# Do personality traits affect productivity? Evidence from the lab*

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**Abstract**

While survey data supports a strong relationship between personality and labor market outcomes, the exact mechanisms behind this association remain unexplored. In this paper, we take advantage of a controlled laboratory set-up to explore whether this relationship operates through productivity. Using a real-effort task, we analyse the impact of the Big Five personality traits on performance. We find that more neurotic subjects perform worse, and that more conscientious individuals perform better. These findings are in line with previous survey studies and suggest that at least part of the effect of personality on labor market outcomes operates through individual productivity. In addition, we find evidence that gender and university major affect the impact of the Big Five personality traits on performance.

*JEL codes:* C91, D03, J3, M5

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# 1 Introduction

Despite the large body of literature on the determinants of labour force participation and earnings, a substantial part of the wage inequality across and even within a range of demographic characteristics and occupations still remains unexplained. In his seminal work, Becker (1964) highlighted the relevance of cognitive skills in explaining earning differences.[1] However, variations in cognitive abilities fail to fully account for the residual wage inequality.[2] More recently, economists have started to focus on the importance of non-cognitive skills in determining earnings (Heckman and Kautz 2012). Soft skills such as self-motivation, planning capabilities, industriousness, self-control or self-esteem are strong candidates to explain the remaining wage inequality (Bowles, Gintis and Osborne 2001).

Within the set of non-cognitive skills, personality traits are one of the most relevant instruments in the study of differences in earnings.[3] Mueller and Plug (2006) show that the effect of personality traits on earnings is of similar magnitude to the one of cognitive skills. In addition, these traits can help to account for the strong intergenerational correlation in labour market outcomes that cannot be attributed to parental education and wealth transmission (Mulligan 1999). Well-established evidence shows that while personality is genetically inherited to a large extent (Bouchard Jr and Loehlin 2001) it is still sensitive to parental investments (Borghans, Duckworth, Heckman and Ter Weel 2008a).

Recent studies have linked job performance and wages to the so-called "Big Five" personality traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism (Heckman et al. 2006, Fletcher 2013). Using survey data, these papers report a strong relationship between some of these personality traits and wages. Conscientiousness, antagonism (inverse of agreeableness) and emotional stability (the inverse of neuroticism) show a robust positive relationship with earnings. There is also some evidence of a positive effect of extraversion and openness to experience on wages. However, these correlations cannot disentangle whether the effects of personality traits on labour market outcomes operate through self-selection into jobs (Cobb-Clark and Tan 2011), engagement

[1] See also Murnane, Willett and Levy (1995), Cawley, Heckman and Vytlacil (2001) or Heckman, Stixrud and Urzua (2006).

[2] For example, Blau and Kahn (2005) find that although cognitive test scores contribute to explain the higher wage dispersion in the US compared to other OECD countries, residual wage inequality is still substantial. Furthermore, Cawley et al. (2001) report that the share of wage variance that can be attributed to cognitive abilities is modest, and Heckman and Rubinstein (2001) present evidence that cognitive abilities fail to explain the variation in wages between GED recipients and high-school graduates.

[3] Personality is defined as the combination of emotional, attitudinal, and behavioural characteristics which are unique to an individual, and hence, are part of her set of productive skills.

in training opportunities (Barrick and Mount 1991), or performance evaluation by supervisors (Caligiuri 2000). Moreover, personality traits may have less measurable effects on earnings through networking skills, bargaining abilities, or the availability of outside options.

To the best of our knowledge, this is the first paper to use a laboratory experiment to directly test the relationship between the Big Five personality traits and individual productivity. This exercise allows us to explore the mechanisms behind the relationship between personality traits and earnings found in observational studies, and to further understand how personality traits can explain the level of output and its distribution among individuals. An increasing number of labour economists are using laboratory experiments to tease out the potential confounds present in survey analysis (Charness and Kuhn 2011). Despite the problem of external validity, which we discuss in detail in Section 5, this methodology can offer a valuable complement to the existing studies on the effect of personality on labour market outcomes. Unlike survey data, information in the lab is generated under closely monitored conditions, which allows a precise measurement of the performance of experimental subjects. In addition, it is possible to assess which personality traits should be directly relevant for performance in a given experimental task. Finally, the laboratory setting controls for other usually unobserved factors such as workplace environment and peer effects.

We find evidence supporting the hypothesis that certain personality traits are correlated with productivity. Our findings are in line with previous survey studies; neuroticism has a significant detrimental effect on productivity, while more conscientious individuals perform better. However, agreeableness is not correlated with worse performance in our experiment, suggesting that the observed link between agreeableness and labour market outcomes operates through channels different from individual productivity. We also find that two other traits, extraversion and openness to experience, have differential effects by gender and major of study. This finding is consistent with previous studies that argue that personality contributes to the gender wage gap. On the other hand, we find limited evidence of family background modulating the impact of the Big Five.

The study of the link between personality and productivity is important for two different reasons: first, employers are naturally interested in the extent to which personality traits influence productivity. Anecdotal evidence shows the importance of personality in the workplace. For instance, Green, Machin and Wilkinson (1998) document that personnel managers find "attitude, motivation and personality" as the most important attributes when hiring. US employers ranked "attitude" as the most important skill among new employees in non-supervisory jobs (Bowles et al. 2001). In fact, employers are using screening based on non-cognitive skills more frequently.[4]

[4]See for instance "Are Workplace Personality Tests Fair?", *Wall Street Journal*, September 29th, 2014. Available

Understanding the impact of personality traits on individual productivity can provide us with a deeper understanding of the key role of heterogeneity in explaining wage dispersion

## 2 Related Literature

Economists have only recently focused their attention on non-cognitive skills. Cognitive skills, while extremely important in determining educational and labour market outcomes (Cawley, Conneely, Heckman and Vytlacil 1997), fail to fully explain observed variation in performance (Heckman and Rubinstein 2001, Heckman and LaFontaine 2010). Early studies showed that traits such as high self-esteem and self-directness −the sense that own actions are the primary determinants of outcomes− positively affect real wages (Osborne 2000, Murnane, Willett, Braatz and Duhaldeborde 2001), in a higher order of magnitude than human capital (Goldsmith, Veum and Darity 1997). More recently, Heckman et al. (2006), Borghans et al. (2008a), and Cobb-Clark and Tan (2011) find that non-cognitive skills such as self-control or self-esteem play a key role determining a wide variety of economic outcomes.

While it is widely accepted in the the literature that cognitive skills can be summarized in a single factor ("g" or general factor), not such agreement has been reached with regard to non-cognitive skills. Some of the measures employed in the early literature, such as feelings of self-efficacy or self-esteem, are likely to suffer from a severe endogeneity problem. For instance, adverse economic shocks such as unemployment spells have a negative impact on self-esteem. Economists and psychologists have lately focused on the Five Factor Model of Personality (Costa and McCrae 1992), commonly called the "Big Five". These five "factors" or personality traits are Extraversion, Agreeableness, Neuroticism, Conscientiousness, and Openness to Experience.[5]

The "Big Five" approach has become tremendously popular for several reasons. First, these personality traits are unlikely to experience ordinal changes (Roberts and DelVecchio 2000, Jones, Livson and Peskin 2006, Cobb-Clark and Schurer 2012), particularly after early adulthood.[6] Changes over time in absolute levels are extreme over childhood, but also likely to occur during adulthood (Roberts, Walton and Viechtbauer 2006). However, they seem to be very gradual and determined by biological maturation rather than life experience (McCrae and Costa Jr 1999, Srivastava, John, Gosling and Potter 2003).[7] Moreover, the Big Five is a robust measure both across cultures and

at http://www.wsj.com/articles/are-workplace-personality-tests-fair-1412044257, accessed 25 September 2015.

[5] We describe each of these traits in more detail in Section 3.3.

[6] For instance, Roberts and DelVecchio (2000) estimated traits consistency, for an interval of 6.7 years, of 0.54 during the college years, increasing to 0.64 at age 30, and to 0.74 between ages 50 and 70.

[7] Some studies (see, among others, Costa, Herbst, McCrae and Siegler (2000) or Sutin and Costa (2010)) report

samples (Barrick and Mount 1991). For instance, McCrae and Terracciano (2005) report similar differences by gender in cultures with very different gender roles and expectations. Finally, the Big Five personality traits are considered to be largely uncorrelated with cognitive skills, defined as the ability to solve abstract problems (McCrae and Costa 1994, Stankov 2005)[8], although they impact performance in cognitive tests (Almlund, Duckworth, Heckman and Kautz 2011). Hence, the Big Five personality traits constitute truly distinct factors in the analysis of labour market outcomes, which in addition are less prone to the endogeneity problem that affects other personality measures such as self-efficacy and self-esteem.

