



# The effects of personality and IQ on portfolio outcomes

Chris Firth<sup>a,\*</sup>, Neil Stewart<sup>a</sup>, Constantinos Antoniou<sup>a</sup>, David Leake<sup>b</sup>

<sup>a</sup> Warwick Business School, University of Warwick, United Kingdom

<sup>b</sup> Lloyds Banking Group, United Kingdom

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## ABSTRACT

We use responses to a self-report survey and matched administrative data to investigate the effects of personality (Big Five traits) and IQ on individuals' stock trading portfolios. Traits have small but significant effects: openness and extraversion are associated with undesirable outcomes whereas conscientiousness is associated beneficially. Higher IQ is associated with lower trading activity but not enhanced investment performance. We postulate these factors influence outcomes in a complex manner, and exert over long timeframes. With portfolio size held constant, financial literacy has little effect. Other factors, such as customer age, portfolio size and portfolio risk, better explain outcomes.

## 1. Introduction

An open question is whether a parsimonious set of factors is able to generate the observed behavior of individuals who make financial decisions (Frydman & Camerer, 2016). The discovery of good predictors could lead to improvements in household financial decisions, leading to a positive impact on those directly affected (Campbell, 2006) and society as a whole (Bhamra & Uppal, 2019). In this study we focus on self-managed investments via stock trading. A range of factors have been reported as important in this domain, including: IQ (Grinblatt et al., 2011); sensation seeking (Grinblatt & Keloharju, 2009); hedonism (Dorn & Sengmueller, 2009); biased self-attribution (Daniel et al., 2005); superstition (Hirshleifer et al., 2016); ambiguity aversion (Dimmock et al., 2016; Li et al., 2016); locus of control (Cobb-Clark et al., 2016); and self-control (Biljanovska & Palligkinis, 2018).

Financial researchers and economists predict decisions using *single* factors of personality, such as overconfidence, and tend to eschew multi-dimensional personality models<sup>1</sup>. In contrast, psychologists are accepting of traits: the non-cognitive patterns of thoughts, feelings and actions that differentiate the personalities of individuals (Roberts et al., 2011). The preeminent model is the "Big Five" (Digman, 1990; McCrae, 2009; Widiger et al., 2016). Heckman et al. (2021), in a review of personality in economics and psychology, point to growing evidence showing that non-cognitive factors rival IQ in predicting educational attainment and labor market

\* Corresponding author at: WBS, University of Warwick, Coventry, West Midlands, United Kingdom.

E-mail address: [chrisfirth@alum.mit.edu](mailto:chrisfirth@alum.mit.edu) (C. Firth).

<sup>1</sup> Only a decade ago Almlund et al. (2011) felt able to write that "most economists view mental states as unnecessary baggage except in so far as they affect choices". It is probably still true that economists believe personality traits lack a secure theoretical footing. Whereas even the single economic concept of ambiguity aversion has been the subject of substantial development of theory (Barberis, 2018), trait models are descriptive schemes and are considered a theoretical (Deary, 2009). The idea of incorporating psychology into models of asset pricing is not new but relies on three psychological frameworks (Barberis, 2018), none of which are models of personality traits.

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success, among other outcomes.

Increasingly, research into financial decision-making straddles or unifies concepts in psychology and economics. For example, [Becker et al. \(2012\)](#) analyze how economic preferences and concepts of personality are related; [Rustichini et al. \(2016\)](#) show that personality traits have a comparable predictive power to economic preferences for measures such as credit score; and [Dean and Ortoleva \(2019\)](#) offer a step toward a parsimonious, unified model of economic choice.

Another factor, that has gained substantial attention, is financial literacy. This is the knowledge and skills required to make informed household finance decisions ([Lusardi & Mitchell, 2014](#)). A meta-analysis by ([Kaiser et al., 2022](#)) suggests that financial education programs have, on average, positive causal treatment effects on downstream financial behaviors (including investing).

Our study empirically analyses the effects of personality and IQ<sup>2</sup> on investment outcomes. We use a combination of detailed brokerage trading records for 1238 individuals<sup>3</sup> matched with their responses to a survey. This includes a score of the financial literacy questions proposed by [Fernandes et al. \(2014\)](#).

