Personality Traits and Portfolio Tilts Towards Value and Size[1]

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Abstract

We show that personality traits are related to an investor's preferences for value versus growth stocks and for small capitalization stocks versus large capitalization stocks. We have detailed personality trait data and official register holdings of stocks for 710 individuals in Finland. The results show that more extravagant individuals tend towards large capitalization growth stocks; more impulsive people tend towards small capitalization growth stocks; more sentimental investors tend towards small capitalization value stocks; and more social investors tend towards small capitalization stocks with a tilt towards value. The results are consistent when looking at the portfolio characteristics across investors, over time, when using aggregate portfolios of investors with similar personality traits, and both widely held and non-widely held stocks.

JEL classification: D14, G02, G11

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1 Introduction

"Fama: … Suppose I tell you I like apples better than oranges.
Thaler: Then that's taste.
Fama: OK, that's value stocks and growth stocks. I'm not arguing for it; I'm just saying it's a possibility."
— *Chicago Booth Review, June 30, 2016*

Recent works have attempted to find explanations for the value premium (Fama & French, 1992) by looking at individual investor portfolios. Cronqvist, Siegel, & Yu (2015) find that an investor's preference for value stocks over growth stocks is related to both hereditary factors and life experiences. Betermier, Calvet, & Sodini (2017) run extensive analysis and find that the investor characteristics associated with a preference for value stocks are more consistent with the idea that the value premium reflects systematic risk. We build on this by showing that the choice of value versus growth stocks and the choice of large versus small capitalization stocks are related to the individual's personality.

We provide clear evidence of a relationship between personality and the preference for value (as measured by market-to-book) and firm size (as measured by firm market capitalization). We find sensation-seeking extravagant types drawn towards large capitalization growth stocks. Impulsive investors have a preference for small-capitalization growth stocks. Sentimental investors prefer smaller capitalization value stocks. And more social investors tend to invest in small stocks, with a slight tilt towards value. The traits' effects are robust to the inclusion of risk aversion, wealth, gender, and education.

The main contribution of this paper is to show that personality traits are related to individual investors' preferences for value and size tilts in their portfolios. If investment decisions are influenced by personality traits apart from risk aversion, wealth, and hedging motives, there is a stronger case to be made that the value and size premiums are due to investor behavior, not underlying risk. The fact that personality traits are related to value and size tilts also provides evidence that the value and size premiums may be persistent even if they are well known by investors. Despite knowing that small-capitalization and value stocks outperform over time, investors may be drawn to large capitalization growth stocks because the large capitalization growth stocks appeal to inherent investor preferences.

The value and size effects in stocks have a long history. The idea of value investing arguably began with Graham and Dodd's "Security Analysis" (1933).

They promoted investing in stocks that had (among other valuation criteria) lower market-to-book ratios. The premise is that these value stocks trade at a discount to their intrinsic value and therefore offer better investment opportunities. Banz (1981) was the first to identify the size effect in stocks, noting that small firms tend to have higher risk-adjusted returns than large firms. Fama and French (1992) showed that the size effect and value effect were independent of CAPM beta. Fama and French (1993) captured these effects in their Three-Factor Model, which added the small-minus-big (SMB) size factor and high-minus-low (HML) value factor to the market factor. Since then, numerous papers have shown the value and size factor premiums over various time periods and in various markets around the world (e.g., Fama and French, 2012; van Dijk, 2011).

While there is little debate about the empirical existence of the value and size effects in equities, the underlying reasons for the premiums remain in question. The arguments can be broken down into two main camps: the premiums are compensation for taking on systematic risk; or the premiums reflect systematic mispricing by investors. Fama and French (1993, 1996) argue that the value and size premiums must reflect systematic risk, otherwise the premiums would have been arbitraged away over time. It is supposed that value stocks and small stocks are riskier because they face increased likelihood of bankruptcy and provide poor returns in poor states of the world. Zhang (2005) argues that value stocks face more business risk than financial risk due to their higher levels of fixed assets. To compensate investors for taking on this risk, the stocks should provide higher returns.

In contrast to the risk argument for the value and size premiums, the behavioral finance argument claims that investor behavior can lead to equity mispricing. Investors may overreact to recent information, pushing up (or down) the price of stocks with recent good (or bad) news by extrapolating the recent news too far into the future (De Bondt & Thaler, 1985). Value stocks get pushed too low and growth stocks get pushed too high, leading to eventual reversals in price. Lakonishok et al. (1994) argue that all investors, both individual and institutional, exhibit a preference for growth over value. Individual investors' preference may be due to psychological biases such as the representative heuristic (Tversky & Kahnemann, 1974). Institutional investors' preference may be due the constraints of performance-based arbitrage (Shleifer & Vishny, 1997). Daniel et al. (2001) develop a model in which investors are overconfident regarding private signals they receive, causing them to overprice certain stocks (e.g., growth stocks and large stocks).

Using personality traits to help explain the value and size premiums currently falls somewhere between the risk-based explanations and the behavioral explanations. Personality traits intuitively fall into the behavioral camp. Traits represent repetitive patterns of thoughts and behavior, and in the stock market these behaviors may be less than optimal. Personality traits may be related to typical behavioral biases. More impulsive investors may behave in an overconfident manner, and more sentimental investors may be prone to narrow framing. We do not, however, pursue the relationship between personality traits and behavioral biases in this paper. The hypothesized relationships between personality traits and the portfolio tilts towards value and size are clear and intuitive and do not require a detour through behavioral biases.

It is harder to fit the personality traits into the risk-based explanation of the value and size premiums. If traits associated with lower levels of risk aversion were also correlated with preferences for value stocks and small stocks, then we could be more confident in the risk-based interpretation of the premiums. However, we find that is not always the case. Conlin et al. (2015) find the trait sentimentality to be negatively related to stock market participation, and Conlin et al. (2017) find sentimentality to be positively related to risk aversion, both in survey measures and real-world revealed preference. For these relationships to be consistent with the risk-based explanation of the premiums, we should find sentimentality positively related to preferences for growth stocks and big stocks. The exact opposite seems to be the case; we find investors with higher scores on sentimentality prefer value stocks and small stocks. Another example is the trait impulsivity-disorderliness, which Conlin et al. (2017) find is negatively related to risk aversion. We find higher scores on impulsiveness-disorderliness to be positively related to portfolio tilts towards small growth stocks, providing mixed evidence for the risk-based explanations of the premiums.

There could be a case made for personality supporting the risk-based explanation of the value and size premiums if the personality traits could be included as separate preference parameters in a non-standard utility function (Almlund et al., 2011). However, we know of no such functional form that allows the inclusion of personality traits as parameters separate from risk aversion. Assuming such a functional form exists, one may be able to show that the preferences for value and size portfolio tilts are rational maximizing behavior on the part of investors. Much work remains to be done in this area.

We cannot claim to solve the puzzle of whether the value and size premiums are rooted in systematic risk or behavioral mispricing. We can claim, however, that personality traits are clearly related to individual investors' portfolio tilts towards value and size. The evidence is strong enough to induce further research using personality traits to explain investor behavior.

The rest of the paper proceeds as follows. Section 2 discusses the personality model we use in detail and presents our hypotheses for how the traits should be related to preferences for value and size. Section 3 describes the data. We present our results in Section 4 and robustness checks in Section 5. Section 6 concludes the paper.

2 Personality, Value and Size

In this paper, we measure personality traits using the temperament part of the Temperament and Character Inventory (TCI) of Cloninger et al. (1993). The model has been used extensively in the fields of medicine and psychiatry, but less than the Five-Factor Model of personality (see McCrae and Costa, 1997) in finance and economics. Two studies papers in finance and economics using the TCI are Conlin et al. (2015) and Ekelund et al. (2005). While the two models differ in their theoretical backgrounds and trait definitions, many of the traits across the models correlate moderately to highly (De Fruyt et al., 2000; Markon et al., 2005).

The TCI of Cloninger et al. (1993) contains four temperament traits.[2] The model hypothesizes that the traits have biological bases in the brain's neurotransmitter pathways. The traits reflect our instinctual "gut response" that we normally display in response to stimuli. The four temperament traits are novelty seeking, harm avoidance, reward dependence, and persistence. For a complete description of the TCI and traits, see Cloninger et al. (1994).

Conlin et al. (2015) show how the TCI temperament traits and their respective subscales are related to stock market participation. In this paper, we focus on two of the traits – novelty seeking and reward dependence. We focus on novelty seeking and reward dependence for the following reasons. Based on the descriptions of the traits (Cloninger et al., 1994) and previous usage of harm avoidance (Ekelund et al., 2005; Paulus et al., 2003), novelty seeking and reward dependence are less likely to be proxies for risk aversion than are harm avoidance and the harm avoidance subscales[3]; and the subscales of novelty seeking and reward dependence can be combined in ways that allow for clear hypotheses regarding the traits' relationship with portfolio characteristics. Novelty seeking measures the degree to which one exhibits active behavior in response to stimuli and actively seeks pleasure and reward when none is currently on offer (Cloninger, 1994). Reward dependence measures the degree to which one is emotional and responsive to social

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[2] The TCI also includes three character traits: self-directedness, cooperativeness, and self-transcendence. We do not have observations for the character traits.