For all the aforementioned reasons, labour economists have increasingly incorporated the Big Five into their toolkit.[9] Using survey data from the Netherlands, Nyhus and Pons (2005) report a negative correlation between neuroticism and wages for both men and women, and a negative correlation of agreeableness with wages for women only. Mueller and Plug (2006) also find heterogeneous effects by gender in US data. More recently, Heineck and Anger (2010) estimate the impact of non-cognitive skills on earnings in a German sample and their interaction with cognitive skills as measured with an ultra-short IQ test. Viinikainen, Kokko, Pulkkinen and Pehkonen (2010) exploit longitudinal data from Finland to estimate the impact of personality traits measured at different points in life (including childhood) on labour income at age 43. Heineck (2011b) explores the tenure effects of past and present personality traits using longitudinal British data. Finally, Fletcher (2013) uses sibling fixed effects to control for family background and genetic endowments, finding robust associations between personality traits and labour market outcomes, but substantial heterogeneity across demographic groups.

To summarize, the take home messages of this literature are: 1) Neuroticism and agreeableness are consistently correlated with lower earnings while more conscientious individuals present better labour market outcomes; 2) gender differences in the effects of personality traits can contribute to explain the gender wage gap; and 3) the estimated effect of personality is of comparable magnitude to that of cognitive skills.

life experiences, such as divorce or hazardous work, to affect personality traits, but there is no consistent evidence on the matter.

[8]This is not the case for other personality traits, such as creativity (Csikszentmihalyi 1997), cognitive style (Perkins and Tishman 2001) or emotional intelligence (Mayer, Caruso and Salovey 1999). These traits, also known as "quasi-cognitive" traits, are strongly correlated with cognitive skills.

[9]Psychologists have profusely studied the link between the Big Five and labour market outcomes (see, for instance, Barrick and Mount (1991), Tett, Jackson and Rothstein (1991), Salgado (1997), Judge, Higgins, Thoresen and Barrick (1999) or Chamorro-Premuzic and Furnham (2005)). This literature shows a consistent strong positive effect of conscientiousness and emotional stability on job performance, while the effects of other personality traits are confined to certain occupations (extraversion has a positive effect on occupations involving social interactions) or particular job aspects (openness to experience is related to training proficiency).

In addition to wages and labour force status, other labour market outcomes are influenced by personality traits. For instance, Cobb-Clark and Tan (2011) report that non-cognitive skills have a different effect in the probability of being employed in certain occupations. Fletcher (2013) finds that emotionally stable and conscientious individuals are more likely to be employed; the latter effect may be due to their effective job seeking behaviour as documented by Uysal and Pohlmeier (2011). On the other hand, Caligiuri (2000) finds a positive correlation between conscientiousness and supervisor-rated performance. Therefore, the correlation between traits and wages or labour force status does not necessarily imply a different productivity of individuals with different distributions of personality traits.

To the best of our knowledge, ours is the first experimental study directly aimed to unbundle the relationship between personality traits and labour market outcomes. In a related study, Müller and Schwieren (2012) use a laboratory experiment to explore whether gender differences in Big Five personality traits can explain the differential entry rates of males and females into competition observed by Niederle and Vesterlund (2007). They run three five-minute rounds of the same task as ours under different compensation schemes. The payment in their first round was piece rate and hence comparable to our design. These authors find that openness to experience is negatively correlated to performance in that piece-rate round. Neither conscientiousness nor neuroticism correlated with performance in that round, although the latter correlated negatively with performance in their tournament round. In our paper, we investigate individual productivity rather than competitiveness. Accordingly, we demand sustained effort from our subjects and ask them to perform the task for twenty minutes. Still, we also find a weak negative effect of openness on performance but only for our first ten-minute round. After that, the effect of this trait becomes insignificant. Moreover, Müller and Schwieren (2012) show only simple correlations between performance and traits whereas our models control for session and subject characteristics.

# 3 The experiment

## 3.1 Design

We used the ORSEE online system (Greiner 2004) to recruit a total of 359 University of New South Wales students as participants in the experiment during August 2013. We ran 15 sessions in the Australian School of Business Lab with around 20-25 students per session.

The experiment consisted of five stages: welcoming and instructions, performance of the task, break, performance of the same task, and administration of the demographic and Big Five questionnaires. Upon arrival, participants were assigned to computer units separated by screens and received paper, pencil and written directions regarding the conditions of their participation in the experiment. Instructions were given orally through headphones (see Appendix A for the transcription of the instructions). This was motivated by three main reasons. First, we wanted to replicate a work environment as closely as possible by recreating a hierarchy between employer and employee. Second, we wanted to isolate this interaction from personal characteristics of the employer as much as possible. It is well known that gender interactions between employer and employee have an impact on productivity (Delfgaauw, Dur, Sol and Verbeke 2013).[10] Finally, we prevent any emotional connotations due to personal affinity or sympathy which might easily appear in live interactions and affect the employer-employee interaction.

The instructions described the task and the payoff scheme. For each correct item in the task, subjects gained 20 experimental dollars and lost 4 per incorrect item. They were also informed that the exchange rate was 0.02 Australian dollar (AU$) per experimental dollar. The piece-rate payment scheme is the most suitable for our research question. Even in real workplaces where wages are fixed, a good performance may lead to better promotion opportunities, better outside options and higher wages in general. Furthermore, a fixed payment treatment would probably exacerbate the importance of intrinsic motivation and the impact of personality traits (Segal 2012). Thus, our design provides a conservative estimation of the effect of personality on performance.

Before the task commenced, subjects were told to raise their hand if they had any clarification question or any technical problem during the session. No such instance took place. No talking or other interaction among participants was allowed during the whole session.

The experimental session was divided into two rounds with a break in the middle. In each round, subjects were asked to answer as many additions of five 2-digit random numbers as possible in 10 minutes. Once an answer was submitted, it could not be changed, and the next sum showed up in the computer's screen immediately. The task was programmed using zTree (Fischbacher 2007). We chose this task because it measures productivity as a function of both cognitive and non-cognitive abilities such as concentration, effort, stress management, perseverance and industriousness. While openness to experience and extraversion might not be relevant traits for this task, we chose it

[10]To minimize any gender interaction effect, we created identical male and female voices. Since a gender is always assigned to a voice, we modified the original instructions to make them sound as given by male and female supervisors. The gender of the voice was randomized by session. Participants only interacted with experimenters of the same sex as the voice they received the instructions from. Gender interactions in hierarchical structures have proven to be relevant not only in working environments but also in educational achievements (Dee 2007).

because we faced a trade-off between the length and complication of the task and the set of non-cognitive traits relevant to it. In addition, there are no gender differences in performance in this task: men usually perform better than women solving abstract math problems, but there are no gender differences in arithmetic or algebra performance (Niederle and Vesterlund 2007).

Within the limitations of the lab, we choose a task and a setting that works towards replicating the context of a workplace. Although no real job involves performing our task, and it requires certain algebraic abilities, it does not demand a high cognitive effort. It rather requires a type of effort (perseverance, focus, determination) which many workers need to exert in their daily job. In addition, this type of effort is required in multiple activities outside of the workplace such as selection of health insurance or cellphone plans or even in daily activities such as parenting and which are likely to benefit from concentration, effort and basic math ability. Nevertheless, we shall elaborate more on the issue of external validity in Section 5.2.

Between the two rounds, participants had a 5-minute break and were not allowed to leave the room or talk to each other. During the break, participants received a brief reminder of the task and conditions of the experiment ahead. No information about their actual performance was given.