An important antecedent to our research is [Kleine et al. \(2016\)](#), who use the Big Five to examine the cross-sectional determinants of individual trading activity. Other related work includes those by [Conlin et al. \(2015\)](#), who find that individual traits<sup>4</sup> predict stock market participation; [Balasuriya and Yang \(2019\)](#), who find Big Five traits correlate with participation and contributions in private pensions; [Oehler and Wedlich \(2018\)](#), who find that extraverted individuals are less risk averse, whereas neurotic and conscientious subjects are more risk averse; [Jiang et al. \(2021\)](#), who find high neuroticism and low openness relate to lower allocation to (risky) equities; [Xu et al. \(2015\)](#), who find that conscientiousness is negatively correlated and neuroticism positively correlated with financial distress in young adults; and [Parise and Peijnenburg \(2019\)](#) who find that people low in noncognitive ability<sup>5</sup> are more likely to experience financial distress. Our contribution is to analyze the effects of the Big Five and IQ on a broad set of investment outcomes, which for the first time provides a more complete picture of customer behavior in this context.

## 2. Data and variables

### 2.1. Data collection

The broker provided transactions of 184,678 accounts (investments in stocks and mutual funds) held by 75,315 of their customers. Their trades are from 2 April 2012 to 10 June 2016. This set is matched with responses to a survey conducted in February and March 2017. The broker emailed an invitation, incentivized by the promise of “a unique opportunity to learn more about your investment personality and how you compare to others” and a chance to win one of ten £100 shopping vouchers. 1318 customers holding 1823 accounts completed the survey.

We merge those with the transactions and eliminate records with invalid values (for example, empty date of birth) and portfolios under £500 mean market value. The result of this filtering is a panel of 1725 accounts held by 1238 customers, as shown in [Table 1](#). Thus, our final sample is 1.64% of the broker’s customers<sup>6</sup>.

### 2.2. Variables and their computation

[Table 2](#) defines our variables. Our eight dependent variables are stock trading portfolio outcomes, grouped into performance (*Sharpe*), biases (*OverCon*, *Disp*, *Idio*) and behavior, that is, activity and choices relating to portfolio self-management (*Turn*, *TraPM*, *Atten*, *Hold*). Values for these variables are computed directly from the account transactions (so, are not self-reported). Values for the independent variables are results of coding the self-reported survey answers, for example, computing a score for Big Five Openness from the related responses. The values for control variables are computed by one or other of these methods. Dependent variables are winsorized at 1%.

Investment information includes stock identification (Stock Exchange Daily Official List (SEDOL) numbers, used for clearing purposes), dates, type (for example: buy, sell), quantities, and prices. We merge in historical prices from DataStream. Sell trades leading to (apparent) short positions are excluded, as these are simply dispositions of unobserved long positions. With this, we are able to reconstruct customer portfolios. The transactional panel is unbalanced, with accounts having being opened during and before the sample period. Accounts opened before the start of transactions available to us had starting positions purchased at prices unknown to us, whereas accounts opened during the panel period have all purchase price and position information. These newer accounts are tagged by the dummy variable *New*. For cases where a customer made no further trade on a pre-2 April 2012 purchase (that is, before the sample begins), we are unable to know of the existence of this holding. For example, if a customer had bought 1000 shares of BHP GROUP in 2011 and no activity was recorded on that holding between 2 April 2012 and 10 June 2016, we would not know of the holding. We view this “missing” information as being equivalent to off-platform holdings; we never know for certain the full investment portfolio of any customer.

<sup>2</sup> A key assumption is that these are exogeneous variables and thus we are able to draw robust conclusions on their effects.

<sup>3</sup> These are spread across 1725 active brokerage accounts. Many customers routinely have two accounts for tax efficiency. We handle this structure by clustering standard errors at the customer level.

<sup>4</sup> They use the Temperament and Character Inventory of [Cloninger et al. \(1993\)](#)

<sup>5</sup> They use measures of emotional stability and conscientiousness developed by [Goldberg \(1992\)](#)

<sup>6</sup> Selection bias appears small and immaterial, and is discussed in the online appendix.