[3] As we do not use harm avoidance and persistence in the analyses, we do not discuss them in the text. We provide a description in this footnote for the reader's benefit. High harm avoidance is associated with fearfulness and passive behavior, and persistence is the ability to maintain effort towards one's goals. Harm avoidance has four subscales: worry/pessimism, fear of uncertainty, shyness, and fatigability. Persistence does not have any subscales in the TCI version IX. See Cloninger et al. (2004) for more information on these two traits.

stimuli (Cloninger, 1994). Novelty seeking has four subscales: exploratory excitability, impulsiveness, extravagance, and disorderliness. Reward dependence has three subscales: sentimentality, attachment, and dependence.

We now briefly describe the subscales, starting with the novelty seeking subscales. Exploratory excitability measures one's willingness and desire to seek new things and avoid boredom. Impulsiveness measures the willingness to make decisions based on hunches and without having complete information. High scores on extravagance reflect a preference for spending money over saving money, even to the point of being careless. People scoring high on disorderliness are willing to do things their own way without much regard for routines or rules. The reward dependence subscale sentimentality measures our tendency to be affected by emotional stimuli, whether it be other people or works of art. People scoring high in attachment are generally warm and open with others. High scores on dependence reflect one's willingness and desire to fit into a social group.

In Cloninger et al.'s (1993) model, an individual's score for a trait is the sum of the subscale scores. We take a novel approach and combine the subscales of the traits in a way that fits a priori notions of the relationship between the traits and investment choices, simplifies the analysis, and helps to avoid potential multicollinearity problems between the subscales of a particular trait. The approach is simple. We add the two subscale scores together to make a new trait. We combine exploratory excitability and extravagance into the trait we call EXPEXT. Impulsiveness and disorderliness are combined to form IMPDIS. Attachment and dependence are combined to form a trait we call ATTDEP. Sentimentality is not combined with another subscale; we use the name SENTIM for brevity. By combining the traits in this manner, we have four measures of personality instead of seven. Prior work provides empirical evidence for these combinations of subscales. Miettunen et al. (2004) run exploratory factor analysis on the TCI temperament trait scores for the NFBC66 survey done in 1997. Their results generally support these combinations of subscales. However, they find explorative excitability and extravagance do not load on the same factor. We choose to retain the EXPEXT combination because of the subscale descriptions and because the combined subscales are easily related to portfolio characteristics.

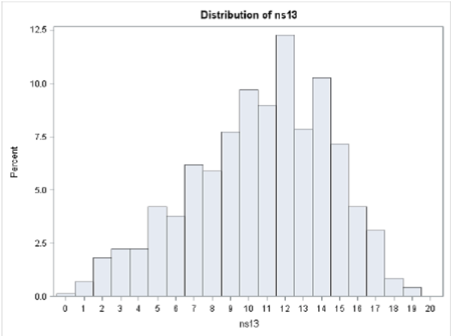
The new trait EXPEXT reflects active behavior, seeking new stimuli, and willingness to spend money. As growth stocks can be seen to be exciting and are more expensive (relative to book value), we expect that higher scores on EXPEXT will be positively related to growth stock ownership. We also expect EXPEXT to be positively related to the size of firms owned. More "action" takes place in large-cap stocks and owning a famous large-cap stock instead of a relatively unknown small-cap stock is likely to appeal to highly extravagant individuals. The combined trait IMPDIS reflects a willingness to act without complete information and to do things against the norm. Based on the likely amount of information available and the fact that they generally have a smaller ownership base, we expect individuals with high scores on IMPDIS to be drawn towards smaller capitalization growth stocks.

The trait ATTDEP reflects one's degree of sociability. Individuals with high scores are more social, feel more a part of a group, and have warmer relationships with others. This higher sociability is likely to help information spread among the group (as in Hong et al., 2004) and may contain information not available through typical channels like television, print, or the Web. We thus expect high scores on ATTDEP to be positively correlated with smaller capitalization value stocks – the type of firms that are usually not discussed in typical media channels. We expect SENTIM to be positively correlated with value stock ownership, especially smaller capitalization firms. It is likely easier for a sentimental person to form an emotional connection to smaller capitalization value firms and to hold these firms in his portfolio.

Figure 1 shows the distributions of the four traits we use. The histograms display all possible scores for the traits that we use. For EXPEXT, there are no individuals with the highest possible score of 20. For IMPDIS, there are no individuals having the two highest possible scores, 19 and 20. Other than these few exceptions, the combined traits cover the full range of possible scores and have relatively humped distributions (but clearly are not normally distributed).

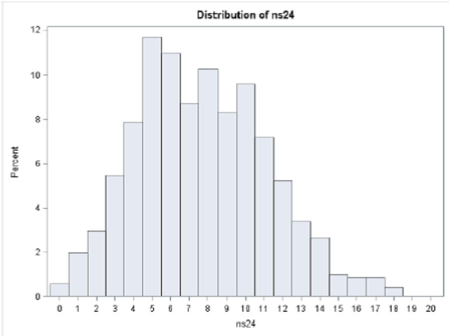
Panel A. EXPEXT

$\mu = 10.66$ $\sigma = 3.82$



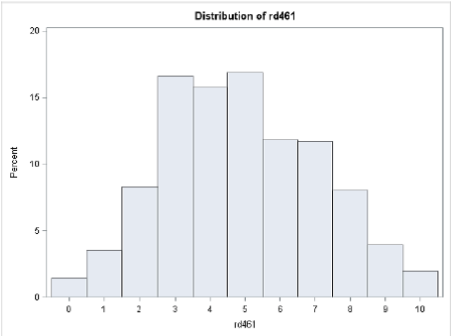
Panel B. IMPDIS

$\mu = 7.67$ $\sigma = 3.52$



Panel C. SENTIM

$\mu = 4.90$ $\sigma = 2.22$



Panel D. ATTDEP

$\mu = 9.20$ $\sigma = 2.75$

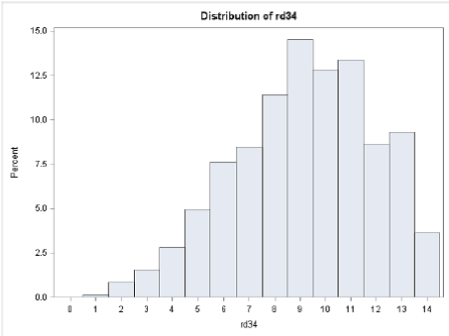


Fig. 1. Distributions of Personality Trait Scores

3 Data and Descriptive Statistics

The Northern Finland Birth Cohort 1966 includes 96.3% of all births in Oulu and Lapland provinces in the year 1966. The most recent data collection took place in 2012.[4] The data include personality traits as measured by the Temperament and Character Inventory of Cloninger et al. (1993). We also have observations on gender, education, and risk aversion from the cohort data. We set the variable Female to 1 for females and to 0 for males. The variable University is set to 1 for those who have completed a bachelor's degree or higher (at a university or university of applied science) and 0 for those who have not completed a bachelor's degree. The variable Risk Aversion is the response to the survey question on general risk aversion (originally in Finnish): "In general, are you fully willing to take risks or do you avoid taking risks?" The response choices are 0 (not at all willing to take risks) to 10 (fully willing to take risks).[5] We reverse the scale so that higher values of the response reflect higher risk aversion.

The stockholdings data come from the Finnish Central Securities Depository (Euroclear Finland), which is the official register of stockholdings in Finland. We use only those stockholdings that were traded on the exchange in Helsinki (NASDAQ OMX). For each individual, we know the stocks held, the number of shares owned of each stock, and the value of each position. We take the end-of-day value of the holdings on the last trading day of each month in the period January 2009 to December 2010. We take each stock's market-to-book ratio (MB) and market capitalization (SIZE) for the last trading day of each month from Thompson-Reuters Datastream. Our data set is thus the investor-stock combinations on the last trading day of each month in 2009–2010 for those investors who are in the NFBC1966. We are able to find value-weighted MB and value-weighted SIZE for each individual's portfolio when the individual holds shares at the end of a month.

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[4] A detailed description of the NFBC1966 and research using the data is available on the cohort website: http://www.oulu.fi/nfbc/ The survey questionnaires are available online (in Finnish only) http://www.oulu.fi/nfbc/node/26627.