The final stage was not timed. We collected various demographic characteristics together with the Big Five personality traits test. Subjects were not allowed to leave the room until all of them had finished the survey. Once they have completed both questionnaires, participants were informed of the total number of correct and incorrect summations they had accomplished. We paid them in cash their total earnings plus a show-up fee of AU$ 5. Sessions lasted less than one hour, and the average participant earned AU$ 28.8 (around 25.8 US $). Australia minimum wage is AU$16.87 per hour, but lower rates occur in many industries for workers under 21. Wages in, for instance, hospitality industry for adult workers with basic training only, are only a little higher than the minimum wage, around AU$20 per hour.[11]

### 3.2 Measures

Table 1 presents the descriptive statistics for the main variables used in the analysis. We designed the recruitment process in order to obtain a sample balanced by gender. On average, participants were 22 years old, and 30% of them were honour students or were following a master or PhD program. Subjects were asked to classify their family income in a seven-level Likert-like scale in order to minimize the non-response rate. We classified subjects as coming from a high income

[11] PayCheck Plus, Australian Government Fair Work Ombudsman http://paycheck.fwo.gov.au/PayCheckPlus.aspx?redirect=no Accessed 17th September 2015

family if they reported a value of 5 or higher. Parental education was considered to be low if parents did not attend college, which was the case for 34% of the fathers and 50% of the mothers.[12]

Contrary to survey studies, the lab environment allows the experimenter to choose the personality questionnaire that best fits the research question. In their study of personality and competitiveness, Müller and Schwieren (2012) employed the 241-item version (Costa and McCrae 1992), but because of its length they asked their subjects to fill the questionnaire a week before coming to the laboratory. For our measures, we administered the 44-item Big Five Inventory (John, Donahue and Kentle 1991, John, Naumann and Soto 2008) at the end of the task. This mid-sized questionnaire ensures an accurate measure of each personality trait without taking an excessively long time, which could induce measurement error after having performed a"real-effort" task. The items are on a 5-point-Likert scale. Each trait is associated with a subset of these items. We use the responses to these subsets to construct the measure for the associated trait.[13] The Big Five Inventory is designed through factor-analysis so each trait is orthogonal to the rest (McCrae and Costa Jr 1999). We obtained a distribution of values that follows a normal distribution, with limited cases in very high or very low values.[14] The absence of participants with very low levels of agreeableness was to be expected given that our subjects are volunteers. As an indirect measure of ability, subjects were asked to report their average grade, according to the standard Australian classification.[15] Along with information on their labour force status and wage, we used these grades to perform a robustness check of our results (see Section 5.1).

Our task allows us to measure individual productivity in a number of ways. Our primary outcome measure is payment received. We also examine the total number of sums answered, and the total number of correct sums in the available time, to check for different individual strategies when performing the task. On average, subject answered 50.5 sums, of which 45.4 were correct.

[12]Seventeen participants fail to report parental education. A dummy for missing information was included in those specifications that control for parental education, but the results are robust to dropping these observations.

[13]As it is standard in the personality literature and suggested for the test used in this setting, we constructed our personality measures by averaging the scores given to the items associated with each trait. Some of these scores needed to be reversed as they capture the lack of the trait. Hence, the original scores for the Big Five personality traits range from 1 to 5, where 1 denotes a very low incidence of the trait and 5 a very high incidence of the trait.

[14]Krueger and Eaton (2010) classify mental disorders as extreme representation of one or more personality traits.

[15]Grades are classified, in ascending order, as Fail (FL), Pass Conceded (PC), Pass (PS), Credit (CR), Distinction (DN) or High Distinction (HD). Unlike in the US, Australian universities do not inflate grades when the distribution does not look normal.

### 3.3 Hypotheses

Before moving to our results, let us describe our hypotheses on the relationship between personality traits and performance in our experimental task. For obvious reasons, we expect the effects of personal traits on performance to be different from the ones observed in previous studies using survey data.

**Neuroticism** This trait is defined as lack of emotional stability and predictability and by the presence of mood changes, anxiety and insecurity. Neuroticism has been consistently found to hinder wages.[16] Some of the mechanisms at play in labour relations, such as lack of self-confidence, are likely to operate as well in our setting. In addition, we expect neuroticism to impair the ability to focus in our task, especially under time pressure. Hence, our hypothesis is that high levels of neuroticism should be correlated with low performance in our experiment.

**Conscientiousness** This trait measures the extent to which individuals are careful, responsible and hard working. Because it is associated to efficient, organized, achievement-oriented and self-disciplined individuals, conscientiousness shows a consistent positive relation with labour market outcomes.[17] In a similar way, we expect a positive relationship between conscientiousness and performance in our experiment, because being careful, efficient and focused should improve accuracy in the task.

**Openness** Individuals who are open to new experiences are typically imaginative, artistic, curious, creative and intellectually oriented. While creativity might be helpful in many occupations, it might be a hindrance in others, especially in occupations which penalize autonomy and non-conformity.[18] In their laboratory study, Müller and Schwieren (2012) observe a negative correlation between openness and performance in the same addition task under piece-rate payment, albeit in a five-minute round. We thus expect a similar result. Our conjecture is that this result might be driven by creative and artistic individuals who are likely to find the task repetitive and boring. They might also be more likely to engage in the experiment, as a new experience, but the characteristics of the task are likely to countervail this initial positive effect. Therefore, we expect a

[16] As in the economic literature, psychologists Barrick and Mount (1991) and Salgado (1997) find that emotional stability has a positive effect on job performance across all occupations.

[17] In the Psychology literature, Barrick and Mount (1991), Tett et al. (1991) and Salgado (1997), also find evidence of this link across occupations and criteria (wages, promotions, training).

[18] Mueller and Plug (2006) and Heineck (2011a) find substantial earnings advantages associated to openness, although Heineck and Anger (2010) find that it is detrimental for males' wages.

negative net effect of openness on performance in our task.

We do not formulate any explicit hypothesis regarding the two other personality traits, agreeableness and extraversion.[19] Survey evidence suggests that the overall effect of agreeableness on labour market outcomes is negative. But none of the potential mechanisms proposed in the literature[20] is present in our setting. On the other hand, it is hard to think that the sociability associated with extraversion could play a role in our experiment, although the facet of extraversion associated to ambition could have a positive impact on performance. We shall return to this last point in Section 4.2.

To conclude this Section, let us summarize the hypothesis that we will take to the data:

**Hypothesis 1** Neuroticism is negatively associated with performance.

**Hypothesis 2** Conscientiousness is positively associated with performance.

**Hypothesis 3** Openness has a negative relationship with performance.

## 4 Results

This section presents our baseline results and investigates whether the relationship between personality traits and productivity is heterogeneous across individual characteristics. We estimate the following specification by Ordinary Least Squares (OLS):

$$Y_i = \alpha + \sum_{k=1}^{5} \beta_k \text{score}_{ki} + \gamma X_i + \varepsilon_i$$

where $Y_i$ is our productivity measure, $k = 1, ..., 5$ are each of the Big Five personality traits (extraversion, agreeableness, neuroticism, conscientiousness and openness to experience), and $X_i$ are personal characteristics. When looking at heterogeneous results, we interact the Big Five scores with personal characteristics such as gender, major of specialization or family background. We favour parsimonious specifications to account for the low statistical power innate to the sample size in experimental settings. All our specifications control for gender, age, major of specialization and level of study. In addition, our results are robust to controlling for parental background, and average grade in college as an imperfect measure of cognitive ability.[21]

[19] Agreeableness is defined as the tendency to cooperate and help others whereas extraversion is defined as an orientation towards the outer world.

[20] Such as worse negotiation skills and excessive cooperation in team work.

[21] These additional controls explain a share of variation similar to the share explained by our baseline controls.

Furthermore, in order to minimize the number of parameters to be estimated, we assume that the effect of personality traits on performance is linear, which we carry on to our estimation of heterogeneous effects. We tested for non-linearities by including a series of dummies for different intervals of values of each trait, and found no evidence of this alternative specification providing a better fit for our data.[22] To allow for an easier interpretation of our estimates, Big Five scores are standardized to have mean zero and standard deviation of one in all reported specifications.

### 4.1 Baseline results

Table 2 presents our baseline estimates of the effect of personality traits on the log of total earnings (Column (1)). The Big Five personality traits are jointly significant, and the individual scores are largely consistent with our hypotheses. As in the previous literature using survey data, and in line with our hypothesis H1, more neurotic subjects perform significantly worse in our task: an increase of a standard deviation in the level of neuroticism is associated with a decrease in performance of about 2.9%, which translates into a 0.1 standard deviation in our distribution of payoffs. Thus, our results support the idea that neuroticism contributes to differences in wages through productivity.

Our hypothesis regarding conscientiousness (H2) is also supported. We find a positive and significant effect of this trait on performance, in line with the results obtained in both the Economics and the Psychology literatures. An increase of a standard deviation in the level of conscientiousness is correlated with an increase of 2.6% in earnings. The coefficients for agreeableness and openness are, although insignificant, negative and of sizeable magnitude.[23] We expected that negative effect of openness given the repetitive nature of the task (H3). The result on agreeableness is in line with the survey literature. Inspection of Figure 5 (in Appendix B) suggests a non-monotonic effect, very high and very low levels of agreeableness are detrimental for performance. Unfortunately, our data does not allow to estimate non-linear effects precisely in order to substantiate this conjecture. Finally, we find no evidence that the level of extraversion of an individual may be correlated with performance in the task.