**Table 1**  
Samples.

Name	Description	Customers	Number of accounts		
			New	Old	Total
ALL	Full sample after data cleaning.	1238	493	1232	1725*
DE	Excludes accounts for which no disposition effect** measure could be computed.	983	290	1025	1315*

\* Some respondents declined to answer the question on Education, hence regressions including variable Edu use account totals of 1670 and 1273 observations. \*\* See the next section for an explanation of disposition effect.

**Table 2**  
Definition of variables.

Variable	Definition
<u>Dependent variable (investment performance)</u>	
Sharpe	Realized portfolio Sharpe ratio. Defined as realized return premium normalized by realized portfolio risk (systematic and idiosyncratic risk) $\frac{r_{port} - r_f}{\sqrt{\sigma_{sys}^2 + \sigma_{idio}^2}}$
<u>Dependent variables (biases)</u>	
OverCon	Customer's self-rated ability (quintile) minus the actual performance quintile. A positive number represents overconfidence. For example, a customer ranking their skill as quintile 4 but who achieves only quintile 2 is assigned an overconfidence score of 2.
Disp	A measure of disposition effect, Proportion of Gains Realized (PGR) less Proportion of Losses Realized (PLR) following definitions in <a href="#">Odean (1998)</a> .
Idio	Idiosyncratic risk share via a CAPM-style regression following <a href="#">Calvet et al. (2007)</a> $IRS_i = \frac{\hat{\Sigma}_{idio,i}}{\hat{\Sigma}_i}$
<u>Dependent variables (behavior)</u>	
Turn	Mean portfolio turnover, per <a href="#">Barber and Odean (2001)</a> and <a href="#">Grinblatt and Keloharju (2009)</a>
TraPM	Log (1 + Mean number of trades per month)
Atten	Log (1 + Mean number of logins per month)
Hold	Mean number of holdings in customer's portfolio
<u>Independent variables</u>	
IQ	The number of items correct (0–9) on the short form of the Raven's Progressive Matrices described by <a href="#">Bilker et al. (2012)</a> .
Big5_O	Openness: The tendency to be open to new aesthetic, cultural, and intellectual experiences. For this and the four following variables we use the Ten-Item Personality Inventory (TIPI) of <a href="#">Gosling et al. (2003)</a> to measure the Big Five personality traits of <a href="#">Goldberg (1992)</a> ; <a href="#">Borghans et al. (2008)</a> and <a href="#">Becker et al. (2012)</a> .
Big5_C	Conscientiousness: The tendency to be organized, responsible, and hardworking.
Big5_E	Extraversion: An orientation toward the outer world of people and things rather than the inner world of subjective experience; being outgoing, gregarious, and openly expressive.
Big5_A	Agreeableness: The tendency to act in a cooperative, unselfish manner.
Big5_N	Neuroticism: A chronic level of emotional instability and proneness to psychological distress. For expositional purposes we reverse the scale of <a href="#">Gosling et al. (2003)</a> 's Emotional Stability so that higher (rather than lower) scores indicate higher Neuroticism.
FinLit	Score of the financial literacy questions proposed by <a href="#">Fernandes et al. (2014)</a> .
<u>Control variables</u>	
Risk	The realized daily portfolio volatility (standard deviation of portfolio returns)
Size	Log(£ value of mean portfolio size)
Edu	Highest level of education achieved in this order <ul style="list-style-type: none"> <li>• GCSEs or equivalent (1)</li> <li>• A-levels or equivalent (2)</li> <li>• Degree or equivalent (3)</li> <li>• Post-graduate degree or equivalent (4)</li> </ul>
Male	1 if account holder is male, 0 otherwise.
Age	Log(Age in years at 2010-01-01). Computed from the earliest date of the response to "decade of birth year". For example, 1960–1969 gives an age of 50.
New	1 if account opening date is on or after 2012-04-01, 0 otherwise
<u>Clustering variable</u>	
CustId	A unique number used to anonymously identify customers.

