Three Essays in Labour Economics: Personality Traits and Labour Market Outcomes

A thesis submitted for the degree of Doctor of Philosophy in Economics

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DECLARATION

No part of this thesis has been submitted for another degree.

Chapter 1 and 2 are exclusively mine.

Chapter 1 was published as a research article in the Bulletin of Economic Research, titled "The relationship between the Big Five personality traits and earnings: Evidence from a meta-analysis" on 07 February 2024.

Chapter 3 is co-authored with Professor Matteo Richiardi.

DEDICATION

To my family and loved ones,

in recognition of their worth.

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SUMMARY

This thesis explores topics concerning personality and labour market outcomes through three complementary studies, supported by an introduction and conclusion.

Chapter One conducts a meta-analysis of the relationship between Big Five traits and earnings. The results reveal that openness to experience, conscientiousness, and extraversion exhibit positive correlations with earnings, whereas agreeableness and neuroticism are inversely correlated with earnings. Overall, personality has a modest-to-small effect on earnings, with variations in results depending on the econometric models used. Accounting for publication bias, socioeconomic background, and cognitive ability in models affects returns to personality. The chapter highlights the potential for omitted variable bias in estimating personality effects on earnings when crucial factors are not accounted for.

Chapter Two compares fluid intelligence and personality traits among children from diverse socioeconomic backgrounds using twin data from the first wave of TwinLife. Utilising a CES production function approach, the study illustrates how parental skills, investments, and socioeconomic status influence children's intelligence and personality development. The results underscore that children from higher SES backgrounds exhibit higher levels of intelligence, openness to experience, extraversion, and emotional stability. The findings suggest that interventions targeting parental investments and fostering desirable personality traits could significantly enhance outcomes, particularly for disadvantaged children, thereby offering a promising avenue for improving child welfare and long-term life prospects.

Chapter Three investigates the behavioural dynamics of social benefit uptake. Utilising data from the first nine waves (2010-2019) of the UK Household Longitudinal Study (UKHLS) and eligibility simulations based on the UKMOD tax-benefit calculator (UKHLS-UKMOD), the study identifies significant dynamics of state dependence once initial conditions and unobserved heterogeneity are considered. While unobserved heterogeneity plays a crucial role in explaining the take-up of social benefits, personality traits and cognitive skills do not exhibit a strong and direct influence on the take-up of social benefits. The chapter concludes by discussing policy implications.

1. INTRODUCTION

Personality plays an important role in shaping an individual's life outcomes, influencing educational achievements and success in the job market. Despite its significance, most research on earnings and labour market outcomes has traditionally focused on human capital characteristics like education level and cognitive skills (e.g., Mincer, 1974; Card, 1999). However, recent studies suggest that personality, evident from a young age, also contribute significantly to better life prospects (e.g., Heckman, Stixrud and Urzua, 2006; Almlund *et al.*, 2011).

While industrial and organisational psychology has extensively studied how personality influences job market success, economists have largely overlooked it. This may be due to a prevailing perception that personality traits are not significantly relevant to productivity, coupled with the complexities of analysing personality and the lack of appropriate data. Consequently, personality traits are often relegated to 'unobserved heterogeneity' within economic research.

Emerging evidence indicates that personality traits affect various aspects of life, including academic achievement, income, health, stress levels, and relationships. However, the findings are inconsistent, with studies showing different signs or levels of significance, and the strength of these effects varies across studies. This thesis seeks to clarify these effects, offering insights that could transform approaches in industrial and organisational psychology, economics, and human resources management.

This thesis aims to enhance the human capital model in economics by integrating personality traits, specifically the Big Five traits, from a behavioural perspective. The Big Five traits include openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism, based on the five-factor model proposed by McCrae and John (1992). The five-factor model was chosen for this thesis due to its broad nature, capturing fundamental aspects of human thought, feeling, and behaviour (John, Naumann and Soto, 2008). Although the five-factor model is not without criticism (Eysenck, 1992; Block, 2010), it has been extensively associated with life outcomes such as earnings, health, and longevity (Heckman, Jagelka and Kautz, 2021) and is widely used in economic research due to its internal consistency, stability, and cross-cultural validation (John, 2021).

The research addresses several key questions. It investigates how and to what extent personality traits affect individual earnings, identifies the sources of heterogeneity in these effects, and examines the impact of publication bias on the overall estimates. The thesis also explores how parental background influences the development of the Big Five personality traits in children, focusing on the mechanisms through which family socioeconomic status (SES) affects these traits, the relative influence of biological versus familial environmental factors, and the impact of parental investments on the personality traits of children from different SES backgrounds. Additionally, the research examines the interplay between personality traits, economic incentives, and social welfare outcomes, using the take-up of social benefits in the UK as a case study.

Following this introduction, the thesis is structured into three chapters, followed by a conclusion summarising the results and the main implications.