Taking advantage of the set-up of our experiment, we also check whether the relationship between personality traits and performance changes with time. In columns (2) and (3) of Table 2,

[22] A graphical representation of the relation between payoffs and each of the personality traits can be found in Figure 5 of Appendix B. Following Krueger and Eaton (2010), we also tested for the role of extreme values by including dummies for top and bottom values (lower than 2 and larger than 4 in a scale from 1 to 5). We found no evidence of extreme values driving our results (results available upon request).

[23] We do not observe subjects with very low scores in either of these traits. This is to be expected, given that subjects needed to volunteer to participate in the experiment and that requires a certain level of empathy and openness to new experiences.

we estimate a separate regression for the main outcome (log of payoffs) in each round of the task. We do not find much evidence of the impact of personality traits varying in magnitude as the task evolves. Significance levels vary slightly, with the negative effects for openness and agreeableness becoming significant in the first and second round respectively. The result with openness is in line with Müller and Schwieren (2012), who find a negative effect of this trait in their five-minute piece rate round of the addition task.

Table 2 also reports two additional measures of performance available from our experiment: the number of correct items in Column (4) and the total number of items answered in Column (5). While the task at hand should be relatively simple for a university student, it is time-limited and wrong answers entail a penalty. Therefore, there is a trade-off between the number of sums answered and the time spent per item, which, conditional on cognitive ability, should increase the probability of answering correctly. The relationship between personality traits and these two measures of performance is very similar to the one with total payoffs. Therefore, we will restrict our attention to the this outcome for the rest of the analysis.

As a further robustness check of the representativeness of our sample, we make use of the information provided in the questionnaire and estimate the relation between personality traits and grades for all individuals and wages for those in the labour force at the time of the experiment. While this estimation (not shown) is severely affected by selection, we find consistent results with prior literature (Fletcher 2013), with more conscientious individuals reporting higher grades and hourly wages.[24]

### 4.2 Heterogeneous effects

We now turn our attention to the possibility that personality traits may be correlated with productivity differently by subsamples. In particular, we are interested in whether individuals of different gender, major of study (as a proxy for occupation), and family background present differential effects of personality traits on productivity.

**Gender** As in previous experiments (Niederle and Vesterlund 2007, Müller and Schwieren 2012, Kanthak and Woon 2014), we do not find any evidence that women and men differ in performance when adding five 2-digit numbers, according to any of our measures, with or without controlling

[24]We find no evidence of a significant effect of the rest of the personality traits on wage, but, due to selection, our sample is reduced to 169 observations.

for personality traits.[25] However, there are significant gender differences in the distribution of two personality traits. Figure 1 suggests, and statistical tests confirm, that women in our sample tend to be more agreeable (two sample $t$-test, $t = 2.171$, $p = 0.015$) and neurotic ($t = 3.878$, $p < 0.001$) than males. This is consistent with a number of studies on gender differences in personality traits (Costa Jr, Terracciano and McCrae 2001, Schmitt, Realo, Voracek and Allik 2008). Thus, we explore whether the relationship between personality and performance differs for men and women.

Table 3 presents our first set of heterogeneous effects. Column (1) includes the baseline results for ease of comparison. Column (2) allows the effect of personality traits to vary between men and women. Interestingly, traits that vary in their distribution by gender (agreeableness and neuroticism) do not appear to impact differently male and female productivity. However, other traits seem to affect productivity differentially by gender. In particular, increases in the level of extraversion are positively correlated with productivity for men and negatively correlated for women. A rise of one standard deviation in extraversion increases earnings by 4% for men and decreases them by 3.5% (point estimate for women -0.035 (0.021)) for women. The differential effect of extraversion by gender is in line with the results obtained by Heineck and Anger (2010) using survey data; they find a wage penalty of 4% for women and a wage premium of 3% for men. Similarly, Fletcher (2013) obtains a wage premium of extraversion for men. The extraversion factor includes facets that might be correlated with productivity differently, and that are differently salient in men and women. Costa Jr et al. (2001) report that men show larger scores in the facets of extraversion associated with ambition (assertiveness and activity) whereas women score higher in the facets associated with sociability (warmth, gregariousness and positive emotions). These two sets of facets may have different effects on productivity. By looking at the specific items of the Big Five Inventory related to extraversion, we find that men report themselves as more assertive than women ($t = 1.681$, $p = 0.047$). This difference in assertiveness might be driving the heterogeneous effect of extraversion. Unfortunately, our sample size does not allow for a more detailed investigation of the source of this result.

Female participants who score highly in openness to experience obtain a significantly lower payoff (point estimate for women -0.059 (0.020)). We observe no relation between performance and openness in men. Although we find no significant gender differences in the scores of openness, women score higher in items measuring how much individuals value artistic and aesthetic experi-

[25] When controlling for personality traits, the point estimates for female is 0.030 (0.028) in our baseline specification (Table 2, column (1)). Dropping the controls for personality traits still delivers a highly non-significant coefficient, 0.232 (1.724).

ences ($t = 3.334$, $p < 0.001$) and the sophistication of their taste in arts and literature ($t = 3.183$, $p < 0.001$). Hence, more open women may find our experimental task to be specially boring and uninteresting, leading them to score worse than more open men.[26]

**Major of study** Next, we explore an additional source of student heterogeneity, major of study. When the entire sample is considered, individuals enrolled in scientific majors perform significantly better, which is not surprising given the nature of the task. Similarly to occupational choice, there might be unobservable characteristics that determine self-selection into a particular major. These unobservables could condition how personality traits influence performance even after controlling for family background and average grades. Therefore, the major of specialization might be capturing an array of individual characteristics. In addition, there are some significant differences in the distribution of traits by major. As suggested by Figure 2, we find that individuals enrolled in majors offered by the Australian School of Business (Business majors hereafter) or in Fine Arts majors score higher in extraversion (two sample $t$-test, $t = 2.063$, $p = 0.019$) and neuroticism ($t = 1.937$, $p = 0.026$). These differences are consistent with those observed in the literature (see, for example, De Fruyt and Mervielde (1996) and Rubinstein (2005)).[27]

Column (3) of Table 3 presents the results when the effects are allowed to vary by major. The omitted category corresponds to students majoring in a scientific discipline. Neuroticism is correlated with lower performance for Science majors, while the net effect is negligible for non-Science majors (point estimate for non-Science majors -0.002 (0.017)). We find no differential effects of extraversion, agreeableness or conscientiousness by major of study. As in the case of female subjects, we do find that higher levels of openness are correlated with lower performance for non-Science majors (point estimate -0.063 (0.017)), with a smaller beneficial effect for Science majors.

While all regressions control for gender and major, it may be the case that some of the differences are driven by the gender composition of the samples of Science and non-Science majors. About 60% of Science majors are men while the percentage goes down to 35% for Business or Fine Arts majors. Hence, it might be that the heterogeneous effect of openness by major is actually driven by the differential effect of openness by gender. The specification presented in Column (4) shows that this is not the case. The effect of openness is different across gender and majors. An increase of one standard deviation in the openness score for a man who chooses a scientific major is correlated with

[26] Müller and Schwieren (2012) find a negative correlation between openness and earnings in their piece-rate round but they do not show separate correlations by gender.

[27] Only 37 subjects reported an major in fine arts, preventing a more detailed analysis in this sample.

an increase in productivity of 5%, while this effect is negligible for women in science (point estimate -0.0005 (0.025)), and negative by almost 9% for women enrolled in Business or Fine Arts (point estimate -0.087 (0.020)). This suggests that the detrimental effect of openness on productivity is not only driven by the gender composition of majors.

As in the case of gender, we find differences by major in one important item: Science majors report themselves to be more inventive than non-Science majors ($t = 2.174$, $p$-value $= 0.015$). Being inventive might be helpful in our task since more inventive individuals can find more efficient ways of adding arrays of two digits numbers. Interestingly, male participants also report themselves to be more inventive than female participants ($t = 2.455$, $p$-value $= 0.007$). Hence, it seems that being more open makes salient different aspects of this trait by gender and major. An increase in openness for women and non-Science majors implies a higher increase in artistic inclination and a lower increase of inventiveness than for men or Science majors. As discussed, these two aspects have plausible opposite effects on performance. Therefore, differences in inventiveness and in the taste for aesthetic and artistic experiences might be responsible for the differential impact of openness on performance in our task.

