** (0.055)	0.096* (0.055)	-0.036 (0.055)	0.130** (0.051)	0.103** (0.051)	-0.008 (0.051)
Post-graduate	0.252*** (0.084)	0.168** (0.086)	-0.102 (0.084)	0.187** (0.079)	0.126 (0.080)	-0.104 (0.079)
Pays the church tax	0.064 (0.043)	0.079* (0.043)	0.106** (0.042)	0.076* (0.040)	0.087** (0.040)	0.110*** (0.039)
Log(Income)	0.059*** (0.020)	0.058*** (0.020)	0.057*** (0.020)	0.063*** (0.019)	0.063*** (0.019)	0.061*** (0.019)
Has one child	-0.056 (0.059)	-0.054 (0.058)	-0.058 (0.058)	-0.046 (0.054)	-0.044 (0.054)	-0.046 (0.054)
Has two or more children	0.002 (0.052)	0.003 (0.052)	-0.007 (0.052)	0.0181 (0.057)	0.014 (0.048)	0.009 (0.048)
Married or cohabiting	-0.204*** (0.061)	-0.205*** (0.061)	-0.180*** (0.060)	-0.181*** (0.057)	-0.182*** (0.056)	-0.164*** (0.056)
Divorced or widowed	0.005 (0.080)	0.007 (0.080)	0.035 (0.079)	0.008 (0.074)	0.010 (0.074)	0.031 (0.073)
Urban residence	0.226*** (0.057)	0.217*** (0.057)	0.164*** (0.056)	0.240*** (0.052)	0.234*** (0.052)	0.193 (0.052)
Swedish-speaker	-0.309* (0.171)	-0.252 (0.172)	-0.210 (0.169)	-0.164 (0.157)	-0.125 (0.157)	-0.088 (0.156)
Constant	1.046* (0.571)	0.255 (0.580)	-1.865*** (0.567)	0.881* (0.528)	0.311 (0.535)	-1.479*** (0.525)
R^2	0.025	0.026	0.046	0.025	0.025	0.042
No. obs.	15,488	15,488	15,488	14,067	14,067	14,067

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.
Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.

Appendix B4

Table B4.1. Marginal effects of regression results for ‘beating the track last 6 months’ and ‘being a winner last 6 months’.

	Model 1		Model 2	
	‘Being a winner last 6 months’		‘Beating the track last 6 months’	
Focus variable	Marg. effect	Standard error	Marg. effect	Standard error
‘Being a winner first 6 months’	0.0456***	0.0113	-	-
‘Beating the track first 6 months’	-	-	0.1065***	0.0108
Composite IQ	0.001	0.0002	0.0013***	0.0004
Controls				
Age	-0.0033	0.0044	0.0062	0.0064
Age^2	0.28×10^{-4}	0.0001	-0.78×10^{-4}	0.0001
Blue-collar	0.0017	0.0080	0.0054	0.0115
White-collar	0.0128	0.0087	0.0045	0.0123
Basic	0.0086	0.0099	0.0020	0.0138
College	0.0119	0.0089	0.0327	0.0127
Post-graduate	0.0171*	0.0139	0.0598	0.0200
Pays the church tax	-0.0099*	0.0068	-0.0008	0.0097
Log(Income)_	0.20×10^{-4}	0.0030	0.0027	0.0045
Has one child	0.0026	0.0093	0.0030	0.0132
Has two or more children	0.0115	0.0083	-0.0084	0.0117
Married or cohabiting	-0.0039	0.0097	-0.0077	0.0138
Divorced or widowed	0.0046	0.0126	0.0099	0.0180
Urban residence	0.0075	0.0086	0.0150	0.0126
Swedish-speaker	0.0153	0.0293	0.0186	0.0408
Pseudo R^2	0.007		0.016	
Log likelihood	-3,145.1383		-5,356.7657	
No. obs.	9,633		9,633	

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.
Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.

Appendix B5

Table B5.1. Regression results: success models with the separate measures of IQ.