1.1 CHAPTER ONE: THE RELATIONSHIP BETWEEN THE BIG FIVE PERSONALITY TRAITS AND EARNINGS: EVIDENCE FROM A META-ANALYSIS

Chapter One investigates the relationship between the Big Five personality traits and individual earnings through a meta-analysis. This chapter provides a foundation by quantifying how personality traits influence economic outcomes, setting the stage for exploring the sources of these traits in the subsequent chapters.

The meta-analysis addresses heterogeneity in the reported returns to personality traits, offering a consolidated view of these effects. This chapter evaluates the consistency of results across various studies and identifies potential sources of variation. It examines whether differences in effects can be attributed to demographic factors, socioeconomic status, methodological approaches, and specific study characteristics or if they are merely due to random variation. Additionally, the meta-analysis sheds light on publication bias and omitted variable bias within the literature. This implies that where publication bias is present, it distorts the results of meta-analyses and systematic reviews. The presence of omitted variable bias also calls for an in-depth view of how personality traits are formed and measured to unravel and understand these biases.

The results suggest that individuals with higher openness to experience and conscientiousness tend to earn more. Although extraversion is positively correlated with earnings, it is not as strong. Conversely, individuals with higher agreeableness and neuroticism tend to earn less. In addition, when accounting for publication bias, the influence of these traits on earnings diminishes, especially for conscientiousness, agreeableness, and neuroticism. The results also indicate that socioeconomic characteristics are the most significant factors affecting the estimated effect of each personality trait. These results suggest that personality traits may be susceptible to omitted variable bias, potentially leading to misleading estimates.

1.2 CHAPTER TWO: THE IMPACT OF PARENTAL BACKGROUND ON THE BIG FIVE TRAITS AND INTELLIGENCE: EVIDENCE FROM A TWIN-BASED STUDY

Building on the insights from Chapter One, Chapter Two explores the interaction between personality traits and socioeconomic factors, delving into the underlying mechanisms of personality formation. This chapter provides context for interpreting the economic effects observed in Chapter One by uncovering the reasons behind observed differences in personality traits. The twin-based study offers an examination of how family socioeconomic status and parental investments contribute to personality formation, thus linking individual earnings potential to early-life factors, an area that has received limited attention in economics.

This chapter utilises data from the first wave of the German Twin Family Panel (TwinLife) involving twins aged 10 to 12 years old (Hahn *et al.*, 2016; Diewald *et al.*, 2021). The dataset includes a unique set of measurements such as personality traits (Big Five traits), family background details, and cognitive ability (fluid intelligence). By using twin data, the chapter provides a unique opportunity to understand better the influences and robustness of genetic and environmental factors on various outcomes such as personality traits and intelligence. As monozygotic (MZ) twins share identical genetic makeup, and dizygotic (DZ) twins share about half of their genetic material, this enables us to compare outcomes between genetically identical and non-identical pairs. The chapter also contributes to the literature by employing a Constant Elasticity of Substitution (CES) production function model, which departs from traditional linear technology assumptions used in similar studies. Unlike linear models that treat parental inputs as perfect substitutes for other parental inputs that contribute to the development of skills, the CES model allows for an unconstrained estimation of the elasticity of the substitution parameter. This approach better explains how parental inputs interact with a child's personality traits. Additionally, the study investigates whether parental investments compensate for or reinforce a child's developmental progress, considering potential correlations between parental inputs and unobserved shocks in development. This exploration addresses biases that may upwardly skew estimates of the impact of parental investment on personality traits, providing deeper insights into the dynamics of parental influence on child development.

The chapter's findings support that a family's SES influences their children's fluid intelligence and personality traits. High SES families tend to have offspring with higher scores in fluid intelligence, emotional stability, and extraversion, although the SES gap is less pronounced for personality traits. This suggests that personality is influenced by factors beyond genetics, aligning with the social investment principle. The study also reveals that lower parental education negatively impacts parental time investments, indirectly leading to differences in fluid intelligence and personality traits among children from various socioeconomic backgrounds. Moreover, the chapter found no evidence that parents from different SES backgrounds have varying investment productivity, implying that similar parental investments could result in similar personality traits for children regardless of their SES. This suggests that the children in low-SES households can be compensated in levels of inputs to close the achievement gap by household SES.

This chapter emphasises the importance of addressing personality development gaps from a very young age. It underscores that psychometric personality measures are not independent of family background, highlighting the contextual nature of such measures.

1.3 CHAPTER THREE: MIND VS MATTER: ECONOMIC AND PSYCHOLOGICAL DETERMINANTS OF TAKE-UP RATES OF SOCIAL BENEFITS IN THE UK

Chapter Three extends the analysis by exploring how personality traits influence the take-up of social benefits in the UK. This chapter integrates the findings from the previous chapters by examining how personality traits, shaped by parental background and linked to earnings, affect social welfare outcomes. The analysis provides a holistic view of the interplay between personality, economic incentives, and social policy, highlighting the broader implications of personality traits on economic behaviour.