[5] We also tested the use of a composite risk aversion measure, obtained from the first principal component of the responses to four survey questions on risk aversion which included: two variations on the traditional lottery question, the risky job questions used in Barsky et al. (1997), and the question on general risk aversion. The composite score showed weaker relationships to portfolio tilts than the general risk aversion question. See Conlin et al. (2016) for further details on the composite risk aversion measure.

For each individual i and each month-end t for which individual i owns stocks, we simply find:

$$MB_{i,t} = \sum_{s=1}^{s'} w_{s,t}^{i} * MB_{s,t} \tag{1}$$

$$SIZE_{i,t} = \sum_{s=1}^{s'} w_{s,t}^{i} * SIZE_{s,t} \tag{2}$$

where s is an index for each stock in the portfolio from one up to s', with s' = the number of stocks in the portfolio at time t; $w_{s,t}^{i}$ is the weight of stock s in individual i's portfolio at time t; $MB_{s,t}$ is the market-to-book ratio of stock s at time t; and $SIZE_{s,t}$ is the market capitalization of stock s at time t. We do not generate values of $MB_{i,t} = 0$ or $SIZE_{i,t} = 0$ for months in which an individual does not hold any stocks on the last trading day of the month. We account for investor differences with respect to timing of holdings and total value of the portfolio by performing three different types of analyses, as explained in Section 4 below.

Observations for market-to-book and market capitalization are available for almost all exchange-traded stocks held during the sample period. There are only three firms for which we do not have complete data. Datastream has neither market-to-book nor market capitalization values for Aktia Oy (ISIN FI0009004733) during the sample period. There are 31 people in the cohort who owned shares in Aktia during the sample period, and for 22 of these individuals Aktia was the only stock owned. Thus we lose 22 individuals because of data unavailability. For the other 9 individuals who owned shares of Aktia as part of their portfolio, their portfolio value-weighted market-to-book and value-weighted market capitalization are not fully accurate. Datastream also reports negative market-to-book values for two firms, Biotie Therapies (ISIN FI0009011571) and Geosentric (ISIN FI0009004204). We change negative market-to-book values to missing for these two firms. Biotie Therapies was owned by 35 individuals, with a mean holding value of €2485 (median €450) among these holders of the stock. Geosentric was owned by 31 individuals, with a mean holding value of €522 (median €72) among these holders of the stock. Only 7 people held shares in both Biotie Therapies and Geosentric during the sample. We do not believe the missing values for these three firms bias our results.

We acknowledge the time difference between the end of the stockholdings data in 2010 and the NFBC survey conducted in 2012. We rely on the stability of personality traits in adulthood (see Josefsson et al., 2013) to justify this analysis. We also find it unlikely that portfolio changes occurring between 2010 and 2012 would affect the measured personality traits. Most individuals in our sample have a small share of wealth invested in stocks: the mean (median) account value at the end of 2010 is 16,434 (3,570) euros while the mean (median) net wealth observed in 2012 is 386,502 (250,000) euros. This small share of wealth invested in stocks leads us to believe that it is unlikely that changes in the portfolio affected the measurement of the personality traits in 2012.

Our sample consists of 710 individuals who owned stocks in the sample period and for whom we have personality trait scores. Table 1 provides descriptive statistics of our sample.

Table 1. Descriptive Statistics

Variable	N	Mean	Median	Std Dev	Minimum	Maximum
Female	710	0.38	0	0.49	0	1
University	676	0.50	0	0.50	0	1
Risk Aversion	693	4.07	4	2.22	0	10
Avg Portfolio Value	710	16434	3570	39189	105	559492
Avg Monthly Return	710	0.0183	0.0182	0.0369	-0.0752	0.6221
Avg Number Stocks	710	3.77	2.00	5.91	1.00	125.63
Avg MB	705	1.89	1.76	0.86	0.00	10.09
Avg SIZE	710	12785	10112	10929	7	40670
Monthly observations	710	21.48	24.00	5.66	1.00	24.00

The table provides descriptive statistics for the sample used. Female is an indicator variable. University is an indicator variable for having a university degree. Risk Aversion is self-reported general risk aversion on a scale of 0–10, with 10 being most risk averse. Portfolio Value is in euros. Avg Monthly Return is in logs. MB is value-weighted market-to-book ratio of the portfolio. Size is the value-weighted market capitalization of the firms in the portfolio, in thousands of euros. For the portfolio values and characteristics, we take the time series average for each individual and then average across individuals. Monthly observations is the number of month-end observations per individual.

The sample has more males than females, and half of the individuals have a university degree. The responses to the risk aversion questions show that the majority of the respondents view themselves as being more willing than unwilling to take risks. For the portfolio characteristics (value, return, number of stocks, market-to-book value, and market capitalization), we first find the average of month-end values for each individual and then average across individuals. If an investor has a month-end portfolio value less than 100 euros, that particular month-end portfolio observation is discarded. Most of the investors had holdings in each of the sample months; 539 people were active for 24 months of the sample period. Only 35 individuals were active for 6 or fewer months.

We show the correlation coefficients in Table 2. EXPEXT and IMPDIS have a fairly high correlation of 0.40, but this is about the same as the correlations (not reported) across all four individual novelty seeking subscales. This reduction in the number of variables helps to avoid a potential multicollinearity problem in the regression analysis of Section 4.1 below. Other than the correlation between EXPEXT and ATTDEP at 0.36, the rest of the correlations are all less than or equal to 0.28 in absolute magnitude.

Table 2. Pearson Correlation Coefficients

	EXPEXT	IMPDIS	SENTIM	ATTDEP	Risk Av.	Female	Univ.
IMPDIS	**0.40**						
SENTIM	0.03	**-0.09**					
ATTDEP	**0.36**	0.01	**0.22**				
Risk Aversion	**-0.24**	**-0.23**	**0.09**	-0.03			
Female	**0.20**	0.02	**0.28**	**0.17**	**0.18**		
University	0.11	0.04	**-0.11**	0.03	0.01	0.07	
PortfolioValue	**-0.11**	-0.01	0.00	0.00	**-0.09**	**-0.10**	**0.09**

EXPEXT is the combination of exploratory excitability and extravagance. IMPDIS is the combination of impulsiveness and disorderliness. SENTIM is sentimentality. ATTDEP is the combination of attachment and dependence. Correlation coefficients in bold are significant at the 5% level.

The correlation table also shows that EXPEXT and IMPDIS are negatively correlated with risk aversion, but the coefficient is only -0.24. This supports our idea that EXPEXT and IMPDIS are not measuring the same thing as general risk aversion. We thus expect that correlations across the explanatory variables do not present a problem for analysis.

4 Results

We present our results in three stages. We first find average values of the month-end observations for each investor's portfolio. We run OLS regressions of the average value-weighted market-to-book ratio (MB) and average value-weighted market capitalization (SIZE) on their personality traits. We then show with simple plots that the personality traits' relationship with MB and SIZE is consistent over time. To take portfolio size into account, we construct aggregate portfolios for high and low levels of the personality traits and compare the value-weighted MB and value-weighted SIZE for these aggregate portfolios. In Section 5.1, we perform a similar analysis but use the portfolio value-weighted loadings for Fama and French (1993) value and size factors. We also address the potential problems of widely held stocks (e.g., Nokia) in Section 5.2.

4.1 OLS Regressions

All of the explanatory variables we use (except ln(portfolio value)) are constant over the sample period, preventing us from using panel regressions. We run OLS regressions, with the dependent variables being the average value of MB and the average value of SIZE for each individual's portfolio over the sample period. The two regression equations are:

$$\begin{aligned}\overline{MB}_i = \alpha^{MB} &+ \beta_1 EXPEXT_i + \beta_2 IMPDIS_i + \beta_3 SENTIM_i \\ &+ \beta_4 ATTDEP_i + \beta_5 X_i^T + e_i^{MB}\end{aligned} \tag{3}$$

$$\begin{aligned}\overline{SIZE}_i = \alpha^{SIZE} &+ \gamma_1 EXPEXT_i + \gamma_2 IMPDIS_i + \gamma_3 SENTIM_i + \gamma_4 ATTDEP_i \\ &+ \gamma_5 X_i^T + e_i^{SIZE}\end{aligned} \tag{4}$$

where the personality traits are defined as in Section 2, and X_i^T is a vector of controls including female, university, risk aversion, and ln(portfolio value). We find $\overline{MB}_i$ and $\overline{SIZE}_i$ by taking the simple average of $MB_{i,t}$ and $SIZE_{i,t}$ (defined in equations (1) and (2), respectively) for those months when individual i holds at least one stock.