Returns since purchase on disposal are calculated by using a quantity weighted average purchase price of a stock for a given account and a closing price of the stock as of one day prior to the sell date. Dividends are included in the calculation of returns. We ignore commissions in the returns computation. For idiosyncratic risk share we compute CAPM parameters from daily returns. Our benchmark equity market is the FTSE All Share Total Return Index and our risk-free rate is the mean 3-Month UK Treasury Bill yield (symbol IUMAJNB) for the period 2010–2016. For the situation where an original purchase price is not included in the data, we compute the disposition effect (variable *Disp* following [Odean, 1998](#)), we use that security's price at 2 April 2012 as an estimate of the original purchase price.

[Table 3](#) presents summary statistics of our variables. Notably, financial literacy (*FinLit*) has a median of 12 correct answers from a maximum 13. This suggests customers in our sample are almost uniformly much more financially literate than is the general UK population. We also note the mean of 0.262 for over-confidence (*OverCon*). One might naively expect zero, but this could be an instance of the "better-than-average-effect" of [Larrick et al. \(2007\)](#) and [Svenson \(1981\)](#).

**Table 3**  
Summary statistics.

	Min	Q1	Q3	Max	Median	Mean
<i>Dependent variables</i>						
Sharpe	-0.074	-0.001	0.048	0.109	0.024	0.023
OverCon	-4	-1	1	4	0	0.262
Disp	-0.667	-0.025	0.108	1.000	0.021	0.054
Idio	10.5	39.5	80.6	100.0	59.2	59.7
Turn	0	0.001	0.004	0.109	0.002	0.006
TraPM	0	0.211	0.799	2.55	0.440	0.595
Atten	0	1.32	3.32	6.54	2.37	2.36
Hold	0.216	2.41	9.46	36.0	5.00	7.09
<i>Independent variables</i>						
Big5_O	2	5	10	14	8	7.6
Big5_C	2	8	12	14	10	9.7
Big5_E	4	11	13	14	12	11.8
Big5_A	2	3	7	13	5	5.4
Big5_N	3	8	12	14	10	9.8
IQ†	0	3	6	9	4	4.6
FinLit	4	11	13	13	12	11.5
<i>Control variables</i>						
Risk	0.0035	0.0082	0.0151	0.1426	0.0109	0.0154
Size	6.22	10.6	12.5	15.4	11.6	11.5
Edu	1	2	4	4	3.00	3.00
Age (years)††	20	50	50	110	60	52.92
Male (0/1 dummy)	0			1		0.855
New (0/1 dummy)	0			1		0.286

Summary statistics of main variables before standardizing. These are taken from sample ALL except for the measure *Disp*, which uses sample DE. †IQ is the number of correct answers out of nine, not a conventional IQ scale centered around 100.

†† One out of 1,238 respondents gave us the reported age maximum value which prima facie could be an input error.

### 3. Results

Table 4 shows the results of multivariate OLS regressions with our full set of covariates. To facilitate comparability, all variables are standardized (mean 0, standard deviation 1) with the exception of dummy variables (*Male* and *New*). The online appendix reports the results of regressions with subsets of the covariates.

#### 3.1. Big five personality traits

Internal consistency, measured by Cronbach's alpha, ranges from 0.31 to 0.72 for the five TIPI-derived traits and is consistent with (Gosling et al., 2003) (who also show strong correlations from a much longer inventory).

Coefficient sizes from the regressions for trait variables are consistently small<sup>7</sup>. Typical is the coefficient of 0.05 on conscientiousness (*Big5\_C*) for the regression on *Sharpe* (investment performance). We interpret this as saying that on average a one standard deviation increase in conscientiousness improves performance by 5% of a standard deviation of the variable *Sharpe*. Despite the weak effects, the presence or not of statistical significance and the signs of coefficients offer useful insights. In summary: openness (*Big5\_O*) has a negative association with login rate and positive associations with overconfidence and idiosyncratic risk; extraversion (*Big5\_E*) has positive associations with overconfidence and negative associations with idiosyncratic risk and investment performance. We could explain this by suggesting that extraverts – being easily bored – take excessive, unrewarded risk. We might also speculate they would trade more and be more vulnerable to the disposition effect but that does not feature in our results.