The data for this study comes from the first nine waves of the UK Household Longitudinal Study (UKHLS), which has been adjusted to use as input data for the UKMOD tax-benefit microsimulation model (Richiardi, Bronka and Popova, 2023). The chapter uses microsimulation techniques and longitudinal data to analyse the take-up rates for various benefits in the UK. It explores the influence of personality traits and social networks on take-up behaviour. By integrating personality traits into economic models, this thesis aims to bridge the gap between psychology and economics, providing a nuanced understanding of how personality impacts life outcomes and informing more effective policy and organisational interventions.

In this chapter, our objectives are multifaceted. Firstly, we aim to provide updated estimates specific to the UK context concerning the take-up rates of various benefits, filling a gap in existing literature caused by limited information and outdated studies. Secondly, we seek to elucidate the dynamics of take-up decisions by differentiating between individual characteristics and state dependence, which holds significant policy implications. Incorporating personality traits into the take-up model enables us to explore whether these traits, typically considered unobservable and contributing to unobserved heterogeneity, have a discernible impact. If proven significant, this would suggest that personality can account for some of the previously unaccounted-for differences among individuals. Finally, the paper delves into examining the influence of social networks on individual take-up behaviour.

The study suggests that the level of benefits, state dependence, and factors related to demographics and socioeconomics play a significant role in determining who claims social benefits. These are categorised as ‘Matter’. Additionally, personality traits have a weak direct relationship with benefit take-up, falling under the category of ‘Mind’. The study also discusses neighbourhood effects, incorporating social norms, stigma, and emulation as psychological factors influencing individuals’ evaluation of costs and benefits. Furthermore, it highlights that greater benefit take-up in the area where an individual resides increases the likelihood of that individual claiming the benefit. The chapter concludes by providing valuable insights for policymakers who aim to design more effective and targeted social interventions.

REFERENCES

Almlund, M. *et al.* (2011) ‘Personality Psychology and Economics’, in E.A. Hanushek, S. Machin, and L. Woessmann (eds) *Handbook of the Economics of Education*. Elsevier (Handbook of The Economics of Education), pp. 1–181. Available at: https://doi.org/10.1016/B978-0-444-53444-6.00001-8.

Block, J. (2010) ‘The Five-Factor Framing of Personality and Beyond: Some Ruminations’, *Psychological Inquiry*, 21(1), pp. 2–25. Available at: https://doi.org/10.1080/10478401003596626.

Card, D. (1999) ‘Chapter 30 - The Causal Effect of Education on Earnings’, in O.C. Ashenfelter and D. Card (eds) *Handbook of Labor Economics*. Elsevier, pp. 1801–1863. Available at: https://doi.org/10.1016/S1573-4463(99)03011-4.

Diewald, M. *et al.* (2021) ‘TwinLife’. [Research data]. Available at: https://doi.org/10.4232/1.13747.

Eysenck, H.J. (1992) ‘Four ways five factors are not basic’, *Personality and Individual Differences*, 13(6), pp. 667–673. Available at: https://doi.org/10.1016/0191-8869(92)90237-J.

Hahn, E. *et al.* (2016) ‘What Drives the Development of Social Inequality Over the Life Course? The German TwinLife Study’, *Twin Research and Human Genetics: The Official Journal of the International Society for Twin Studies*, 19(6), pp. 659–672. Available at: https://doi.org/10.1017/thg.2016.76.

Heckman, J.J., Jagelka, T. and Kautz, T. (2021) ‘Some contributions of economics to the study of personality’, in *Handbook of personality: Theory and research*. 4th edn. New York, NY, US: The Guilford Press, pp. 853–892.

Heckman, J.J., Stixrud, J. and Urzua, S. (2006) ‘The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior’, *Journal of Labor Economics*, 24(3), pp. 411–482. Available at: https://doi.org/10.1086/504455.

John, O.P. (2021) ‘History, measurement, and conceptual elaboration of the Big-Five trait taxonomy: The paradigm matures’, in *Handbook of personality: Theory and research, 4th ed*. New York, NY, US: The Guilford Press, pp. 35–82.

John, O.P., Naumann, L.P. and Soto, C.J. (2008) ‘Paradigm shift to the integrative Big Five trait taxonomy: History, measurement, and conceptual issues’, in *Handbook of personality: Theory and research*. 3rd edn. New York, NY, US: The Guilford Press, pp. 114–158.

McCrae, R.R. and John, O.P. (1992) ‘An Introduction to the Five-Factor Model and Its Applications’, *Journal of Personality*, 60(2), pp. 175–215. Available at: https://doi.org/10.1111/j.1467-6494.1992.tb00970.x.

Mincer, J. (1974) *Schooling, experience, and earnings*. New York: National Bureau of Economic Research; distributed by Columbia University Press (Human behavior and social institutions, 2.).

Richiardi, M., Bronka, P. and Popova, D. (2023) 'UKHLS input data for UKMOD (2010-2019)', *Centre for Microsimulation and Policy Analysis Working Paper Series* [Preprint]. Available at: https://ideas.repec.org//p/ese/cempwp/cempa7-23.html (Accessed: 7 May 2024).