This simple method gives equal weights to each investor, and abstracts from changes in the portfolio over time. For example, consider investor j who holds stocks for 3 months, makes no trades during those 3 months, and has portfolio value-weighted characteristics $\overline{MB}_j$ and $\overline{SIZE}_j$. Also consider investor k who holds stocks for all 24 months of the sample, makes numerous trades during the two-year window, and has portfolio value-weighted characteristics of $\overline{MB}_k$ and $\overline{SIZE}_k$. In the OLS regressions, the assumption is that the relationships between personality traits and value and size are equally strong for these two individuals, despite the differences in holding periods and trading frequency.

We present the results for these OLS regressions in Table 3. Across the three models for MB, there is consistent evidence that individuals with higher sentimentality hold lower MB portfolios. Higher SENTIM corresponds with a tilt towards value portfolios. There is some evidence that high IMPDIS is related to a preference for growth over value, but the evidence is not as compelling. The coefficient for IMPDIS is statistically significant only at the 10% level and only in the models with controls. When there are no controls in the model, IMPDIS is not significant. Our results do not show a relationship between gender and value stock preference. General risk aversion is also not significantly related to a value or growth preference.

There is a stronger relationship between the personality traits and the SIZE[6] of an individual's portfolio. EXPEXT is positively related to SIZE, while IMPDIS and ATTDEP are negatively related to SIZE. The only trait that is not significant is SENTIM. For the controls, Risk Aversion is significantly related to SIZE, with more risk-averse people holding larger stocks on average. Gender, education, and ln(portfolio value) are not related to SIZE.

[6] SIZE is measured in thousands of euros. Using ln(SIZE) produces nearly identical results in terms of variable significance.

Table 3. MB, SIZE, and Personality Traits

	Market-to-Book			Size		
EXPEXT	0.026	0.009	0.022	854*	1222**	1277**
	(0.81)	(0.30)	(0.70)	(1.79)	(2.43)	(2.50)
IMPDIS	0.027	0.056*	0.057*	-1004**	-755	-749
	(0.77)	(1.77)	(1.82)	(-2.26)	(-1.64)	(-1.63)
SENTIM	-0.074**	-0.061**	-0.054*	17	32	63
	(-2.41)	(-2.02)	(-1.74)	(0.04)	(0.07)	(0.14)
ATTDEP	0.000	-0.010	-0.017	-1010**	-1181***	-1210***
	(0.00)	(-0.30)	(-0.51)	(-2.33)	(-2.69)	(-2.75)
Female		-0.011	0.009		-833	-752
		(-0.15)	(0.12)		(-0.86)	(-0.77)
University		0.219***	0.199***		-89	-176
		(3.67)	(3.27)		(-0.11)	(-0.21)
Risk Aversion		0.006	0.009		755***	771***
		(0.43)	(0.66)		(3.72)	(3.75)
Ln(PortValue)			0.044**			192
			(2.09)			(0.76)
Intercept	1.892	1.741	1.365	12785	10035	8390
	(58.43)	(27.03)	(6.62)	(31.39)	(10.77)	(3.31)
N	705	661	661	710	666	666
R-squared	0.010	0.035	0.043	0.012	0.034	0.035

The table shows OLS coefficients for portfolio characteristics regressed on personality traits. The dependent variables are the average portfolio value-weighted market-to-book (MB) and average portfolio value-weighted market capitalization (SIZE). EXPEXT is the combination of exploratory excitability and extravagance. IMPDIS is the combination of impulsiveness and disorderliness. SENTIM is sentimentality. ATTDEP is the combination of attachment and dependence. The personality traits are standardized to mean zero and standard deviation of one. Female is an indicator variable. University is an indicator variable for having achieved a bachelor's degree or higher. Risk Aversion is general risk aversion, measured from 0 to 10. Ln(PortValue) is the log of the average euro-value of the portfolio. t-statistics calculated from heteroscedasticity-consistent standard errors are in parentheses below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

The effects of the personality traits are large. For SENTIM, the average coefficient across the three models for MB is -0.063. Thus a one-standard-deviation change in SENTIM is associated with a roughly 3.3% change in MB (at the mean). The effects of EXPEXT, IMPDIS, and ATTDEP are even greater, with one standard deviation changes being associated with a change in SIZE of up to 10% (at the mean).

We find both similarities and differences for the results of our control variables when comparing to previous works. We find no relationship between gender and the portfolio tilts towards value and size. Gender has been shown to be a significant predictor of investment behavior, including portfolio value tilt (Betermier et al., 2017), trading frequency (Barber & Odean, 2001) and percentage of financial wealth in risky asset holdings (Halko et al., 2012). Higher education is positively related to a preference for growth stocks, in line with Cronqvist et al. (2015) and Betermier et al. (2017), providing support to the idea that highly educated individuals hedge their human capital by investing more in growth stocks than in riskier value stocks. However, if individual investors actually perceived value stocks to be riskier, we would expect to find a positive relationship between risk aversion and investment in growth stocks. We find no significant relationship between risk aversion and the portfolio's value-weighted market-to-book ratio. We also find investors with larger portfolios have a greater tilt towards growth stocks than those with smaller portfolios. If value stocks are riskier, wealthier investors should be more willing to hold value because of their greater capacity for bearing risk.

4.2 Average MB and SIZE over Time

The OLS regressions in Table 3 give equal weight to all individuals, regardless of the number of month-end portfolio observations. Individuals who hold a portfolio for only a few months affect the slope coefficient as much as individuals who hold a portfolio for all 24 months of the sample. We cannot run panel regressions using monthly MB or monthly SIZE as dependent variables because all of our explanatory variables are fixed. The portfolio value does change month-to-month, but these changes will reflect 100% of the changes in MB and SIZE unless the stock's book value changes month-to-month or the investor has made some trades. In our sample, the book values used in market-to-book ratios seem to be updated annually, and many of the investors are not active traders. Being unable to run panel regressions, we need another method to look at portfolio differences over time.

We choose to proceed as follows. We divide the investors into two groups in each month based on their personality trait scores. Individuals with personality trait scores above the median are in the "high" group, and those with trait scores at or below the median are in the "low" group. For each month t in the sample period, we find the average of $MB_{i,t}$ and the average of $SIZE_{i,t}$ for both the low and the high group. (In Section 4.1, we found the average values over time for each person and then compared the averages.) Note that the group members may change over time as individuals enter or exit the market. However, if an individual returns to the market after exiting, she enters in the same group because the personality trait variables do not change over the sample period. We present the plots for MB in Figure 2 and the plots for SIZE in Figure 3.

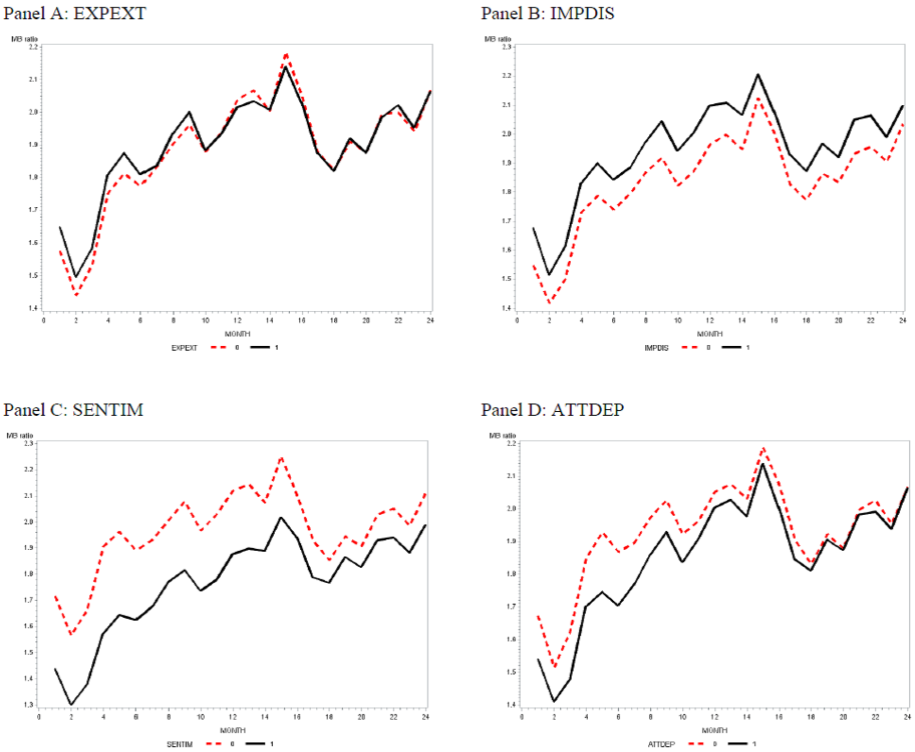

Fig. 2. Aggregate Equally-Weighted Portfolios, MB. Investors are sorted by their personality traits score into two groups: high (above median) and low (at or below median). We find the average value of $\mathrm{MB}_{i,t}$ (portfolio value-weighted market-to-book) for each group in each month. In each panel, the solid black line represents the high group and the dashed red line represents the low group.