Conscientiousness (*Big5\_C*) has positive associations with overconfidence and investment performance. Roberts et al. (2011) report that conscientious people earn more money, which is comparable to our finding of a positive link between conscientious individuals and better returns. Kleine et al. (2016) report that openness tends to have a negative impact on portfolios; we too see that openness is associated with less desirable portfolio outcomes.

#### 3.2. IQ

The IQ scores in our sample are as expected for a general population (see online appendix); we may reasonably state that the brokerage customers are not exceptionally intelligent. The regressions indicate that IQ very weakly predicts lower portfolio activity<sup>8</sup>.

<sup>7</sup> Roberts et al. (2011) also remark on the small effect sizes of Big Five traits.

<sup>8</sup> Using an alternative specification of IQ we observe qualitatively the same findings, though with statistically significant coefficients for portfolio activity measures *Turn*, *Atten* and *TraPM*, see online appendix. This alternative is the Cognitive Reflection Test of Frederick (2005), that survey respondents also undertook.

**Table 4**  
Results of multivariate regressions (full variable set) on the eight independent variables.

	Behavior Turn	Atten	TraPM	Hold	Biases OverCon	Disp	Idio	Performance Sharpe
Big5_O	−0.0279 (0.0321)	−0.0607* (0.0314)	−0.0351 (0.0292)	−0.0319 (0.0271)	0.0618** (0.0291)	0.00896 (0.0342)	0.0539** (0.0264)	−0.00816 (0.0251)
Big5_C	−0.0239 (0.0377)	−0.0536 (0.0335)	0.00171 (0.0289)	0.00736 (0.0264)	0.0514* (0.0295)	−0.0276 (0.0316)	−0.0184 (0.0254)	0.0507** (0.0246)
Big5_E	0.0140 (0.0254)	0.0200 (0.0307)	0.00130 (0.0273)	0.000200 (0.0262)	0.0802*** (0.0289)	−0.00845 (0.0330)	−0.0545** (0.0258)	−0.0494** (0.0243)
Big5_A	0.0473 (0.0308)	0.0157 (0.0290)	0.0233 (0.0266)	−0.0271 (0.0266)	0.0246 (0.0266)	−0.0332 (0.0308)	0.00595 (0.0257)	−0.0126 (0.0237)
Big5_N	0.0115 (0.0343)	−0.0198 (0.0323)	0.00904 (0.0311)	0.0182 (0.0303)	−0.0417 (0.0291)	−0.0189 (0.0297)	0.00879 (0.0263)	0.000791 (0.0265)
IQ	−0.0290 (0.0269)	−0.0145 (0.0307)	−0.0306 (0.0275)	0.0268 (0.0245)	−0.0538* (0.0287)	0.00420 (0.0323)	−0.0331 (0.0244)	0.0349 (0.0268)
FinLit	−0.0412 (0.0330)	−0.0122 (0.0327)	−0.0433 (0.0319)	−0.0279 (0.0256)	0.0963*** (0.0286)	−0.0484* (0.0284)	−0.0143 (0.0242)	0.0227 (0.0256)
Risk	0.154*** (0.0516)	0.0785*** (0.0256)	0.0779** (0.0346)	−0.0491 (0.0364)	0.207*** (0.0272)	0.0193 (0.0271)	0.378*** (0.0281)	−0.265*** (0.0328)
Size	−0.0542* (0.0316)	0.273*** (0.0313)	0.221*** (0.0285)	0.304*** (0.0267)	0.0154 (0.0299)	−0.0923** (0.0404)	−0.174*** (0.0254)	0.178*** (0.0262)
Edu	−0.00733 (0.0315)	−0.0945*** (0.0313)	−0.0133 (0.0291)	−0.00168 (0.0271)	0.0124 (0.0267)	−0.0320 (0.0294)	−0.00539 (0.0249)	0.0117 (0.0236)
Male	0.118* (0.0637)	0.221*** (0.0824)	0.255*** (0.0613)	0.0713 (0.0682)	0.0434 (0.0701)	−0.0190 (0.0784)	0.114* (0.0693)	−0.127* (0.0649)
Age	−0.0116 (0.0274)	0.0147 (0.0296)	−0.00454 (0.0272)	0.0394* (0.0225)	−0.0793*** (0.0287)	−0.113*** (0.0341)	−0.0440* (0.0249)	0.0731*** (0.0255)
New	−0.00801 (0.0559)	0.179*** (0.0577)	0.0393 (0.0553)	0.0688 (0.0542)	0.485*** (0.0573)	−0.110 (0.0774)	−0.242*** (0.0537)	−0.548*** (0.0535)
Constant	−0.0954* (0.0558)	−0.246*** (0.0774)	−0.235*** (0.0551)	−0.0823 (0.0639)	−0.169*** (0.0652)	0.0307 (0.0728)	−0.0265 (0.0641)	0.259*** (0.0605)
adj. R <sup>2</sup>	0.033	0.093	0.053	0.100	0.123	0.027	0.214	0.218
N	1670	1670	1670	1670	1670	1273	1670	1670