2. CHAPTER ONE: THE RELATIONSHIP BETWEEN THE BIG FIVE PERSONALITY TRAITS AND EARNINGS: EVIDENCE FROM A META-ANALYSIS

2.1 INTRODUCTION

Over the past three decades, it has become clear that while cognitive skills are important, they are not the sole determinants of labour market outcomes (Almlund et al., 2011). Noncognitive skills have gained importance in labour economics, with the evolving literature also recognises that personality traits may interact with labour market outcomes, in addition to economic preferences and social skills.

Various mechanisms come into play when personality traits influence labour market outcomes. Similar to cognitive skills, personality traits can enter the production function separately, as employers often reward workers whose traits align with the ideal requirements of the job (Bowles, Gintis and Osborne, 2001; Heckman, Stixrud and Urzua, 2006; Borghans *et al.*, 2008; Almlund *et al.*, 2011) or whose traits reduce coordination costs among workers (Deming, 2017). Personality traits can also be linked to economic preferences, such as risk, time and social preferences, which, in turn, explain health, educational and labour market outcomes (Becker *et al.*, 2012). Therefore, it is not surprising that personality traits can predict earnings.

This chapter explores the relationship between personality and earnings through a meta-analysis. While there has been a recent increase in research on personality and earnings, no single study offers a comprehensive overview of the entire body of literature. The estimated personality effects vary among studies, with some reporting negative effects, others indicating positive ones, and with different statistical power, leaving it uncertain which personality traits affect earnings, to what degree, and in what specific ways.

The relationship between personality traits and earnings is complex and multifaceted and likely influenced by various factors, such as a person's education, skills, and advancement opportunities. Individuals with higher levels of education tend to have personality traits, such as openness to experience and conscientiousness, which are associated with higher earnings. Additionally, they may enjoy greater access to resources and opportunities that positively affect their earnings. However, the presence of omitted variables can introduce bias into the estimator of the personality trait under investigation. Even in the absence of unobserved heterogeneity, controlling for variables like education (which is both influenced by personality and has an impact on earnings) can still result in an overcontrol bias.

In this chapter, I conduct a meta-analysis to combine empirical findings from multiple studies and determine the overall effect size of each personality trait on earnings. The meta-analysis also provides an opportunity to evaluate the consistency of results across studies and identify potential sources of variation in the reported findings in the literature. Identifying these sources can help uncover moderators or confounding factors contributing to observed heterogeneity. Additionally, this study examines the presence of publication bias, which occurs when journals and authors tend to favour reporting statistically significant results. This bias can lead to an overestimation of the true earnings effects of personality traits.

While a previous study has already provided a meta-analytical review of the empirical literature on this relationship (Alderotti, Rapallini and Traverso, 2023), this chapter offers a distinct perspective. Firstly, my analysis aims to enhance comparability by focusing on estimates derived from a semi-log wage equation, where the dependent variable is in logarithmic form. Secondly, I include all estimates from the selected studies in the meta-analysis to identify the sources of observed heterogeneity in reported effects. Thirdly, I integrate all identified control variables, including standard errors of reported effects used to detect publication bias, in the meta-regression; whilst ensuring that multicollinearity is not unduly high. This strategy offers clear advantages over bivariate analysis as it allows for an exploration of the relationships between multiple variables. Lastly, I assess the robustness of the meta-regression model through sensitivity tests, considering the potential interdependence among estimates within a single paper and the uncertainties surrounding the main sources of heterogeneity in the studies under analysis.

The results indicate that openness to experience and conscientiousness have a positive relationship with earnings, while extraversion also shows a positive but weaker correlation. On the other hand, agreeableness and neuroticism are negatively associated with earnings. These relationships vary across studies due to control factors such as educational level, family background, cognitive ability, and career path, which play pivotal roles in explaining the varying effects of personality on earnings. Additionally, the analysis reveals the presence of publication bias in the reported personality effects on earnings. Accounting for this bias substantially reduces the strength and significance of the effect sizes.

The chapter is structured as follows: Section 2 delves into the theoretical underpinnings of how personality traits can influence earnings. Section 3 outlines the methodology for study selection and provides an overview of the dataset. Section 4 presents and discusses the empirical results. Finally, Section 5 provides a summary of the results and conclusion.

2.2 CONCEPTUAL FRAMEWORK

Personality traits are "relatively enduring patterns of thoughts, feelings, and behaviours that differentiate individuals from one another (Roberts, 2009, p. 2). They are believed to consist of behavioural and emotional patterns prevalent in all situations rather than in isolated occurrences. The Big Five taxonomy proposes five dimensions of personality, namely: openness to experience (ability to be creative, curious, intellectually engaged, honest/humble and inquisitive), conscientiousness (self-discipline, punctuality, and organised and general competence), extraversion (how talkative, friendly, energetic, and outgoing the person is), agreeableness (the tendency to be kind, charitable, warm, and generous), and neuroticism (fear, worry, paranoia, and stress).[1] Each of these traits contributes to behaviour *ceteris paribus,* meaning they are not the sole determinant of behaviour. Together with other factors, these traits can be utilised to comprehend a person's motives, objectives, and preferences as well as to predict and understand a person's behaviour.