Fig. 3. Aggregate Equally-Weighted Portfolios, SIZE. Investors are sorted by their personality traits score into two groups: high (above median) and low (at or below median). We find the average value of $SIZE_{i,t}$ (portfolio value-weighted firm market capitalization) for each group in each month. In each panel, the solid black line represents the high group and the dashed red line represents the low group.

Figure 2 and Figure 3 show that the results in Section 4.1 are generally consistent over time and are not due to extreme outliers and/or short-term investors. There is only one exception: the positive relationship between EXPEXT and SIZE in Table 3 is not evident in Figure 3. All other trait effects are in line with the regression results in Table 3 and with our hypotheses. Higher scores on IMPDIS are associated with higher market-to-book and smaller stocks. Higher scores on SENTIM and ATTDEP are associated with lower market-to-book and smaller stocks. The fact that the lines closely track each other is due to the fact that many people own the same stocks – the Finnish market has only about 130 stocks to choose from and there are a few large capitalization stocks that dominate the market (e.g., Nokia;

this issue is addressed in Section 5.2). However, most of the plots show consistent differences across the groups over time, indicating that the relationship between the traits and choices for value and size are consistent over time.

4.3 Personality Trait-sorted Aggregate Portfolios

The above analyses give equal weight to all investor portfolios, regardless of the portfolio value in euros. A portfolio worth €1,000 has the same effect as a portfolio worth €100,000. In this section, we form groups based on the personality traits, and we construct aggregate portfolios for each group in each month. We can then compare the portfolios across groups and over time.

For each month in the sample, we divide the investors into two groups based on the personality traits. The "high" group has those investors with personality trait scores above the median, and the "low" group has investors with personality trait scores at or below the median. We combine the holdings of all the group members to form an aggregate portfolio for the group. We thus have an aggregate portfolio for the high group and an aggregate portfolio for the low group in each month. We find the value-weighted MB and value-weighted SIZE of the portfolios in each month. Figure 4 contains the plots for MB, and Figure 5 contains the plots for SIZE.

Fig. 4. Aggregate Value-Weighted Portfolios, MB Investors are sorted by their personality traits score into two groups: high (above median) and low (at or below median). We find the value-weighted MB (market-to-book) for the aggregate portfolio of each group in each month. In each panel, the solid black line represents the high group and the dashed red line represents the low group.

Fig. 5. Aggregate Value-Weighted Portfolios, SIZE Investors are sorted by their personality traits score into two groups: high (above median) and low (at or below median). We find the value-weighted SIZE (market capitalization) for the aggregate portfolio of each group in each month. In each panel, the solid black line represents the high group and the dashed red line represents the low group.

The plots generally show clear differences in the value and size tilts of the aggregate portfolios. We see confirmation of our earlier results: IMPDIS: growth stocks; EXPEXT: large capitalization stocks; SENTIM and ATTDEP: small capitalization stocks. The plots for EXPEXT-MB and ATTDEP-MB are the only plots that contrast with our results in analyses above. The contrasting results seem to be due to the effects of a few wealthy individuals. If we exclude individuals with portfolios greater than €100,000, neither the EXPEXT-MB plot nor the ATTDEP-MB plot shows a large difference between the high and low groups.[7] The exclusions do not affect the plot for EXPEXT-SIZE or the plot for ATTDEP-SIZE. For thoroughness, we perform a means test of the average MB and average SIZE of the aggregate portfolios. The results are presented in Table 4. The plots that show clearly visible differences in MB and SIZE across the high and low trait groups' aggregate portfolios have significant differences in the means of MB and SIZE for the aggregate portfolios.

Table 4. Personality-sorted Portfolios' Means

	MB			SIZE			Number Investors	
	low trait	high trait	t-stat	low trait	high trait	t-stat	low trait	high trait
EXPEXT	2.00	1.91	1.91**	9696	11121	-3.50***	345	291
IMPDIS	1.76	2.20	-8.58***	10282	10122	0.43	326	310
SENTIM	1.98	1.96	0.30	11138	8530	7.39***	396	239
ATTDEP	1.83	2.12	-5.67***	11383	8961	6.45***	329	307

The table presents the mean values and t-tests of mean differences for the aggregate portfolios used in Figure 3 and Figure 4. In each month, we sort individuals by their personality trait scores into two groups: high (above median) and low (at or below median). We combine the holdings of the group members into aggregate portfolios. We find the value-weighted MB and value-weighted SIZE for the aggregate portfolio of each group. Since the number of investors in each group may change over time, we present the average number of investors in each group over the sample period. MB is the aggregate portfolio's value-weighted market-to-book ratio, and SIZE is the aggregate portfolio's value-weighted firm market capitalization. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

[7] The median portfolio value is only 3,570. Only 24 individuals have portfolios with an average value greater than €100,000.

5 Further Tests

5.1 Value and Size Factor Loadings

Section 4 showed that the personality traits have a consistent relationship with value and size tilts in the portfolio when the tilts are measured by the simple characteristics market-to-book and market capitalization. However, an investor's personality traits may or may not show a consistent relationship with her portfolio's systematic risk exposure to the HML (value) and SMB (size) risk factors of the Fama & French (1993) Three-Factor Model. An individual stock may not have a high beta with respect to a particular risk factor despite the stock clearly having the "correct" characteristic for the risk factor (i.e., not all value stocks necessarily have high HML betas). The investors in our sample generally hold only a few stocks; it is possible that the stocks' betas with respect to HML and SMB do not match the stocks' characteristics. For personality to have an effect on asset prices, beyond simply being correlated with characteristics of investors' portfolios, personality traits should also be significantly related to asset pricing risk factors. We therefore test the relationship between the personality traits and exposure to HML and SMB risk factors.

We find each stock's beta with respect to the two factors by running the Three-Factor Model of Fama and French (1993). We calculate the betas for each stock in each month by using returns from the previous 60 months.[8] We use the market return, HML return, SMB return, and risk-free rate provided by AQR Capital Management, LLC.[9] The portfolio's beta with respect to HML (SMB) is calculated as the value-weighted sum of the individual stocks' HML (SMB) betas. Table 5 displays the average betas for the stocks in our sample.

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[8] There are a few stocks that were issued within the 60 months prior to the start of our sample period. We start calculating betas when the return history reaches 36 months. Even though these stocks have a short return history, we use the betas to find the portfolio's value-weighted betas for HML and SMB. In an unreported analysis, we find nearly identical results if we exclude those investors who hold more than 20% of their portfolio in stocks with a return history between 36 and 60 months. The stocks with short return histories seem to have no impact on our results.

[9] The data were downloaded on 4 May 2016 from https://www.aqr.com/library/data-sets.

Table 5. Mean Factor Loadings

	N	Mean	Median	Std Dev	Minimum	Maximum
HML	136	0.44	0.45	0.39	-0.97	1.76
SMB	136	0.69	0.65	0.58	-0.95	2.79
MKT	136	0.79	0.72	0.31	0.05	1.54

We calculate each stock's factor loading using the Fama-French (1993) Three-Factor Model. We calculate the factor loadings on a rolling basis in every month of the sample period 2009–2010, using the previous 60 months of return history. The HML factor, SMB factor, market return, and risk-free rate we use are from AQR Capital Management, LLC.

We run OLS regressions similar to those in Table 3, but in Table 6 the dependent variables are the portfolio's betas with respect to HML and SMB. We see in Table 6 that the relationship between personality traits and factor loadings is consistent with the relationship between the traits and stock characteristics. Individuals with higher scores for EXPEXT have less exposure to the value factor and less exposure to the size factor. Higher scores on IMPDIS are associated with more exposure to the size factor, but IMPDIS does not have a significant relationship with the value factor. ATTDEP has a positive relationship with value, but not with size. While not all of the results confirm our hypotheses (e.g., IMPDIS would be expected to have a negative relationship with HML; SENTIM should be positively related to both HML and SMB), none of the results here are in contrast to the results in the previous sections.

The magnitude of the relationships is also large. An increase of one standard deviation in EXPEXT implies a decrease of 10–13% (of the mean) in HML-loading and a decrease of 11–14% in the SMB-loading of the individual's portfolio. An increase of one standard deviation in IMPDIS is associated with roughly a 7% increase (at the mean) in exposure to the SMB factor. For ATTDEP, a one-standard-deviation increase implies an increase of 11% (at the mean) in the portfolio's HML beta.

It is interesting to compare our results for value loadings to those of Betermier et al. (2017). They find financial wealth to be positively related to portfolio value loadings, while we find wealth is not significantly related to the portfolio value loading. (In our sample, wealthier individuals have a preference for stocks with higher market-to-book ratios, i.e., generally lower value loadings; see Table 3.) Betermier et al. (2017) find males to have portfolios with a growth tilt. In our tests, gender has no significant relationship with the portfolio tilt towards value or growth. Betermier et al. (2017) also find a generally consistent positive relationship between higher education and a preference for value stocks. We find that individuals with higher education have portfolios with higher market-to-book ratios, but the relationship between education and portfolio HML beta is not significant.