	Success Model 3	Success Model 4	Success Model 5	Success Model 6	Success Model 7	Success Model 8
	Probit					
	'Being a winner'			'Beating the track'		
Focus variables	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)
Visuospatial IQ	0.12×10^{-5} (0.0002)	-	-	-0.0001 (0.0002)	-	-
Verbal IQ	-	0.65×10^{-4} (0.0002)	-	-	0.0004 (0.0003)	-
Maths IQ	-	-	0.0003* (0.0002)	-	-	0.0017*** (0.0003)
Controls						
Age	0.0088*** (0.0032)	0.0089*** (0.0032)	0.0089*** (0.0032)	0.0178*** (0.0047)	0.0184*** (0.0047)	0.0186*** (0.0047)
Age^2	-0.0001*** (0.10×10^{-4})	-0.0001*** (0.40×10^{-4})	-0.0001*** (0.40×10^{-4})	-0.0002*** (0.0001)	-0.0002*** (0.0001)	-0.0002*** (0.0001)
Blue-collar	-0.0011 (0.0060)	-0.0010 (0.0060)	-0.0006 (0.0060)	0.0032 (0.0087)	0.0036 (0.0087)	0.0057 (0.0087)
White-collar	0.0007 (0.0064)	-0.0005 (0.0064)	-0.0003 (0.0063)	0.0011 (0.0094)	-0.0005 (0.0094)	-0.0050 (0.0093)
Basic	-0.0067 (0.0070)	-0.0064 (0.0070)	-0.0052 (0.0070)	-0.0206** (0.0100)	-0.0181* (0.0101)	-0.0126 (0.0102)
College	0.0206*** (0.0069)	0.0202*** (0.0069)	0.0184*** (0.0069)	0.0331*** (0.0097)	0.0300*** (0.0097)	0.0216** (0.0096)
Post-graduate	0.0332*** (0.0113)	0.0322*** (0.0115)	0.0283*** (0.0112)	0.0797*** (0.0158)	0.0724*** (0.0159)	0.0538*** (0.0154)
Pays the church tax	-0.0047 (0.0050)	-0.0046 (0.0050)	-0.0042 (0.0050)	-0.0040 (0.0073)	-0.0029 (0.0073)	-0.0012 (0.0073)
Log(Income)	0.0026 (0.0025)	0.0026 (0.0025)	0.0026 (0.0025)	0.0026 (0.0035)	0.0025 (0.0035)	0.0025 (0.0035)
Has one child	0.0030 (0.0069)	0.0030 (0.0068)	0.0029 (0.0069)	-0.0052 (0.0099)	-0.0051 (0.0099)	-0.0055 (0.0099)
Has two or more children	-0.0037 (0.0061)	-0.0037 (0.0060)	-0.0040 (0.0061)	-0.0077 (0.0088)	-0.0077 (0.0088)	-0.0085 (0.0088)
Married or cohabiting	-0.0026 (0.0072)	-0.0025 (0.0072)	-0.0022 (0.0072)	-0.0160 (0.0105)	-0.0161 (0.0105)	-0.0145 (0.0105)
Divorced or widowed	0.0127 (0.0099)	0.0127 (0.0099)	0.0131 (0.0099)	0.0148 (0.0138)	0.0150 (0.0138)	0.0168 (0.0137)
Urban residence	0.0162*** (0.0063)	0.0161*** (0.0063)	0.0154** (0.0063)	0.0147 (0.0095)	0.0140 (0.0096)	0.0105 (0.0096)
Swedish-speaker	-0.0153 (0.0183)	-0.0148 (0.0185)	-0.0142 (0.0185)	-0.0396 (0.0269)	-0.0358 (0.0273)	-0.0334 (0.0274)
Pseudo R^2	0.006	0.006	0.006	0.006	0.0061	0.009
Log likelihood	-3,145.217	-3,144.8167	-3,144.9604	-5,363.4321	-5,359.0451	-5,345.3951
No. obs.	15,488	15,488	15,488	15,488	15,488	15,488

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.
Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.

Appendix B6.

Table B6.1. Regression results: log(Total stakes) and log(Net spending) with composite IQ for regular bettors.

	Consumption Model 1		Consumption Model 2	
	OLS			
	log(Total stakes)		ln(Net spending)	
Focus variable	Coefficient	Standard error	Coefficient	Standard error
Composite IQ	0.009***	0.002	0.006***	0.002
Controls				
Age	0.077**	0.031	0.066**	0.032
Age^2	-0.001***	0.000	-0.001**	0.000
Blue-collar	-0.122**	0.052	-0.091*	0.053
White-collar	0.005	0.056	-0.012	0.057
Basic	0.217***	0.062	0.170***	0.064
College	-0.037	0.056	0.016	0.057
Post-graduate	0.090	0.086	0.048	0.088
Pays the church tax	-0.063	0.044	-0.031	0.045
Log(Income)	0.084***	0.020	0.095***	0.021
Has one child	0.005	0.061	0.048	0.062
Has two or more children	-0.038	0.055	-0.034	0.056
Married or cohabiting	-0.003	0.063	0.021	0.064
Divorced or widowed	0.114	0.080	0.129	0.083
Urban residence	0.201***	0.061	0.220***	0.062
Swedish-speaker	-0.009	0.194	0.154	0.197
Constant	5.274***	0.673	4.371***	0.690
R^2	0.029		0.021	
No. obs.	4,573		4,143	

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.
Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.