Robust standard errors, clustered by CustId, are shown in parentheses \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.0$ .

We observe no significant associations between IQ and biases of disposition effect and idiosyncratic risk, though there is a lessening effect for overconfidence. We report no statistically significant effect of IQ on the economically relevant measure (*Sharpe*). Although these coefficients are directionally consistent with results in (Grinblatt et al., 2012), their lack of statistical significance is somewhat surprising. However, there could be plausible reasons this. Firstly, we have a much smaller sample size than do Grinblatt et al. (2012), and, secondly, the IQ measure we use – from Raven and Court (Raven and Court, 1998) – is arguably independent of formal education (Almlund et al., 2011) which avoids potentially confounding IQ with numeracy<sup>9</sup>. Numeracy is known to be an important predictor of success in everyday risk and financial decisions (Cokely et al., 2012; Peters, 2012, Smith et al., 2010).

### 3.3. Financial literacy

Financial literacy (*FinLit*) shows no statistically significant effects across six of the regressions, the main exception being the (undesirable) positive coefficient on overconfidence (*OverCon*). There is also weak evidence of a reduction in the disposition effect (*Disp*). Fernandes et al. (2014) find that effects of financial literacy diminish when variables for psychological traits are added. Instead, we observe an analogous role for portfolio size (*Size*). In regressions with *Size* excluded, financial literacy shows significant effects (see

<sup>9</sup> IQ in (Grinblatt et al., 2011, 2012) is measured from questions that assess mathematical skill, among other areas.

online appendix). These coefficients moderate sharply with *Size* included (expressed alternatively: with portfolio size held constant, financial literacy does not affect outcomes). For example, excluding *Size*, a one standard deviation increase in financial literacy lowers idiosyncratic risk by 8% of a standard deviation of the variable *Idio*. With *Size*, the effect of literacy is not distinguishable from zero and the coefficient for *Size* is 17% (see Table 4). We record a correlation of 0.21 (significant at 1%) between IQ and financial literacy (see online appendix). Muñoz-Murillo et al. (2020) likewise find that individuals with higher cognitive abilities are more financially literate.

Taken together, these results hint at a nuanced causal relationship in which those with larger portfolios are more financially literate—either because those more literate are confident enough to hold larger portfolios or because those who plan to hold larger portfolios deliberately acquire a higher level of literacy—but that variance in financial literacy over and above that due to portfolio size has no further effect.

We repeat our earlier caution that the high but uniform financial literacy of our sample customers – in itself noteworthy – could hinder inferences. Moreover, financial literacy could be endogenous, leading to biased parameter estimates. We attempt to overcome this by conducting age-instrumented estimates of the effects of financial literacy (see online appendix) based on the premise that customer age is exogenous, together with evidence from Agarwal et al. (2009) that financial mistakes decrease with age (until the onset of mental impairment). While our IV results are consistent with the overall pattern in our main analysis, we conclude that the methodological hurdles surrounding our financial literacy variable leave the question of its effects unsettled.

### 3.4. Control variables

Portfolio risk (*Risk*) is associated positively with portfolio turnover, login rates and also overconfidence. It is negatively associated with investment performance. Size of the portfolio (*Size*) is associated positively with the number of holdings, login rates and investment performance. Larger portfolios are associated with lower disposition effect and lower idiosyncratic risk. Education (*Edu*) plays little or no role, whereas men (*Male*) on average trade more frequently and have lower investment performance than women. Older (*Age*) clients tend to do better on measures of bias and have better investment performance.