Table 6. HML and SMB Loadings and Personality

	HML			SMB		
EXPEXT	-0.043**	-0.057***	-0.058***	-0.074***	-0.092***	-0.098***
	(-2.32)	(-2.88)	(-2.84)	(-2.89)	(-3.43)	(-3.60)
IMPDIS	0.006	0.001	0.001	0.055**	0.047**	0.047**
	(0.36)	(0.06)	(0.06)	(2.43)	(2.00)	(1.99)
SENTIM	0.008	0.012	0.012	0.010	-0.002	-0.006
	(0.46)	(0.67)	(0.64)	(0.44)	(-0.08)	(-0.24)
ATTDEP	0.046***	0.050***	0.051***	0.021	0.026	0.030
	(2.74)	(2.91)	(2.91)	(0.90)	(1.12)	(1.27)
Female		0.047	0.046		0.088*	0.078
		(1.28)	(1.23)		(1.73)	(1.52)
University		0.006	0.008		-0.038	-0.028
		(0.19)	(0.23)		(-0.83)	(-0.61)
Risk Aversion		-0.024***	-0.024***		-0.032***	-0.033***
		(-3.00)	(-2.95)		(-3.05)	(-3.16)
Ln(PortValue)			-0.003			-0.023*
			(-0.27)			(-1.75)
Intercept	0.249	0.327	0.351	0.144	0.260	0.462
	(15.84)	(8.66)	(3.27)	(6.79)	(4.99)	(3.31)
N	702	658	658	702	658	658
R-squared	0.014	0.031	0.031	0.015	0.030	0.035

The table shows OLS coefficients for HML and SMB loadings regressed on personality traits. The dependent variables are the average of the monthly observations of portfolio value-weighted HML- and SMB loadings for each individual. EXPEXT is the combination of exploratory excitability and extravagance. IMPDIS is the combination of impulsiveness and disorderliness. SENTIM is sentimentality. ATTDEP is the combination of attachment and dependence. The personality traits are standardized to mean zero and standard deviation of one. Female is an indicator variable. University is an indicator variable for having achieved a bachelor's degree or higher. Risk Aversion is general risk aversion, measured from 0 to 10. Ln(PortValue) is the log of the average euro-value of the portfolio. t-statistics calculated from heteroscedasticity-consistent standard errors are in parentheses below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

We also look at the HML loadings and SMB loadings of the aggregate trait-based portfolios, in an analysis analogous to that in Section 4.3. As a reminder, in each month we sort the investors into two groups: the high group has a score above the median for the personality trait, and the low group has scores at or below the median. We aggregate the holdings of the group members and find the value-weighted HML and SMB betas of this aggregate portfolio. The plots for HML betas are in Figure 6 and the plots for SMB betas are in Figure 7. The results are consistent with the results in Table 6 and our earlier analyses. Higher scores for EXPEXT are associated with lower HML loadings and lower SMB loadings. IMPDIS is related to lower HML betas and generally higher SMB betas. SENTIM is associated with higher HML betas and higher SMB betas (albeit a weak relationship with SMB). The plots for ATTDEP show that higher scores are related to higher HML loadings and generally higher SMB loadings.

Gender seems to be very weakly related to the SMB factor loading, with females preferring stocks with a lower loading on SMB. Gender is not related to the HML loading. Education shows no relationship with either the HML or the SMB loading. Risk aversion is negatively related to both the HML tilt and SMB tilt of the portfolio. Higher levels of risk aversion should be negatively correlated with value and (small) size tilts, under the interpretation of risk-based explanations for the value and size premiums. However, this is the only significant relationship we find between an investor's general level of risk aversion and the preference for growth; no significant relationship is observed in Table 3 (above) or Table 8 and Table 9 (below). We find this intriguing because a stock's market-to-book ratio is much more easily obtained than the stock's beta with respect the HML factor.[10]

[10] Most free financial websites seem to provide "key statistics" including price-to-book and market capitalization, among others. For an example, see www.nasdaqomxnordic.com.

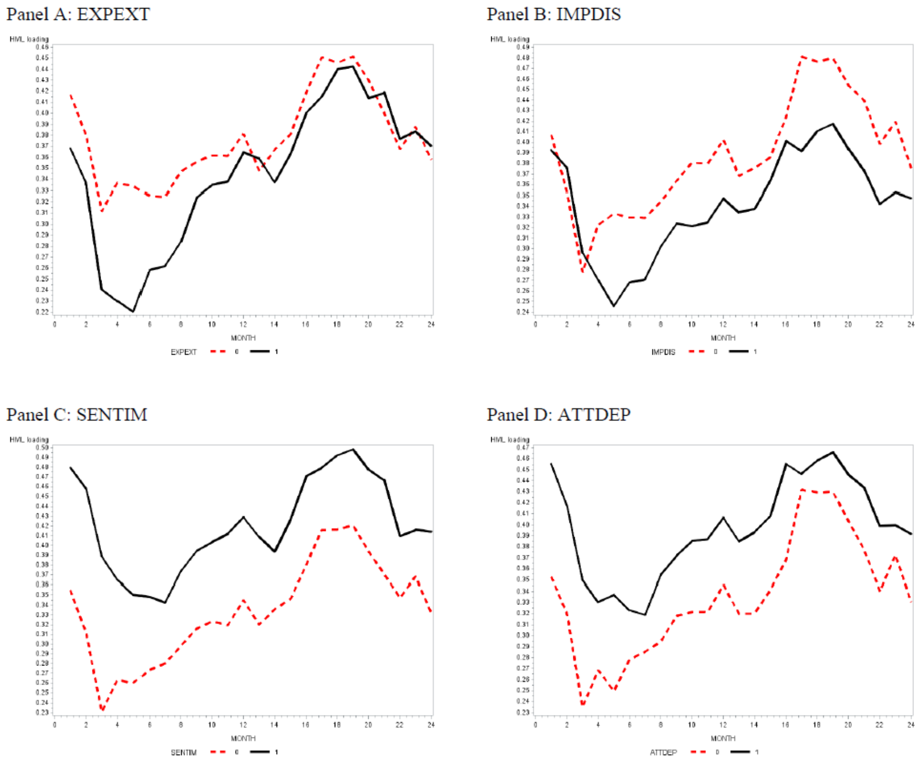

Fig. 6. Aggregate Value-Weighted Portfolios, HML Beta Investors are sorted by their personality traits score into two groups: high (above median) and low (at or below median). We find the value-weighted HML beta for the aggregate portfolio of each group in each month. In each panel, the solid black line represents the high group and the dashed red line represents the low group.

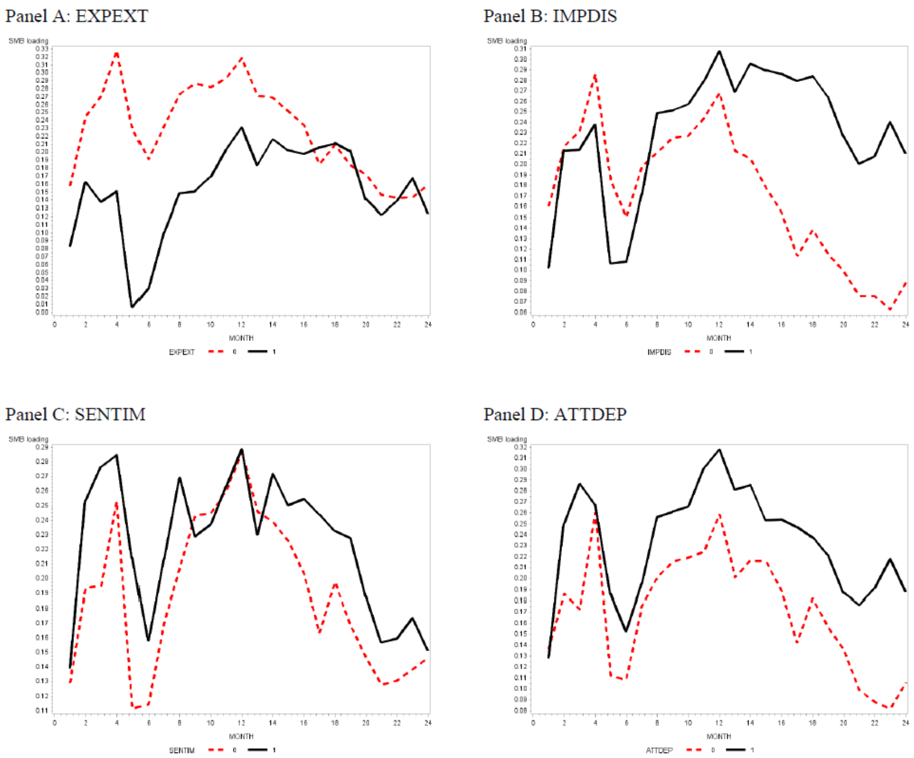

Fig. 7. Aggregate Value-Weighted Portfolios, SMB Beta Investors are sorted by their personality traits score into two groups: high (above median) and low (at or below median). We find the value-weighted SMB beta for the aggregate portfolio of each group in each month. In each panel, the solid black line represents the high group and the dashed red line represents the low group.