Table B6.2. Regression results: log(Total stakes) and log(Net spending) with the separate measures of IQ for regular bettors.

	Consumption Model 3	**Consumption Model 4**	**Consumption Model 5**	**Consumption Model 6**	**Consumption Model 7**	**Consumption Model 8**
	OLS					
	log(Total stakes)			log(Net spending)		
Focus variables	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)	Coefficient (std. error)
Visuospatial IQ	0.004*** (0.002)			0.0026* (0.0015)		
Verbal IQ		0.003* (0.002)			0.002 (0.002)	
Maths IQ			0.014*** (0.002)			0.010*** (0.002)
Controls						
Age	0.075** (0.032)	0.077** (0.032)	0.078** (0.031)	0.064** (0.032)	0.066** (0.032)	0.066** (0.032)
Age^2	-0.001*** ($<0.10\times10^{-4}$)	-0.001*** ($<0.10\times10^{-4}$)	-0.001*** ($<0.10\times10^{-4}$)	-0.001** ($<0.10\times10^{-4}$)	-0.001** ($<0.10\times10^{-4}$)	-0.001** ($<0.10\times10^{-4}$)
Blue-collar	-0.127** (0.052)	-0.128** (0.052)	-0.118** (0.052)	-0.093* (0.053)	-0.093* (0.053)	-0.089* (0.053)
White-collar	0.025 (0.056)	0.023 (0.056)	-0.013 (0.055)	0.002 (0.057)	0.001 (0.057)	-0.025 (0.057)
Basic	0.191*** (0.062)	0.189*** (0.062)	0.227*** (0.062)	0.151** (0.063)	0.150** (0.064)	0.178*** (0.063)
College	0.002 (0.055)	-0.0003 (0.056)	-0.068 (0.055)	0.043 (0.056)	0.040 (0.057)	-0.006 (0.057)
Post-graduate	0.173** (0.084)	0.167* (0.086)	0.026 (0.085)	0.104 (0.087)	0.099 (0.088)	0.003 (0.088)
Pays the church tax	-0.075* (0.044)	-0.078 (0.044)	-0.057 (0.044)	-0.040 (0.045)	-0.042 (0.045)	-0.027 (0.045)
Log(Income)	0.084*** (0.020)	0.087*** (0.020)	0.085*** (0.020)	0.096*** (0.021)	0.098*** (0.021)	0.095*** (0.021)
Has one child	0.004 (0.061)	0.007 (0.061)	0.003 (0.060)	0.047 (0.062)	0.049 (0.062)	0.049 (0.062)
Has two or more children	-0.037 (0.055)	-0.035 (0.055)	-0.046 (0.054)	-0.033 (0.056)	-0.032 (0.056)	-0.037 (0.056)
Married or cohabiting	0.008 (0.063)	-0.005 (0.063)	0.006 (0.062)	0.017 (0.064)	0.019 (0.064)	0.026 (0.064)
Divorced or widowed	0.102 (0.081)	0.102 (0.081)	0.124* (0.080)	0.120 (0.083)	0.121 (0.083)	0.133* (0.083)
Urban residence	0.213*** (0.061)	0.214*** (0.061)	0.185*** (0.060)	0.228*** (0.062)	0.227*** (0.0612)	0.210*** (0.062)
Swedish-speaker	-0.054 (0.194)	-0.035 (0.195)	0.006 (0.193)	0.124 (0.197)	0.136 (0.198)	0.156 (0.196)
Constant	5.808*** (0.669)	5.802** (0.679)	4.671*** (0.670)	4.728*** (0.685)	4.718*** (0.695)	3.955*** (0.689)
R^2	0.024	0.023	0.041	0.019	0.019	0.028
No. obs.	4,573	4,573	4,573	4,143	4,143	4,143

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.
Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.

Appendix B7.

Table B7.1. Regression results of success models with composite IQ for regular bettors.

	Success Model 1		**Success Model 2**	
	Probit			
	'Being a winner'		'Beating the track'	
Focus variable	Marginal effect	Standard error	Marginal effect	Standard error
Composite IQ	0.0006*	0.0003	0.0014**	0.0006
Controls				
Age	0.0086	0.0067	0.0188*	0.0110
Age^2	-0.0001	0.0001	-0.0002*	0.0001
Blue-collar	0.0048	0.0114	0.0155	0.0184
White-collar	0.0157	0.0122	0.0233	0.0196
Basic	0.0018	0.0136	0.0226	0.0222
College	0.0042	0.0119	0.0146	0.0196
Post-graduate	0.0108	0.0186	0.0877***	0.0310
Pays the church tax	-0.0089	0.0095	-0.0128	0.0155
Log(Income)	-0.0018	0.0040	0.0041	0.0072
Has one child	-0.0053	0.0125	-0.0249	0.0209
Has two or more children	-0.0078	0.0113	-0.0262	0.0189
Married or cohabiting	-0.0007	0.0132	-0.0240	0.0219
Divorced or widowed	0.0049	0.0172	0.0151	0.0282
Urban residence	0.0158	0.0123	0.0198	0.0212
Swedish-speaker	-0.0142	0.0383	-0.0406	0.0657
Pseudo R^2	0.007		0.007	
Log likelihood	-1,416.3628		-2,959.6298	
No. obs,	4,573		4,573	

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.
Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.