These discoveries are intuitively plausible and many are established in the literature. Aspects of financial behavior vary with age and wealth (Campbell, 2006): age relates to financial experience and financial product needs, while wealth allows customers to buy financial sophistication (advice) or to spend more time in acquiring it; sophisticated households invest more efficiently (Calvet et al. 2007), and customers who feel competent have more diversified portfolios (Graham et al. 2009).

### 3.5. Explanatory power

Fig. 1 shows adjusted  $R^2$  values of two models for the eight dependent variables, an expositional technique due to Becker et al. (2012). For example, for *OverCon* the left bar ( $R^2$  of 0.025 when only our independent variables are included in the model) contrasts markedly with the right bar ( $R^2$  of 0.12 when control variables are also included in the model). An obvious implication is that our control variables explain a much larger fraction of variance than do the variables capturing personality traits, IQ, and financial literacy.

This is not entirely surprising. Ajzen (1991) contends that traits alone are poor predictors of specific behaviors, with situational factors and other beliefs interacting too, and Figner and Weber (2011) note that risk taking is not a single trait but a behavior influenced by characteristics of, and linkages between, the situation and the decision maker. Yet, earlier studies show that the Big Five predict a range of life outcomes (Almlund et al., 2011), sometimes decades in advance (Widiger et al., 2015). How can we reconcile these seemingly opposing views? One possibility is that weak short-term effects of personality take many years to compound to large

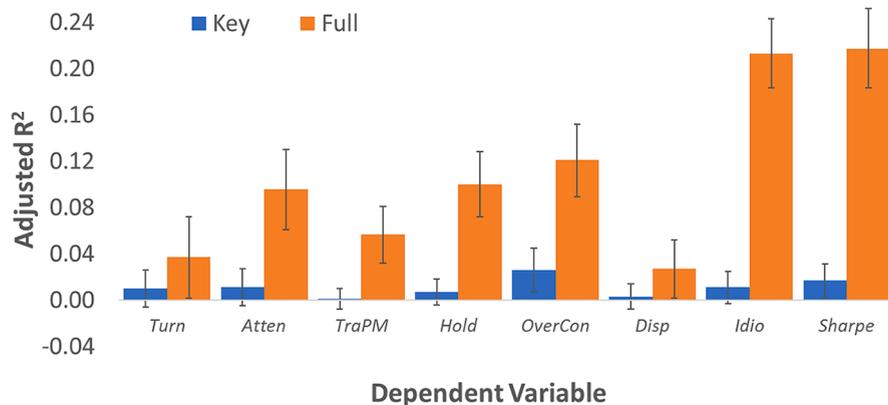


Fig. 1. Explanatory power for two regression models on each of the dependent variables.

Variables in key: *IQ*, *Big5\_O*, *Big5\_C*, *Big5\_E*, *Big5\_A*, *Big5\_N*, *FinLit*. Variables in full: Those in key plus control variables *Risk*, *Size*, *Edu*, *Age*, *Male*, *New*. Plots are using sample ALL except DE for disposition effect. The 95% confidence intervals shown are computed from a bootstrap procedure, each with 10,000 repetitions.

effects. Thus, the role of personality is detectable in studies with long time horizons but not easily observed in shorter, complex tasks – such as stock trading – especially where domain-specific choices are highly influential.

#### 4. Conclusion

A full understanding of factors that predict the behavior of individuals who make financial decisions could lead to improved financial life choices. Using an exceptionally rich data set from a UK brokerage we provide new evidence of the effects of personality and IQ on individuals' stock-trading outcomes. We conjecture that these factors predict investment outcomes but their effects are complex, and, in the case of traits, impactful only when compounded over long timeframes.

#### CRedit authorship contribution Statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript.

#### Declaration of Competing Interest

None

#### Data availability

The authors do not have permission to share data.

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#### Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.frl.2022.103464](https://doi.org/10.1016/j.frl.2022.103464).

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