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[1] The five-factor model (McCrae and John, 1992) was the natural candidate for the basis of the current meta-analysis because these dimensions are believed to be broad and capture the fundamental and general aspects of thought, feeling, and behaviour that people typically do differently (John, Naumann and Soto, 2008). The five-factor model has also taken a prominent place in economic research and is considered a standard module in most longitudinal data sets. Although the five-factor model is not without criticism (Eysenck, 1992; Block, 2010), it has been extensively linked to life outcomes, such as wages, health, and longevity (Heckman, Jagelka and Kautz, 2021). The five-factor model has long been recognised as internally consistent, stable, and enjoys cross-cultural support (John, 2021).

The personality traits of each individual are not directly observable and are typically measured through self-report questionnaires that ask people to rate their positive to negative level of agreement with the statement that describes their personality on a Likert scale (for example, a 7-item Likert scale range from 1 = ‘does not apply to me at all’ to 7 = ‘applies to me perfectly’). Instead of relying on self-reported information, peer-report measures involve evaluating someone's personality traits based on the observations of others. Objective measures, on the other hand, are based on observed behaviour.

After collecting responses, various methods can be employed for analysis. In economics studies, factor analysis is common approach to identify latent variables within the responses. This method uses the correlation structure among the observed self-report items to calculate factor scores, representing the dimensions of the underlying factors. These scores are linear combinations of the observed items, with each item's weight determined by its factor loading. Each factor's scale has a mean of zero and a standard deviation of one. The Five Factor Model identifies five distinct latent factors. Factor analysis has the appealing feature of not assuming that all items contribute equally to the construct being evaluated.

A simpler alternative involves summing or averaging a pre-selected set of items, assigning equal weight to each survey item. However, this method may not account for the possibility that different items measure different aspects of the construct being studied and may still correlate with unobserved factors, such as skills (e.g., Borghans et al., 2008).

The relationship between personality traits and earnings can be expressed as an extension of the Mincer's earnings function. The standard model used to estimate the personality effects on earnings can be formulated as follows:

$$ln\, Y_i = \alpha + \beta P_i + \gamma X_i + \varepsilon_i \tag{2.1}$$

where Y_i represents earnings; P_i is a vector of personality traits; X_i is a vector of characteristics affecting earnings (e.g., educational attainment, occupation, cognitive ability); and ε_i represents the error term. The parameter of interest is β, a vector capturing the strength of the relationship between earnings and each personality trait, holding other factors constant. The percentage effect of a one standard deviation increase in P_i on Y_i can be calculated as $\{\exp(\beta) - 1\} \cdot 100$.

Certain personality traits are expected to correlate with higher earnings. For example, traits like conscientiousness, extraversion, and openness to experience tend to be associated with higher income, as they encompass qualities such as a strong work ethic, effective teamwork, and critical thinking, all highly valued in the labour market. Conversely, individuals with higher scores in agreeableness and neuroticism may earn less.

That being said, the relationship between personality traits and earnings is not always straightforward. The estimated personality effects vary among studies, with some reporting negative effects and others indicating positive ones. Various factors influence this relationship, including six key factors I will discuss below.

Educational Attainment

In the literature, there is consensus that the person's level of education, typically measured by years spent in education or degrees earned, can influence the relationship between personality traits and earnings. A wealth of evidence links the Big Five traits with educational attainment. For example, a meta-analysis by Vedel and Poropat (2017) and other studies (e.g., Bergold and Steinmayr, 2018; Brandt et al., 2020; Lechner et al., 2019; Spengler et al., 2016, 2013) highlight conscientiousness and openness to experience as the most relevant traits for educational achievement. In contrast, there is no strong association between higher education and traits like agreeableness, emotional stability, and extraversion (e.g., Caspi et al., 2005; Gensowski, 2018; Lechner et al., 2019; Poropat, 2014; Vedel and Poropat, 2017).

In many economic studies estimating the effects of personality traits on earnings, education is typically included as a control variable. While interpreting these coefficients as direct effects of personality on earnings is technically incorrect, as education itself captures individual predispositions such as personality traits, this practice aligns with the methodological approaches employed by numerous studies in this field.

Furthermore, there is also good reason to believe that education mediates the relationship between personality traits on earnings. This means that education may act as an intermediary through which personality traits influence labour market outcomes. For example, personality traits like conscientiousness and openness to experience may lead to better educational attainment, which in turn enhances earnings potential. Several programs that invest in enhancing both cognitive and noncognitive skills during early childhood, such as the General Educational Development (GED) Program (Heckman and Rubinstein, 2001), the Perry Preschool Project (Heckman, Stixrud and Urzua, 2006), the Jamaican Study (Gertler *et al.*, 2014), and the Columbia study (Attanasio *et al.*, 2020), have demonstrated positive effects on the life outcomes of participants.

Reverse causality is another important consideration. While some personality traits may directly influence educational choices, it is also plausible that education can shape personality traits. Higher education may expose individuals to experiences that impact both their personality development and earnings potential. To mention some, Heckman and Kautz (2013), Gertler et al. (2014), Attanasio et al. (2020) and Allemand et al. (2023) showed that high-quality early childhood and elementary school programs improve character skills – personality traits, goals, motivations, and preferences – that are valued in the labour market. Further research is warranted to gain a deeper understanding of these complex relationships.