**Family background** We now turn our attention briefly to family characteristics that could influence the link between personality traits and productivity. Figure 3 presents the density functions for the subsamples of subjects by parental income and education. Individuals who classify their family income as high are more extroverted ($t =$ -2.178, $p$-value $= 0.030$) and less neurotic ($t = 1.983$, $p$-value $= 0.048$) than the rest. However, we do not find any consistent evidence that individuals with high family income experience a different relation between personality traits and productivity (Column (2) of Table 4).[28]

Column (3) of Table 4 explores the possibility that parental education may affect the relationship between personality and productivity. Individuals from low education families present a positive correlation between conscientiousness and productivity which is absent in individuals from families with high education (point estimate 0.017 (0.018)). Finally, Column (4) presents the results including interactions with both proxies for family background. Our results still show that individuals from more disadvantaged educational backgrounds benefit more from conscientiousness than those from more advantaged ones. As Figure 4 indicates, individuals who report their parental education to be low (both parents without any college education) score higher in this trait than subjects from more favourable backgrounds ($t = 1.790$, $p$-value $= 0.074$). Because we are only con-

[28] Due to budgetary restrictions we could not recruit enough subjects to ensure a 95% power in these estimations.

sidering university students, this difference suggests that higher conscientiousness is instrumental for educational attainment when parental education is not high. The differential effect of this trait might be capturing that earnings in the experiment are more substantial for subjects who come from less favourable backgrounds (the average payoff in the experiment of AU$ 28.8 is 1.8 times the minimum hourly wage in Australia). These subjects may thus have higher incentives to perform well and conscientiousness is a useful trait to attain this goal.

# 5 Discussion

In this section, we address the issues of identification and external validity which can affect the soundness and interpretation of our results.

## 5.1 Identification

There is evidence showing a strong link between cognitive and non-cognitive skills (Almlund et al. 2011). This link is partially driven by non-cognitive skills affecting performance in cognitive tests. For instance, Borghans, Meijers and Ter Weel (2008b) report strong correlations between performance in IQ testing and certain personality traits. This can impact our estimates in two ways. First, if cognitive ability is not properly controlled for, our estimates will suffer from omitted variable bias. For instance, if neurotic individuals have also lesser cognitive skills, and if task performance is affected by IQ, we would be overestimating the negative impact of neuroticism on productivity. Second, it might be the case that our estimates are just capturing the same effect of personality traits on cognitive test outcomes that has already been identified in the literature.

To address these concerns, we first discuss the possibility that our task might be determined by cognitive ability. We then present additional evidence by employing grades in a two-step model in order to asses the bias due to omitted controls for cognitive skills.

**Is our task determined by cognitive ability?**

Psychologists and economists have profusely studied the impact of non-cognitive skills on the measurement of cognitive ability (see, for instance, Borghans, Golsteyn, Heckman and Humphries (2011) or Duckworth, Quinn and Tsukayama (2012)). Ideally, when seeking an IQ measure, one would like to abstract from other confounding factors. However, measures of cognitive ability often correlate with non-cognitive skills. We next argue that our results are unlikely to capture the same underlying mechanisms driving the aforementioned correlations.

First, if our task is a proxy of intelligence, we should expect our coefficients on personality to display similar patterns to the well-established relationships between performance in cognitive tests and non-cognitive skills. Borghans et al. (2008a) find 1) no significant relationship between cognitive ability and conscientiousness or neuroticism; 2) a positive relationship between extroversion and the probability of giving a correct answer; and 3) a negative relationship between agreeableness and cognitive test performance. We find instead that neuroticism undermines performance in our task, that conscientiousness enhances it, and that extraversion and agreeableness have no significant effect. The only relationship reported that would be consistent with our results picking up a correlation between cognitive performance and personality traits would be the negative relationship between cognitive test outcomes and openness to experience, which in our task is also negative albeit rather weak. All this is certainly no definitive proof of our model being correctly specified, but it is somewhat reassuring that the majority of the signs of our coefficients is not consistent with previous findings on the relationship between the Big-Five and standardized tests.[29]

Second, although traditional intelligence tests have a mathematical component, they are markedly different from our task. For instance, the Wechsler Intelligence Scales (WAIS-IV), one of the most frequently used IQ test for adults, contains arithmetic operations in only one sub-section that differs from our task in a variety of ways. First, the 20 questions are formulated orally, they require several different types of arithmetic operations, and they must be solved without paper or pencil. Hence, in addition to basic math knowledge, this part of the test measures systematic problem solving abilities and concentration. Moreover, recent versions of the test have reduced the relevance of mathematical skills in order to emphasize working memory instead.[30]

There are also a variety of numeracy tests that use easy arithmetic operations. To the best of our knowledge, most of these tests use a structure of increasing difficulty, even if they are comprised by a short number of questions.[31] Hence, while intelligence and numeracy would certainly be useful skills in our task, it is unlikely that our results are a good measure of any of these skills, as the repetition of a given, easy task is not used to measure them.

This is particularly relevant for our subject pool of university students, who are likely to have a minimum level of numeracy high enough for it not to be the main determinant of performance in our experimental task. This can be seen in the average number of summations answered correctly (45.42), which is only slightly lower than the number of summations attempted (50.48). In addition,

[29] For a review of the evidence, see Almlund et al. (2011)

[30] http://images.pearsonclinical.com/images/assets/WAIS-IV/WAISIV2_6_08.pdf, accessed 17th September 2015

[31] See, for instance, the test included in the English Longitudinal Study of Ageing (ELSA), which is a strong predictor of retirement saving choices (Banks, o'Dea and Oldfield 2010)

the distribution of IQ scores within university students is of lower variance and first stochastically dominates the distribution of scores in the general population (Herrnstein and Murray 1994). Furthermore, there is strong variation in average general intelligence by major of study (Frey and Detterman 2004), suggesting that this control may be already capturing a substantial part of the effect of cognitive abilities on performance in our task. Therefore, our results are likely to be picking up, at least partially, something altogether different from the relation between IQ/numeracy testing and non-cognitive abilities.

**Accounting for cognitive ability**

If our task is mainly reflecting cognitive ability, we should observe a change in the magnitude of non-cognitive skills' coefficients when adding plausible controls for cognitive skills −major of study and university grades− to our baseline specification.[32] While this is not the case, it can be argued that grades might also partly capture non-cognitive skills. In fact, in line with Poropat (2009), we find that more conscientious individuals obtain higher grades. Thus, to obtain an unbiased estimate of personality on performance, we would need a flexible control of cognitive ability net of personality traits.

To tackle this issue we perform a two-step estimation. In the first stage, we flexibly regress grades on our measures of personality traits and background characteristics.[33] This allows for a more precise measure of cognitive ability, defined as the residuals of the grades that are left unexplained by background characteristics and non-cognitive skills. In the second stage, we run the model of interest, controlling for our constructed measure of cognitive ability. In Table 5 in Appendix B, column (1) presents our baseline results, and column (2) controls directly for the university grades. Controlling directly for university grades does not affect our estimates. Columns (3) and (4) present the results controlling for grades net of personality (first stage of *ln(payment)* with flexible OLS specification of personality traits). Additional results with Probit first stages are robust and available from the authors. As expected, this constructed measure (not shown) is significant and predicts performance in the task. Reassuringly, these flexible estimates including our constructed control to our main findings shown in column (1) are not significantly different from each other, which supports our interpretation that non-cognitive abilities are driving our results on

[32] We also control for performance at the very beginning of the task (e.g., time to complete the first sum), in case this measure would be informative of cognitive ability. Our results do not change (available from the authors).

[33] For the sake of simplicity, grades have been reconverted to their numerical equivalent: fail (22), pass-conceded (48), pass (57), credit (69.5), distinction (79.5), high distinction (92.5). Alternative non-linear specifications do not change our main conclusions and are available upon request to the authors.

its own, rather than through the interaction with cognitive skills.

### 5.2 External validity

Experimental methods may suffer two fair criticisms regarding their external validity: artificiality of the task and the use of undergraduate students as subjects. We believe that our experimental setting still provides valuable insights. While it is true that it is not possible to replicate a real work-environment in the lab, we chose a "real-effort" task, costly for the subjects. Adding arrays of five two-digit numbers for 20 minutes is a mentally taxing activity. It requires concentration, determination, perseverance and problem-solving skills under time-pressure, all valuable assets in the labour market. Furthermore, except from workers in managerial and professional occupations, which only accounted for 25% of the Australian labor force in 2014 (Australian Government, Department of Employment 2015), most jobs involve performing a certain degree of repetitive, monotonous and often boring albeit simple tasks. In addition, the vast majority of the workforce have superiors from whom they have to carefully follow instructions. We therefore emphasized in our instructions that we were simulating a work-environment in which subjects had to adhere to simple directions. Although the subjects in our experiment are more likely to end up in creative, managerial or professional occupations than the general population, most of them will still enter the labour force as apprentices, trainees, or subordinates.[34] Hence, it would be safe to conclude that our results are applicable to the workplace, at least qualitatively.