5.2 Popular Stocks

In a market with only a few large stocks, it is likely that many investors hold many of the same stocks. Nokia is the clearly dominant firm in the Finnish stock market during our sample period, with 556 individuals in our sample (out of 710) holding shares of Nokia at some point during the sample period 2009–2010. The next most commonly held stock is that of Nordea Bank, held by 316 investors during the sample period. The average investor has 61% of his portfolio invested in the ten most popular stocks, and 232 investors have portfolios consisting of only stocks among the ten most popular. Table 7 lists the ten most popular stocks in the sample and the stocks' market capitalizations as of December 30, 2010. Nine of the ten most popular stocks in our sample are also in the top ten most-widely held stocks in January 2015 (Keloharju & Lehtinen, 2015). Elektrobit, a company based in Oulu (many of the cohort members still live in the Oulu region), is the only company among the top ten popular stocks in our sample that is not among the most widely held in Finland in 2015.

Table 7. Most Commonly Held Stocks

Company	# holders	Market Cap.(millions)
Nokia	556	28986
Nordea Bank	316	32987
TeliaSonera	288	23934
Fortum	228	20015
Neste Oil	189	3064
Elektrobit	186	87
UPM-Kymmene	182	6874
Elisa	181	2706
Sampo	147	11230
Outokumpu	143	2540

The table shows the most commonly held stocks in our sample. An individual is counted as a holder of the stock if she is observed to hold the stock on any of the month-end dates during the sample period 2009–2010. We place no minimum on the holding period.

There are two approaches to disentangling the effect of popular stocks on an investor's portfolio. One can simply partition the portfolio into popular and non-popular stocks and find the value-weighted market-to-book ratio and firm market capitalization (or factor loadings) of each partition separately. This approach is problematic because the stocks' weights in the partitions are not the same as the stocks' weights in the overall portfolio; these changes in weights may lead to inaccurate values for the value-weighted MB, SIZE, and factor loadings calculated for the partitions. For example, assume an investor has 80% of her portfolio in a popular large-capitalization growth stock and 20% in a non-popular small capitalization value stock. The overall preference for this investor is large-capitalization growth stocks. After partitioning the portfolio into popular and non-popular stocks, the investor would have a popular partition with 100% invested in large-cap growth and a non-popular partition with 100% invested in small-cap value. The partitioning leads to the investor's personality traits being associated with both large-cap growth and small-cap value. In this case, the non-popular partition provides an inaccurate description of the investor's overall preference.

We avoid this partitioning problem by separately analyzing those investors who have held only popular stocks in their portfolio and those investors who have never held popular stocks in their portfolio during the sample period. While the number of investors fitting these restrictions is small (232 individuals have held only popular stocks; 93 individuals have never held popular stocks), the restrictions allow for much more accurate tests of the relationship between personality traits and portfolio characteristics in the presence/absence of widely held stocks. The results of OLS regressions of portfolio factor loadings on the personality traits for the popular stocks are in Table 8, and the results for the non-popular stocks are in Table 9.[11]

Table 8. Personality, Value- and Size Loadings for Popular Stocks

	HML			SMB		
EXPEXT	-0.097***	-0.120***	-0.123***	-0.125***	-0.159***	-0.163***
	(-3.14)	(-3.79)	(-3.95)	(-3.37)	(-4.06)	(-4.23)
IMPDIS	0.010	0.026	0.022	0.035	0.036	0.030
	(0.30)	(0.80)	(0.72)	(0.92)	(0.95)	(0.81)
SENTIM	0.071**	0.064*	0.053	0.042	0.019	0.001
	(2.25)	(1.92)	(1.62)	(1.07)	(0.44)	(0.03)
ATTDEP	0.059*	0.046	0.042	0.041	0.043	0.037
	(1.78)	(1.33)	(1.27)	(1.01)	(1.01)	(0.93)
Female		0.188***	0.167***		0.207**	0.176**
		(2.87)	(2.65)		(2.45)	(2.19)
Univ.		0.066	0.081		-0.017	0.006
		(1.04)	(1.32)		(-0.22)	(0.08)
Risk Av.		0.000	0.003		-0.028*	-0.023
		(0.01)	(0.26)		(-1.67)	(-1.41)
Ln(PortValue)			-0.081***			-0.124***

[11] We report only the regression results using the factor loadings as dependent variables. Regressions using market-to-book ratio and market capitalization as dependent variables produce similar results. Those results are available on request from the contact author.

	HML			SMB		
			(-3.72)			(-3.98)
Intercept	0.011	-0.112	0.488	-0.148	-0.102	0.811
	(0.39)	(-1.43)	(2.65)	(-3.88)	(-1.02)	(3.11)
N	232	218	218	232	218	218
R-squared	0.068	0.118	0.173	0.042	0.078	0.158

The table show the OLS regression results for the subsample of individuals whose portfolios contained only those stocks among the top ten most widely held stocks in our sample. The dependent variables are the average of the monthly observations of portfolio value-weighted HML- and SMB loadings for each individual. EXPEXT is the combination of exploratory excitability and extravagance. IMPDIS is the combination of impulsiveness and disorderliness. SENTIM is sentimentality. ATTDEP is the combination of attachment and dependence. The personality traits are standardized to mean zero and standard deviation of one. Female is an indicator variable. Univ. is an indicator variable for having achieved a bachelor's degree or higher. Risk Av. is general risk aversion, measured from 0 to 10. Ln(PortValue) is the log of the average euro value of the portfolio. t-statistics calculated from heteroscedasticity-consistent standard errors are in parentheses below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

For those individuals who have held only popular stocks, we find results generally in line with our expectations and with our results presented in earlier sections. The personality trait EXPEXT has the strongest effect, with higher scores on EXPEXT leading to lower loadings on both the HML factor and the SMB factor. There is evidence that high scores on SENTIM are related to a preference for value, but the statistical significance drops as we add controls to the model (in the model with all controls, the p-value for the SENTIM coefficient is 0.106). ATTDEP is weakly positively related to the value loading (significant at the 10% level), but only in the model with no controls. Neither SENTIM nor ATTDEP is related to the SMB factor loadings among this subset of stockholders. The lack of a statistically significant relationship between IMPDIS and the factor loadings is likely due to the fact that the popular stocks are generally larger capitalization stocks and few in number, while IMPDIS has been associated with a preference for small capitalization stocks.

Table 9. Personality, Value- and Size for Non-Popular Stocks

	HML			SMB		
EXPEXT	0.004	0.018	0.016	-0.132	-0.221**	-0.218**
	(0.08)	(0.37)	(0.31)	(-1.49)	(-2.44)	(-2.35)
IMPDIS	-0.041	-0.030	-0.046	0.147**	0.135*	0.151**
	(-1.14)	(-0.84)	(-1.22)	(2.06)	(1.98)	(2.26)
SENTIM	0.046	0.074**	0.068*	0.046	-0.004	0.003
	(1.36)	(1.89)	(1.72)	(0.71)	(-0.05)	(0.04)
ATTDEP	0.057	0.093**	0.097**	-0.034	-0.077	-0.080
	(1.52)	(2.20)	(2.21)	(-0.53)	(-1.10)	(-1.16)
Female		-0.212**	-0.223***		0.369**	0.379**
		(-2.59)	(-2.71)		(2.28)	(2.37)
Univ.		0.129	0.134*		-0.157	-0.162
		(1.61)	(1.69)		(-1.08)	(-1.12)
Risk Av.		-0.008	0.001		-0.074**	-0.082**
		(-0.50)	(0.03)		(-2.19)	(-2.46)
Ln(PortValue)			-0.051*			0.052
			(-1.68)			(1.05)
Intercept	0.552	0.621	0.957	0.555	0.816	0.472
	(15.03)	(5.99)	(4.05)	(8.15)	(4.20)	(1.20)
N	93	87	87	93	87	87
R-squared	0.061	0.156	0.187	0.064	0.150	0.161

The table shows the OLS regression results for the subsample of individuals whose portfolios contained only those stocks *not* among the top ten most widely held stocks in our sample. The dependent variables are the average of the monthly observations of portfolio value-weighted HML- and SMB loadings for each individual. EXPEXT is the combination of exploratory excitability and extravagance. IMPDIS is the combination of impulsiveness and disorderliness. SENTIM is sentimentality. ATTDEP is the combination of attachment and dependence. The personality traits are standardized to mean zero and standard deviation of one. Female is an indicator variable. Univ. is an indicator variable for having achieved a bachelor's degree or higher. Risk Av. is general risk aversion, measured from 0 to 10. Ln(PortValue) is the log of the average euro value of the portfolio. t-statistics calculated from heteroscedasticity-consistent standard errors are in parentheses below the coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

In Table 9 we use the same regression models, but here we restrict the sample to those that have never held (in the sample period) popular stocks.[12] These 93 individuals have held only those stocks not among the top 10 most widely held in our sample. Again we find supportive evidence that EXPEXT is negatively related to the size factor loading; IMPDIS is positively related to the size factor loading; and SENTIM and ATTDEP are weakly positively related to the value factor loading. There are no statistically significant personality trait coefficients which conflict with earlier results – the evidence is either supportive or neutral.