Occupation and Selection Effects

The relationship between personality traits and earnings can also be influenced by an individual's career choices. The selection effect suggests that certain personality traits may lead individuals to choose specific occupations. For example, openness to experience is particularly significant for women, with notable differences from men, where it is associated with higher probability of being employed as managers and being employed in professions such as science, engineering, business, and education, while decreasing their likelihood of working as intermediate production workers. Agreeableness, on the other hand, reduces the probability of women working as managers or science and engineering associates, similar to its effect on men. In contrast to men, women with higher levels of extroversion are more likely to secure managerial positions and less likely to work in intermediate production roles. (Cobb-Clark and Tan, 2011). Antecol and Cobb-Clark (2013)'s findings also indicate that firms' hiring and promotion practices may steer workers who demonstrate a strong work ethic, a proactive approach to problem-solving, and, in the case of women, a willingness to take risks, toward male-dominated occupations.[2] Consequently, the link between personality traits and earnings may be more pronounced among those who have selected professions that require or value particular personality traits, compared to individuals whose aptitudes do not align with the demands of the occupation.

Evidence from various meta-analyses supports this idea. For instance, conscientiousness is a strong predictor of job performance (Salgado *et al.*, 2003; Ones *et al.*, 2007), while openness to experience is important in roles that require training (Lepine, Colquitt and Erez, 2000). Extraversion is valuable in contexts involving social interaction and leadership roles, whereas agreeableness is positively correlated with performance in team-based environments (Peeters *et al.*, 2006; Bell, 2007). On the other hand, neuroticism tends to be associated with underperformance across diverse organisational settings (Ones *et al.*, 2007).

[2] Related to this, personality traits can also influence labour market participation. Studies show that individuals with a positive attitude and hope are more likely to be hired than pessimistic ones (Mohanty, 2010). In the case of female employment, Wichert and Pohlmeier (2010) find that women with higher scores in extraversion and conscientiousness experience more favourable employment outcomes, while traits like neuroticism and openness are linked to a lower likelihood of employment. Additionally, Mosca and Wright (2018) and Risse et al. (2018) provide evidence that females are more likely to return to employment if they score higher in agreeableness and extraversion.

The empirical literature on agreeableness presents mixed views, which can partly be explained by selection effects. On the one hand, agreeableness is associated with improved performance through better interpersonal interactions and in tasks requiring teamwork (Peeters *et al.*, 2006; Bell, 2007). On the other hand, less agreeable personalities may be favoured in obtaining managerial or higher-paying positions (Wells, Ham and Junankar, 2016). Selection effects are evident in the fact that more agreeable workers tend to cluster in lower-paying caregiving occupations, such as teaching and nursing, where attributes such as empathy and cooperation are valued. Additionally, more agreeable individuals are less effective at negotiating wages and often hold more egalitarian views on work and pay structures (Nyhus and Pons, 2005). These selection effects imply that personality traits not only affect performance but also occupational sorting and wage determination.

Cognitive Skills

It is well known in the existing literature that omitting cognitive skills measures from earnings specifications can introduce omitted variable bias, potentially compromising the accuracy of personality trait effect estimates.

While intelligence and personality have traditionally been viewed as distinct constructs, recent research suggests that cognitive skills and personality traits are conceptually and empirically related. DeYoung (2020) provides a detailed account of why such correlations exist. An explanation for the relationship between personality traits and cognitive ability is that some aspects and facets of personality traits are also considerably related to cognitive ability. For example, individuals scoring high on openness to experience often engage in training, enhancing their cognitive development, while those with low emotional stability measures may experience anxiety that can hinder cognitive growth (Moutafi, Furnham and Tsaousis, 2006).

Another important consideration is the shared measurement error between personality traits and cognitive ability. This error stems from the fact that the tests employed to measure personality traits and cognitive ability are often administered to the respondent under the same conditions, consequently inducing a common response bias. Although conceptually, cognitive ability and personality traits are two separate constructs, the fact that the measures were impurely measured implies that they are linked systematically (Borghans *et al.*, 2011). Indeed, personality traits like conscientiousness and neuroticism are closely associated with cognitive ability due to shared skills, such as attention to detail, organisation, and anxiety management.

Family Background

SES plays a crucial role in predicting an individual's labour market outcomes, encompassing factors like education, occupation, and income of the individual or their parents. Higher SES families tend to lead to better life trajectories, including higher earnings, improved education, increased social capital, and access to well-paying jobs and social networks.

The relationship between personality traits and earnings is intertwined with SES, meaning that the impact of personality traits on earnings can differ among individuals from varying socioeconomic backgrounds. For example, Collischon (2020), using unconditional quantile regressions to estimate the effect of personality traits on wages at different points of the wage distribution, found that the effects of agreeableness, conscientiousness, and neuroticism on wages are stronger for workers at the top of the wage distribution, and these effects increase across the wage distribution.