Regarding the second critique, ordinal changes in the Big Five personality traits are rare once early adulthood is reached (Roberts et al. 2006). Hence, our subjects are likely to be endowed with the same set of personality traits that they will bring to the market, given that they have already reached early adulthood. Another advantage of employing a student population who has not entered the labour force yet in the majority of cases, is that our study is largely free from the self-selection bias arising from prior labour history. This, of course, comes at the potential cost of having a less representative sample.

## 6 Conclusions

An increasing body of literature explores the relationship between personality traits and a wide variety of economic outcomes, such as educational attainment and labour income. In this paper, we

[34] Borghans and Ter Weel (2004) report a positive effect of math skills on wages, while computer skills do not affect earnings.

report the first lab experiment on the link between personality traits and individual productivity. Our aim is to unbundle the channels behind the correlations between personality and labour market outcomes reported using survey data. The controlled environment of the lab allows us to disentangle whether previous results operate through individual productivity rather than through other factors such as occupational choice, wage bargaining or personal interactions in the workplace.

As conjectured in Section 3.3, we find a robust negative correlation between neuroticism and performance (H1), and some evidence supporting a positive correlation between conscientiousness and productivity (H2). Similar effects are present in most of the studies on personality and labour market outcomes. Our results thus support the hypothesis that at least part of the effect of neuroticism and conscientiousness on earnings operates through individual productivity. On the other hand, we found only a very weak negative effect of openness to experience (H3) and agreeableness on performance. This suggests that the strong negative correlation between these traits and labour market outcomes observed in survey data is mostly driven by occupational choices, wage bargaining, or by cooperative behaviour being penalized in the labour market.

When looking at the interaction between personality traits and personal characteristics, we find noticeable heterogeneous effects. Stronger traits are correlated with productivity differently for men and women, even in our setting, where we can abstract from many factors affecting labour market relations. More extroverted women, for instance, exhibit lower performance, while more extroverted men earn a higher payoff than their less extroverted counterparts. We report some heterogeneous effects by major, reinforcing the idea that our experimental setting can alleviate the problem of selection bias by occupation present in survey studies. Finally, we do not find consistent evidence that family background is shaping the impact of personality traits, suggesting that policies designed to alter non-cognitive skills may be effective across the entire income distribution.

The present paper contributes to the literature which highlights the relevance of heterogeneity in individual characteristics and personality in the design of policy interventions aimed to enhance workers' performance. In our experiment, we employed a task that is a reasonably good approximation to a wide variety of occupations and job relationships. This is not to say that it is an all-encompassing measure of job productivity, though. Other tasks could be used to highlight other aspects such as team work or negotiation skills. In addition, our sample is composed by university students which despite having some advantages present the caveat of a limited representativeness. Further research would also be needed to achieve a comprehensive understanding of the role played by personality traits in labour market outcomes in general and in productivity in particular. As with any branch of the literature of recent development, measures are sometimes unsatisfactory, encompassing too much or too little information on the underlying characteristics that drive the relations reported. For instance, openness to experience and extraversion seem to encompass facets with very different economic implications, while facets across different factors may have similar economic effects. We are aware that the consensus on the validity and usefulness of the Big Five factor model is not universal among psychologists. While we cannot contribute to this debate, economists should learn more about the link between personality and economic outcomes by looking inside each trait for the facets of personality relevant to their specific research question. Non-cognitive skills can be more shapable than cognitive skills (see Almlund et al. (2011) and references therein). But any policy intervention designed to affect them requires a deep understanding of their potential impact on productivity across different populations.

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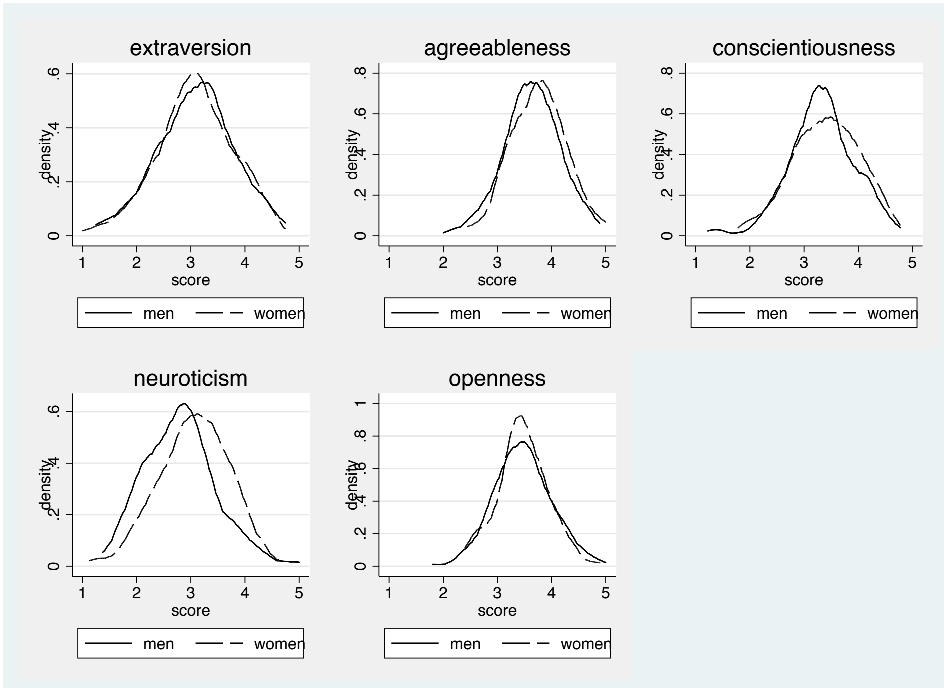