Table B7.2. Regression results of success models with the separate measures of IQ for regular bettors.

	Success Model 3	Success Model 4	Success Model 5	Success Model 6	Success Model 7	Success Model 8
	Probit					
	'Being a winner'			'Beating the track'		
Focus variables	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)	Marg. Effect (std. error)
Visuospatial IQ	-0.0002 (0.0003)			-0.0001 (0.0005)		
Verbal IQ		0.0007** (0.0003)			0.0010* (0.0006)	
Maths IQ			0.0008** (0.0003)			0.0025*** (0.0005)
Controls						
Age	0.0084 (0.0067)	0.0088 (0.0067)	0.0087 (0.0067)	0.0147 (0.0100)	0.0152 (0.0100)	0.0153 (0.0100)
Age^2	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0002 (0.0001)	-0.0002 (0.0001)	-0.0002 (0.0001)
Blue-collar	0.0038 (0.0113)	0.0045 (0.0113)	0.0051 (0.0114)	0.0176 (0.0182)	0.0184 (0.0182)	0.0200 (0.0183)
White-collar	0.0175 (0.0122)	0.0152 (0.0122)	0.0149 (0.0121)	0.0271 (0.0194)	0.0239 (0.0194)	0.0185 (0.0194)
Basic	-0.0011 (0.0133)	0.0024 (0.0136)	0.0022 (0.0136)	0.0137 (0.0218)	0.0191 (0.0220)	0.0237 (0.0220)
College	0.0080 (0.0120)	0.0034 (0.0118)	0.0028 (0.0118)	0.0232 (0.0193)	0.0167 (0.0194)	0.0078 (0.0193)
Post-graduate	0.0204 (0.0193)	0.0092 (0.0184)	0.0079 (0.0181)	0.1008*** (0.0297)	0.0857*** (0.0301)	0.0655** (0.0298)
Pays the church tax	-0.0103 (0.0095)	-0.0089 (0.0095)	-0.0085 (0.0095)	-0.0149 (0.0154)	-0.0129 (0.0153)	-0.0100 (0.0153)
Log(Income)	-0.0017 (0.0040)	-0.0017 (0.0040)	-0.0017 (0.0040)	0.0041 (0.0071)	0.0039 (0.0071)	0.0036 (0.0071)
Has one child	-0.0052 (0.0125)	-0.0049 (0.0125)	-0.0056 (0.0125)	-0.0241 (0.0207)	-0.0237 (0.0207)	-0.0250 (0.0207)
Has two or more children	-0.0075 (0.0113)	-0.0073 (0.0113)	-0.0084 (0.0113)	-0.0248 (0.0187)	-0.0247 (0.0187)	-0.0271 (0.0187)
Married or cohabiting	-0.0008 (0.0132)	-0.0008 (0.0131)	-0.0002 (0.0131)	-0.0246 (0.0217)	-0.0240 (0.0217)	-0.0223 (0.0217)
Divorced or widowed	0.0038 (0.0171)	0.0048 (0.0172)	0.0057 (0.0173)	0.0123 (0.0279)	0.0142 (0.0279)	0.0171 (0.0280)
Urban residence	0.0175* (0.0122)	0.0171 (0.0122)	0.0151 (0.0123)	0.0255 (0.0209)	0.0237 (0.0209)	0.0194 (0.0210)
Swedish-speaker	-0.0176 (0.0371)	-0.0117 (0.0393)	-0.0140 (0.0382)	-0.0376 (0.0650)	-0.02837 (0.0659)	-0.0273 (0.0659)
Pseudo R^2	0.006	0.007	0.008	0.0056	0.0061	0.0094
Log likelihood	-1,417.7351	-1,415.6179	-1,414.5797	-2,962.5455	-2,961.0589	-2,951.4505
No. obs.	4,573	4,573	4,573	4,573	4,573	4,573

Notes: The reference categories for socioeconomic status are: Pensioner, Unemployed, Student, Entrepreneur and Other. The reference category for education is Secondary. The reference category for number of children is Has no children. The reference category for marital status is Single.
Statistical significance: ***Significant at 1%, **Significant at 5%, *Significant at 10%.