This interplay between personality traits, earnings, and family socioeconomic background is influenced by the different resources and opportunities available to individuals from high SES backgrounds. Those with higher SES have better access to resources that enhance their career-related attributes, thereby amplifying the influence of personality traits on earnings. Deckers et al. (2015) demonstrated a robust link between a child's personality and their parents' SES, emphasising the enduring impact of family background on personality development. A meta-analysis by Ayoub et al. (2018) also indicated correlations between parental SES and personality traits, although the effect sizes are relatively modest. Ignoring SES would erroneously attribute the entire influence to personality traits, as SES directly affects earnings.

Gender

The effect of gender on the relationship between personality traits and earnings is a subject of mixed findings (Nyhus and Pons, 2012). For instance, regarding agreeableness, Mueller and Plug (2006) found that antagonistic men earned more than their agreeable counterparts, but other studies (Heineck and Anger, 2010; Cobb-Clark and Tan, 2011; Heineck, 2011) discovered a negative relationship between agreeableness and earnings for both men and women.

Similar mixed results were observed for neuroticism. While higher neuroticism is generally associated with lower earnings, Heineck (2011) found this negative association only among female workers. Gender-specific patterns were also noted for other personality traits. Women with higher openness to experience tend to earn more, while among men, higher openness to experience was linked to lower earnings. Additionally, women with higher extraversion levels tended to earn less, whereas extroverted men commanded higher salaries compared to their counterparts with lower scores in this trait.

Age

Age is an important factor in the context of personality development. While the overall personality profile tends to remain stable after puberty, adolescents typically become more outgoing, conscientious, and emotionally stable as they mature, known as the "maturity principle" (Roberts, Walton and Viechtbauer, 2006; Bleidorn *et al.*, 2022). This suggests that age is linked to personality development.

It is reasonable to assume that the effect of personality traits on earnings may vary with age. Some studies, such as Maczulskij and Viinikainen (2018), suggest that these effects might be more pronounced among younger workers than older ones, while others like Cobb-Clark and Schurer (2012) do not find significant variation in the relationship by age.

2.3 EMPIRICAL STRATEGY

This study employs a meta-analysis approach to synthesise the estimated personality effects from the existing literature. This statistical approach allows us to generalise the findings across multiple studies, providing a more accurate and reliable estimation, especially since individual study results can vary significantly.

The overall effect size would be the mean or median of the regression coefficients, if all studies had the same research design and sample size. However, when these conditions do not hold, we want to assign more weight to studies that are more precise. One way to implement this is by considering the standard error of the regression coefficient when determining the weight of each study. This is because the accuracy of the regression coefficient is measured by its standard error, which also represents the degree of uncertainty surrounding the estimate. The inverse variance method, therefore, implies that studies with larger sample sizes with smaller standard errors are given more weight than those with smaller sample sizes and larger standard errors.

Estimation Strategy

To determine the overall effect size of each personality trait, I extract the regression coefficient of interest (known as semi-elasticity, as shown in Equation (2.1) and its corresponding standard error (σ_i) from each identified study i.

The meta-analysis model used is the random-effects model. This model assumes that the observed differences in effects are due to within-study sampling error and actual heterogeneity in the true effects between studies. In this context, "random-effects" models are different from those in econometrics. The random-effects in meta-analysis works under the assumption that any variation in observed effects are a result of within-study sampling error, ϵ_i, and actual heterogeneity in the true effects between studies, u_i.[3] It assumes that the true effect size (θ_i) follows a normal distribution around the mean true effect, θ. Equivalently,

$$\hat{\beta}_i = \theta + \epsilon_i + u_i, \tag{2.2}$$

where $\hat{\beta}_i$ is the estimated coefficient in study i, $\theta_i \sim N(\theta, \tau^2)$, $\epsilon_i \sim N(0, \sigma_i^2)$ and $u_i \sim N(0, \tau^2)$. ϵ_i is the sampling error, and τ^2 represents the between-study variance and is estimated from the data.[4] Equation (2.2) can be estimated using ordinary least squares (OLS). However, there are two problems in estimating this specification.

First, the estimates may violate the assumption of homoskedasticity, where error variances differ systematically among observations. To address this, equation (2) is adjusted by weighting it with the inverse of the square root of the within-study variance, σ_i^2, plus the between-study variance, τ^2 (represented by ω). When ω is large, the data is less informative, and observations are given less weight. This transformation of Equation (2.2) is as follows:

$$\hat{\beta}_i \frac{1}{\omega} = \theta \frac{1}{\omega} + v_i \frac{1}{\omega} \tag{2.3}$$

where $v_i = \epsilon_i + u_i$ and $\omega = \sqrt{\sigma_i^2 + \tau^2}$. Estimating Equation (2.3) by OLS is equivalent to estimating Equation (2) by weighted least squares (WLS) using the weights discussed above (Stanley and Doucouliagos, 2015).