Figure 1: Personality traits density distribution by gender

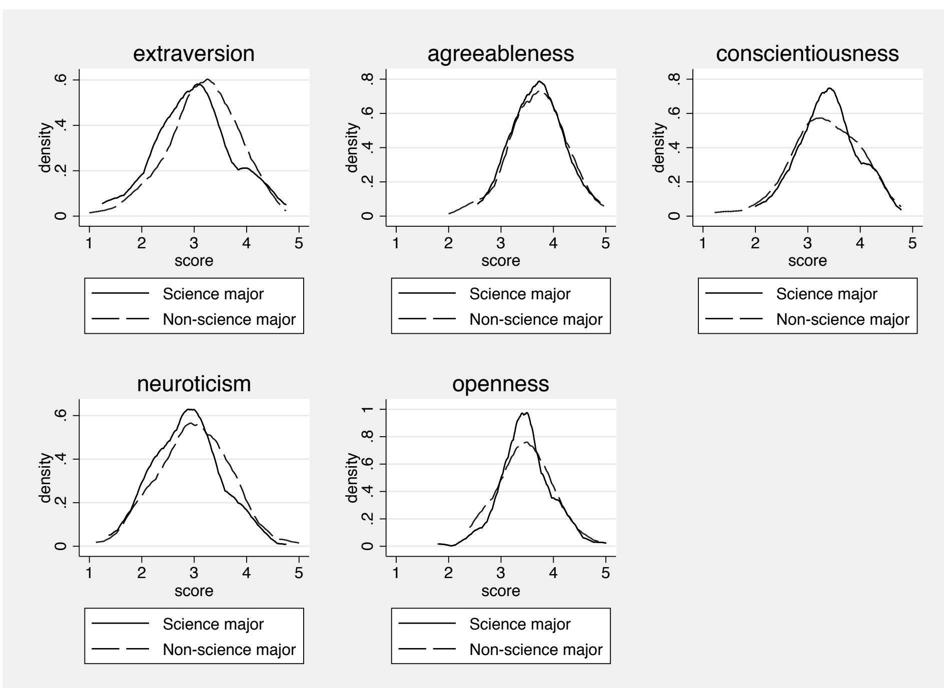


Figure 2: Personality traits density distribution by major

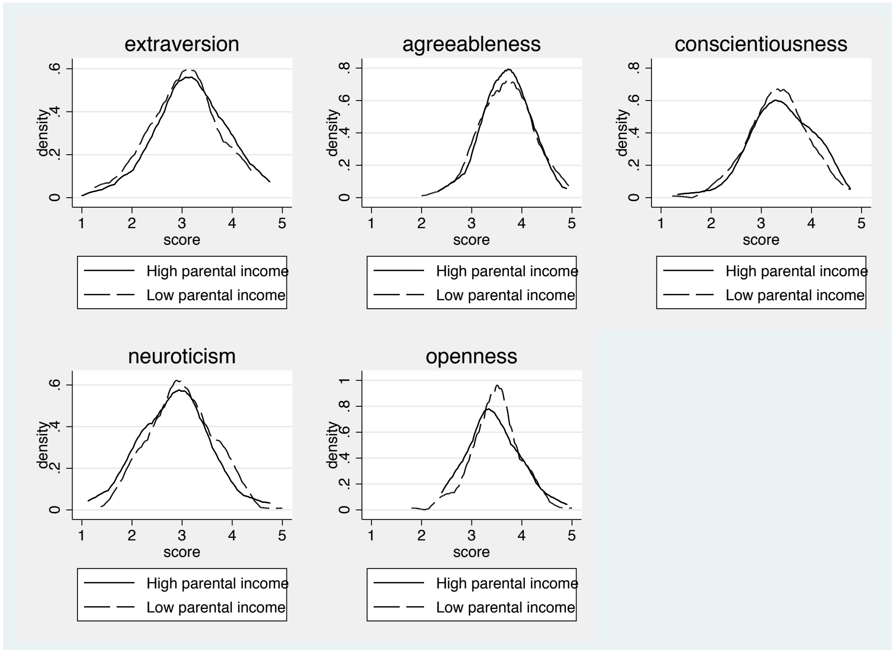


Figure 3: Personality traits density distribution by family income

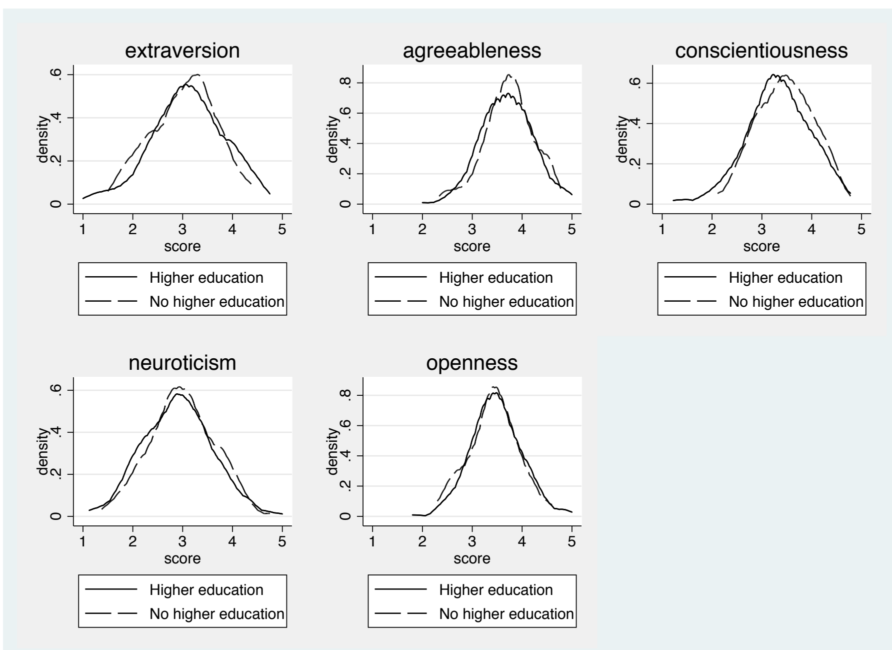


Figure 4: Personality traits density distribution by parental education

Table 1: Summary statistics

| Variable | Mean | Std. Dev. | N |
|---|---|---|---|
| *Individual characteristics* | | | |
| Female | 0.501 | 0.501 | 359 |
| Age | 22.08 | 3.25 | 359 |
| Science major | 0.482 | 0.5 | 359 |
| Honour, Master or PhD student | 0.301 | 0.459 | 359 |
| High family income | 0.432 | 0.496 | 359 |
| Father education: less than college | 0.339 | 0.474 | 342 |
| Mother education: less than college | 0.503 | 0.501 | 342 |
| Family size | 2.29 | 1.091 | 359 |
| *Big Five personality traits* | | | |
| Extraversion | 3.089 | 0.706 | 359 |
| Agreeableness | 3.698 | 0.518 | 359 |
| Conscientiousness | 3.371 | 0.619 | 359 |
| Neuroticism | 2.928 | 0.665 | 359 |
| Openness | 3.468 | 0.501 | 359 |
| *Average grade* | | | |
| Fail (FL) | 0.003 | 0.053 | 359 |
| Pass Conceded (PC) | 0.003 | 0.053 | 359 |
| Pass (PS) | 0.114 | 0.319 | 359 |
| Credit (CR) | 0.501 | 0.501 | 359 |
| Distinction (DN) | 0.295 | 0.457 | 359 |
| High Distinction (HD) | 0.084 | 0.277 | 359 |
| *Labour force status* | | | |
| Working | 0.474 | 0.5 | 359 |
| Unemployed | 0.061 | 0.24 | 359 |
| Out of labour force | 0.465 | 0.499 | 359 |
| Hourly wage (if working) | 22.19 | 10.28 | 169 |
| *Task outcomes* | | | |
| Total payoff received (AU$) | 22.864 | 5.803 | 359 |
| Payoff round 1 (AU$) | 10.810 | 2.875 | 359 |
| Payoff round 2 (AU$) | 11.953 | 3.123 | 359 |
| Total correct answers | 45.421 | 14.555 | 359 |
| Total items answered | 50.485 | 15.41 | 359 |

Table 2: Big Five personality traits and productivity (OLS)

| | *ln payment* | | | *Total correct* | *Total items* |
|---|---|---|---|---|---|
| | Total | Round 1 | Round 2 | *answers* | *answered* |
| | (1) | (2) | (3) | (4) | (5) |
| Extraversion | 0.002 | 0.005 | -0.002 | 0.317 | 0.268 |
| | (0.016) | (0.022) | (0.023) | (0.882) | (0.934) |
| Agreeableness | -0.025 | -0.023 | -0.052** | -1.047 | -1.018 |
| | (0.016) | (0.024) | (0.024) | (0.874) | (0.929) |
| Conscientiousness | 0.026* | 0.032 | 0.044* | 1.275 | 1.257 |
| | (0.015) | (0.021) | (0.023) | (0.819) | (0.866) |
| Neuroticism | -0.029** | -0.041** | -0.036 | -1.616** | -1.554* |
| | (0.014) | (0.019) | (0.023) | (0.743) | (0.812) |
| Openness | -0.018 | -0.037* | -0.022 | -0.638 | -0.994 |
| | (0.015) | (0.020) | (0.021) | (0.846) | (0.856) |
| N | 359 | 359 | 359 | 359 | 359 |
| F-stat (Big Five) | 2.70 | 2.63 | 2.49 | 2.33 | 1.97 |
| F-stat | 1.873 | 1.686 | 1.762 | 1.646 | 1.294 |
| $R^2$ | 0.053 | 0.046 | 0.063 | 0.046 | 0.038 |

Robust standard errors are reported in parentheses. *** denotes significance at 1%, ** at 5% and * at 10%. All specifications control for session characteristics, gender and age of the subject, whether the student is a science major or a honour, masters or Ph.D. student. Our explanatory variables of interest have been standardized to have a mean zero and a standard deviation of one.

Table 3: Big Five personality traits and productivity: gender and major of specialization (OLS)

| *y=ln(total payment)* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Extraversion | 0.002 | 0.043* | 0.005 | 0.034 |
| | (0.016) | (0.022) | (0.022) | (0.024) |
| Extraversion*female | | -0.078** | | -0.079** |
| | | (0.031) | | (0.034) |
| Extraversion*non-science major | | | -0.008 | 0.021 |
| | | | (0.030) | (0.033) |
| Agreeableness | -0.025 | -0.018 | -0.023 | -0.018 |
| | (0.016) | (0.020) | (0.027) | (0.029) |
| Agreeableness*female | | -0.005 | | -0.007 |
| | | (0.032) | | (0.031) |
| Agreeableness*non-science major | | | -0.007 | -0.001 |
| | | | (0.032) | (0.032) |
| Conscientiousness | 0.026* | -0.004 | 0.006 | -0.008 |
| | (0.015) | (0.020) | (0.021) | (0.027) |
| Conscientiousness*female | | 0.032 | | 0.015 |
| | | (0.026) | | (0.025) |
| Conscientiousness*non-science major | | | 0.034 | 0.026 |
| | | | (0.027) | (0.025) |
| Neuroticism | -0.029** | -0.040** | -0.067*** | -0.071*** |
| | (0.014) | (0.018) | (0.020) | (0.021) |
| Neuroticism*female | | 0.022 | | 0.002 |
| | | (0.026) | | (0.028) |
| Neuroticism*non-science major | | | 0.065** | 0.076*** |
| | | | (0.027) | (0.028) |
| Openness | -0.018 | 0.015 | 0.036* | 0.051** |
| | (0.015) | (0.019) | (0.019) | (0.022) |
| Openness*female | | -0.073*** | | -0.050* |
| | | (0.027) | | (0.026) |
| Openness**non-science major | | | -0.098*** | -0.088*** |
| | | | (0.026) | (0.026) |
| N | 359 | 359 | 359 | 359 |
| F-stat | 1.873 | 2.516 | 2.125 | 2.589 |
| $R^2$ | 0.053 | 0.113 | 0.116 | 0.161 |

Robust standard errors are reported in parentheses. *** denotes significance at 1%, ** at 5% and * at 10%. All specifications control for session characteristics, gender and age of the subject, whether the student is a science major or a honour, masters or Ph.D. student. The omitted category are scientific majors.