Gender has a large effect in these regressions, with females preferring greater size factor exposure for both the popular and non-popular groups. The gender effect on value exposure switches, however, from positive (popular stockholders) to negative (non-popular stockholders). The coefficient for university education in the HML regressions is positive and significant at the 10% level in the model with all controls. Higher levels of risk aversion are related to lower size factor loadings, but there is no relationship between risk aversion and the value factor loadings. The larger the euro value of the portfolio, the lower the value factor loading tends to be.

5.3 Value and Size in the Finnish Stock Market

Lastly, we would like to address concerns about potential correlations between the value and size characteristics and factor loadings. The Finnish stock market contains relatively few stocks (compared to larger markets in the USA), and it is dominated by a small number of large capitalization firms. One may be concerned that the stocks in the market generally fall into distinct categories of large-cap growth and small-cap value. This is not the case for the Finnish market during our sample period 2009–2010. There is no relationship between market-to-book ratio and firm market capitalization, and there is no relationship between a firm's HML beta and its SMB beta. We find a very even distribution of market-to-book values across the size distribution; similarly we find a nice spread of HML betas across the SMB betas. Plots of market-to-book ratio against ln(market capitalization) and HML loading against SMB loading are in Appendix A.

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[12] The ”popular-only” and ”non-popular-only” groups show only minor differences in values for the personality traits and controls. The mean of ATTDEP is higher for the non-popular stock investors (9.5 vs 8.9, p-value = 0.08) and ln(PortValue) is higher for the popular stock investors (7.5 vs 7.2, p-value = 0.06). No other differences across the groups are statistically significant.

6 Conclusion

We show that personality traits are significantly related to investors' choices of value vs. growth stocks and large capitalization vs. small capitalization stocks. We find consistent relationships between personality traits and these portfolio characteristics: when looking at average portfolio characteristics for each investor in relation to personality traits; when looking at average portfolio characteristics across investors in monthly cross-sections and over time; and when looking at characteristics of aggregate portfolios for groups formed on high vs. low scores for the personality traits. The traits are significantly related to both simple measures (value: market-to-book ratio; size: market capitalization) and portfolio loadings on the standard value and size risk factors. The effects of the traits are in line with intuitive hypotheses formed from the definitions of the traits. More explorative-extravagant individuals have a tendency to hold big growth stocks. People with higher scores for impulsiveness-disorderliness prefer small growth stocks. Higher scores on sentimentality and more social people hold portfolios tilted towards small value stocks.

While our paper provides evidence of the relationship between personality traits and preferences for value and size tilts, we are unable to determine if the value and size premiums are reflective of systematic risk or behavioral mispricing. Despite not being able to solve this long-standing problem, our paper shows that individual differences are a potential explanation for at least part of the value and size premiums. By showing that personality traits are related to value and size preferences, we add to the literature linking personality traits and individual investment decision-making. Assuming that institutional money managers' investment decisions are influenced by their personality traits, personality traits may have a larger role to play in overall asset pricing than previously thought. Much work needs to be done to determine the mechanism by which personality traits affect behavior. The link may be psychological if personality traits are proxies for or causes of investment biases. The link may be rational, and personality traits reflect preference parameters in a non-standard utility function.

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Appendix A

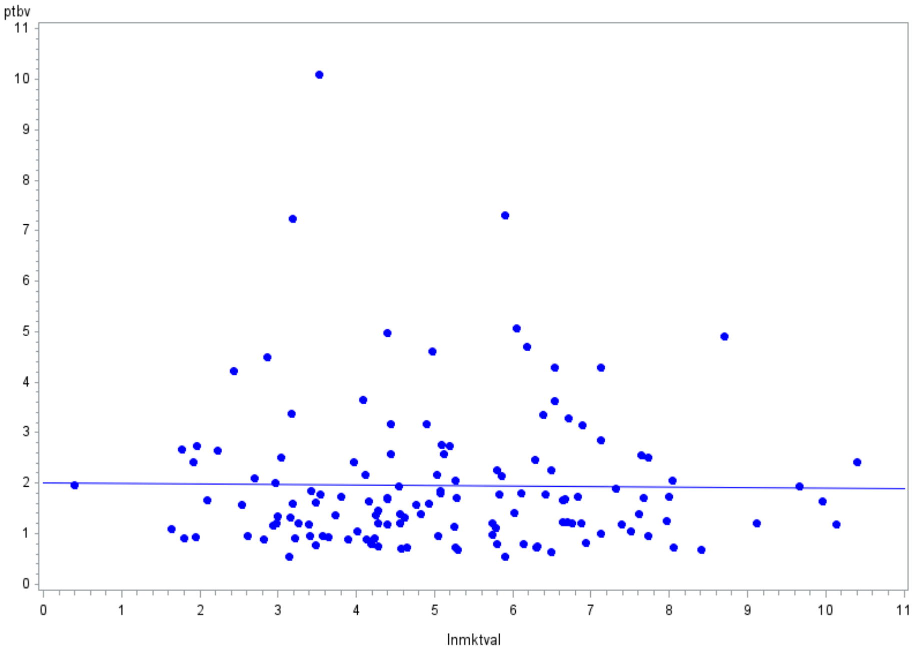

Fig. 8. Plot of Firms' Average Price-to-Book Ratio against Average Market Capitalization
The plot shows each firm's average price-to-book ratio and average ln(market capitalization) over the sample period. The fitted OLS regression line is [price-to-book ratio = 2.01 - 0.0109*ln(market cap)]. The t-statistic for the coefficient is -0.17.

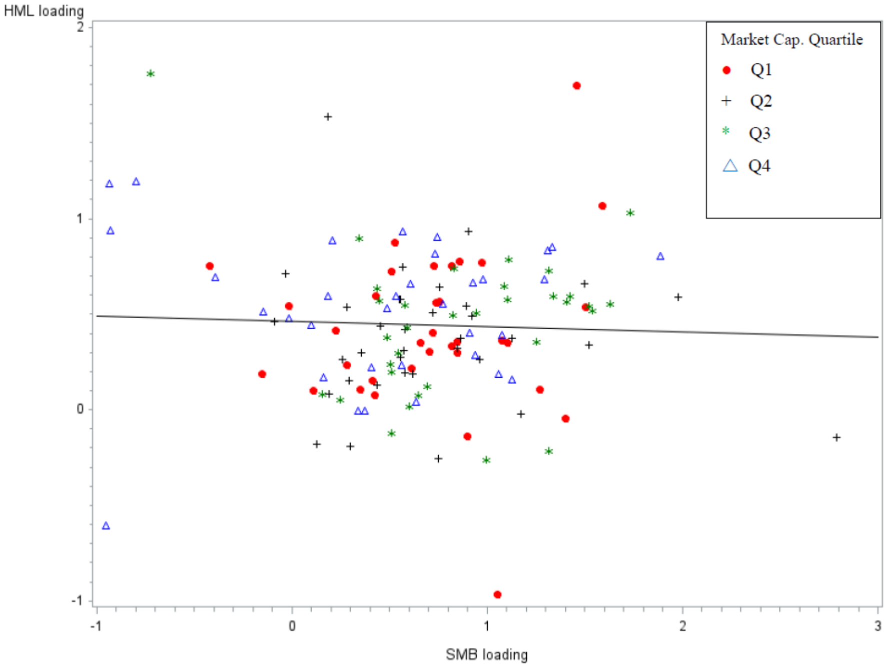

Fig. 9. Plot of Firms' Average HML Beta against Average SMB Beta We take the average of each firm's HML beta and SMB beta over the sample period. Firms with less than 36 months of return history are excluded. The symbols reflect firm market capitalization, by quartile. The fitted OLS regression line is $[\beta_{i,HML} = 0.46 - 0.027\beta_{i,SMB}]$. The t-statistic for the coefficient is -0.47.