Table 4: Big Five personality traits and productivity: family background (OLS)

| *y=ln(total payment)* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Extraversion | 0.004 | 0.015 | -0.008 | 0.001 |
| | (0.016) | (0.020) | (0.025) | (0.027) |
| Extraversion*high family income | | -0.018 | | -0.018 |
| | | (0.032) | | (0.032) |
| Extraversion*high parental education | | | 0.017 | 0.018 |
| | | | (0.031) | (0.032) |
| Agreeableness | -0.024 | -0.012 | 0.005 | 0.011 |
| | (0.016) | (0.021) | (0.020) | (0.023) |
| Agreeableness*high family income | | -0.035 | | -0.035 |
| | | (0.032) | | (0.033) |
| Agreeableness*high parental education | | | -0.040 | -0.032 |
| | | | (0.029) | (0.031) |
| Conscientiousness | 0.024 | 0.013 | 0.042* | 0.039* |
| | (0.015) | (0.017) | (0.022) | (0.023) |
| Conscientiousness*high family income | | 0.011 | | 0.017 |
| | | (0.027) | | (0.027) |
| Conscientiousness*high parental education | | | -0.025 | -0.039 |
| | | | (0.028) | (0.027) |
| Neuroticism | -0.026* | -0.052*** | -0.024 | -0.043* |
| | (0.014) | (0.018) | (0.020) | (0.023) |
| Neuroticism*high family income | | 0.043 | | 0.044 |
| | | (0.027) | | (0.029) |
| Neuroticism*high parental education | | | -0.003 | -0.014 |
| | | | (0.026) | (0.027) |
| Openness | -0.018 | 0.004 | -0.008 | 0.009 |
| | (0.015) | (0.020) | (0.024) | (0.026) |
| Openness*high family income | | -0.044 | | -0.046 |
| | | (0.028) | | (0.030) |
| Openness*high parental education | | | -0.014 | -0.007 |
| | | | (0.031) | (0.030) |
| N | 344 | 344 | 344 | 344 |
| F-stat | 1.615 | 1.438 | 1.375 | 1.284 |
| $R^2$ | 0.058 | 0.087 | 0.067 | 0.096 |

Robust standard errors are reported in parentheses. *** denotes significance at 1%, ** at 5% and * at 10%. All specifications control for session characteristics, age and gender of the subject, parental education, family composition and income, whether the student is a science major or a honour, masters or Ph.D. student, and average grade. A family is considered to be of high income if the subject reported 4 or higher in a 7 step classification of income. A parent is consider to have high education if he/she has at least some college education.

# Appendix A

**Transcription of Instructions**

Hello,

Thank you for coming. From now on, I will provide you with all necessary information. Please listen carefully to my instructions. Turn your mobile phone off until the completion of the session. Communication of any nature with any other participant is strictly forbidden. If you have any questions, please raise your hand. You may leave the session at any time.

The objective of this session is to study the determinants of productivity in certain tasks. This session is designed to simulate a work environment. If you follow the instructions and focus on your task, you can earn a considerable amount of money.

The Australian Business School Research Grant funds this research. All data collected will be kept confidential and will be only used for scientific purposes.

The session is in two parts with a short intermission between each section.

In each section, you have 10 minutes to perform a series of simple mathematical sums. For each correct answer you provide, you will receive 20 experimental dollars. 50 experimental dollars are worth 1 [Australian Dollar (AUD)]. The more correct sums you calculate, the more money you will earn. You will lose 4 experimental dollars per incorrect answer. Once you have submitted your answer, you cannot change it.

Five two-digit numbers will appear on your screen. Add the numbers and type the answer in the designated box. Click proceed once you have entered the number. Another series of numbers will appear on the screen. Answer as many sums as you can.

For your calculations, you may use the paper and pencil provided in your workstation. You are not allowed to use mobile phones or calculators during the session.

Remember, you only have 10 minutes in each session to answer as many sums as you can. The clock on the screen will show you how much time you have left.

After the first part you will have a short break. Please remain seated. I will be monitoring your performance and I will speak to you again during the break.

After you finish the two parts of the session, I have a short questionnaire for you to complete. I kindly ask you to fill it carefully and truthfully.

After filling in the questionnaire, please wait until you are paid before you leave. Today you will earn a 5AUD attendance fee, plus the outcome of your performance. Remember, you gain 20 experimental dollars per correct answer; you lose 4 experimental dollars per incorrect answer. 50 experimental dollars are worth 1 AUD. The more correct sums you calculate, the more money you will earn. The minimum amount you will receive will be 5 AUD. You must sign and hand in the consent form and receipt for the payment at the end of the session.

# Appendix B

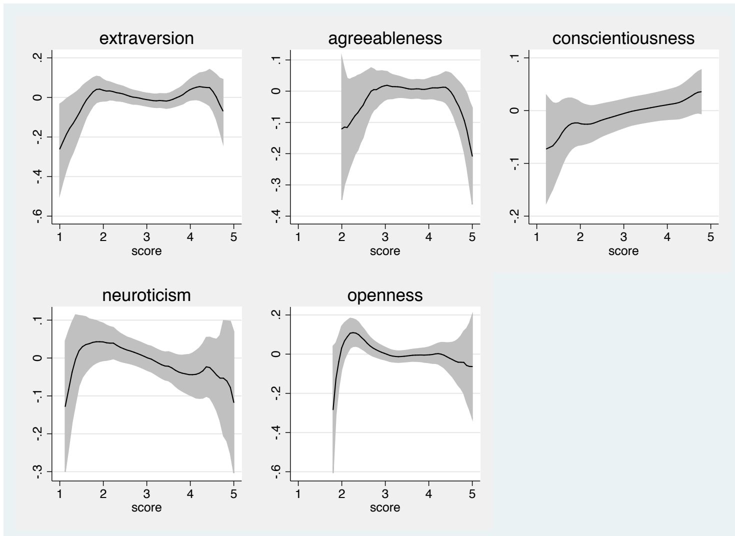


Figure 5: Non-linear relationship between personality traits and ln(payoff)

Table 5: Big Five and performance: Two-stage estimates of *log(payment)*

| First stage *grades=f(personality)* | None (1) | None (2) | OLS quadratic (3) | OLS quadratic full controls (4) |
|---|---|---|---|---|
| Extraversion | 0.002 | 0.003 | -0.001 | 0.004 |
| | (0.016) | (0.016) | (0.015) | (0.015) |
| Agreeableness | -0.025 | -0.023 | -0.027 | -0.023 |
| | (0.016) | (0.016) | (0.016) | (0.015) |
| Conscientiousness | 0.026* | 0.019 | 0.027* | 0.023 |
| | (0.015) | (0.015) | (0.015) | (0.014) |
| Neuroticism | -0.029** | -0.027** | -0.032** | -0.029** |
| | (0.014) | (0.014) | (0.013) | (0.014) |
| Openness | -0.018 | -0.018 | -0.018 | -0.018 |
| | (0.015) | (0.014) | (0.014) | (0.015) |
| Grades | | 0.028** | | |
| | | (0.013) | | |
| $Grades\ \hat{r}esiduals$ | | | 0.031** | 0.029** |
| | | | (0.013) | (0.014) |
| N | 359 | 359 | 359 | 359 |
| F-stat (Big Five) | 2.70 | 1.78 | 3.16 | 2.44 |
| F-stat | 1.873 | 2.196 | 2.06 | 1.70 |
| $R^2$ | 0.053 | 0.064 | 0.052 | 0.080 |

Robust standard errors are reported in parentheses and corrected for the use of predicted variables in columns (3)-(4). *** denotes significance at 1%, ** at 5% and * at 10%. All specifications control for session characteristics, gender and age of the subject. Our explanatory variables of interest have been standardized to have a mean zero and a standard deviation of one. Columns (3)-(4) include residuals of a first stage-estimation of grade conditional on background characteristics and personality traits, by OLS with quadratic terms on personality. Grades were standardized to have mean 0 and standard deviation of 1 in all cases for comparison purposes.