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[3] In the context of meta-analysis, the term "fixed-effect" also has a different definition than "fixed-effects" in econometrics. The fixed-effect meta-analysis model assumes that there is only one true effect size, θ, and that any differences in the observed study-specific regression coefficients are due only to random error. The assumption of a single true effect size is not appropriate when the studies are heterogeneous, for example in terms of design and survey population. The fixed-effect method results in excessive Type I errors when residual or unexplained heterogeneity is present.
[4] The procedure used to estimate τ^2 is the residual maximum likelihood method.

Second, there is a concern that effect sizes may be correlated, especially if they are from the same study. To address this issue, I use cluster-robust standard errors at the study level to account for any correlation within studies. As an additional robustness test, I compare the findings of two sets of specifications: one that gives equal weight to each estimate, and one that gives equal weight to each study. Appendix B discusses the results.

To better understand the differences in reported effects, Equation (2.2) can be adjusted by including k-dummy variables, where each variable represents a specific study characteristic (Aloe and Becker, 2012). The considered variables include factors like whether the model controls for the individual's education, skills, socioeconomic background, and the chosen econometric method. A value of 1 is assigned to each dummy variable if the study characteristic is prevalent in the study, and 0 if it is not. If the regression coefficient of a dummy variable is significantly different from zero, it indicates that the particular characteristic exerts a significant effect on the overall effect size. This method also addresses typical concerns in meta-analysis about combining studies in a meaningful way, ensuring comparability in terms of study design, variables, and other relevant characteristics.

If θ is a linear function of X_i, then Equation (2.2) can be expressed as:

$$\hat{\beta}_i = \theta + \sum_{k=1}^{K} \alpha_{1,k} X_{i,k} + \epsilon_i + u_i, \tag{2.4}$$

where the true effect size of each study is $\theta_i \sim N(\theta + \sum_{k=1}^{K} \alpha_{1,k} X_{i,k}\, , \tau^2)$. $X_{i,k}$ represents characteristic k for study i, which explains variations in estimated effects. $\alpha_{1,k}$ is the coefficient to estimate, and K is the total number of identified variables explaining heterogeneity. θ represents the overall effect size after accounting for the other relevant characteristics $X_{i,k}$.

Publication Bias

Equation (2.3) is susceptible to publication bias which arises when journals and authors are more likely to publish studies that support a particular conclusion, typically those with expected signs and significant results. For this reason, θ may be overestimated due to this bias. This overestimation can occur if only studies with anticipated signs and significance levels are published, making the effects of personality traits seem to be larger and more significant than they are.

Publication bias manifests in two ways. The first way is selective reporting. Results that align with a priori expectations tend to be more attractive to researchers and journals, leading to substantial publication bias, which often takes the form of incidental truncation (Stanley and Doucouliagos, 2014). In this context, only statistically significant estimates are typically published or disseminated. This selective reporting can significantly distort the overall understanding of an effect, as some of the findings are often omitted from the literature. Consequently, this leads to a skewed distribution of reported coefficients relative to their standard errors. Significant coefficients with large t-statistics (i.e., large effect sizes relative to their standard errors) are overrepresented, while insignificant or unexpected results are often omitted. This creates an asymmetrical distribution, with findings clustering at one end, particularly when there are directional expectations. For example, in the case of conscientiousness, significant positive results are likely to cluster at one end of the distribution, while negative or insignificant results are sparse or absent.

Alternatively, publication bias can also result from researchers working with small sample sizes, which leads to larger standard errors. In their attempts to achieve statistical significance, these researchers may scrutinise their model specifications and econometric methodologies more rigorously. This situation often results in a positive correlation between reported effect sizes and their standard errors, as researchers may inadvertently present inflated estimates to meet significance thresholds. In contrast, researchers with larger sample sizes, which generally yield smaller standard errors, may be less likely to explore various model specifications, resulting in a tendency to report smaller empirical effects.

To assess the effect of publication bias, I employ the method outlined by Stanley and Doucouliagos (2011), wherein I regress the collected regression coefficients against their corresponding standard errors. The intuition behind this test is that researchers with smaller sample sizes – and thus higher standard errors of the estimates – may play with the specification until they get estimates that are large enough to achieve statistical significance. This results in the following formulation of Equation (2.3):

$$\hat{\beta}_i = \theta + \sum_{k=1}^{K} \alpha_{1,k} X_{i,k} + \alpha_2 \sigma_i + \epsilon_i + u_i, \qquad (2.5)$$

The regression test in Equation (2.5) is commonly known as the Funnel Asymmetry Test Precision Effect Test (FAT-PET) method, proposed by Egger et al. (1997). If publication bias is present, the term α_2 is expected not to be statistically different from zero, indicating that there is correlation between precision (often proxied by standard error) and the reported coefficient size. In the presence of publication bias, if the true effect size is positive (e.g., as with conscientiousness), $\alpha_2 > 0$, and if the true effect size is negative (e.g., as with neuroticism), $\alpha_2 < 0$. This can lead to an overestimation of θ_i.

Similar to Equation (2.3), to account for heteroskedasticity, Equation (2.5) is weighted by the inverse of ω.

The Dataset

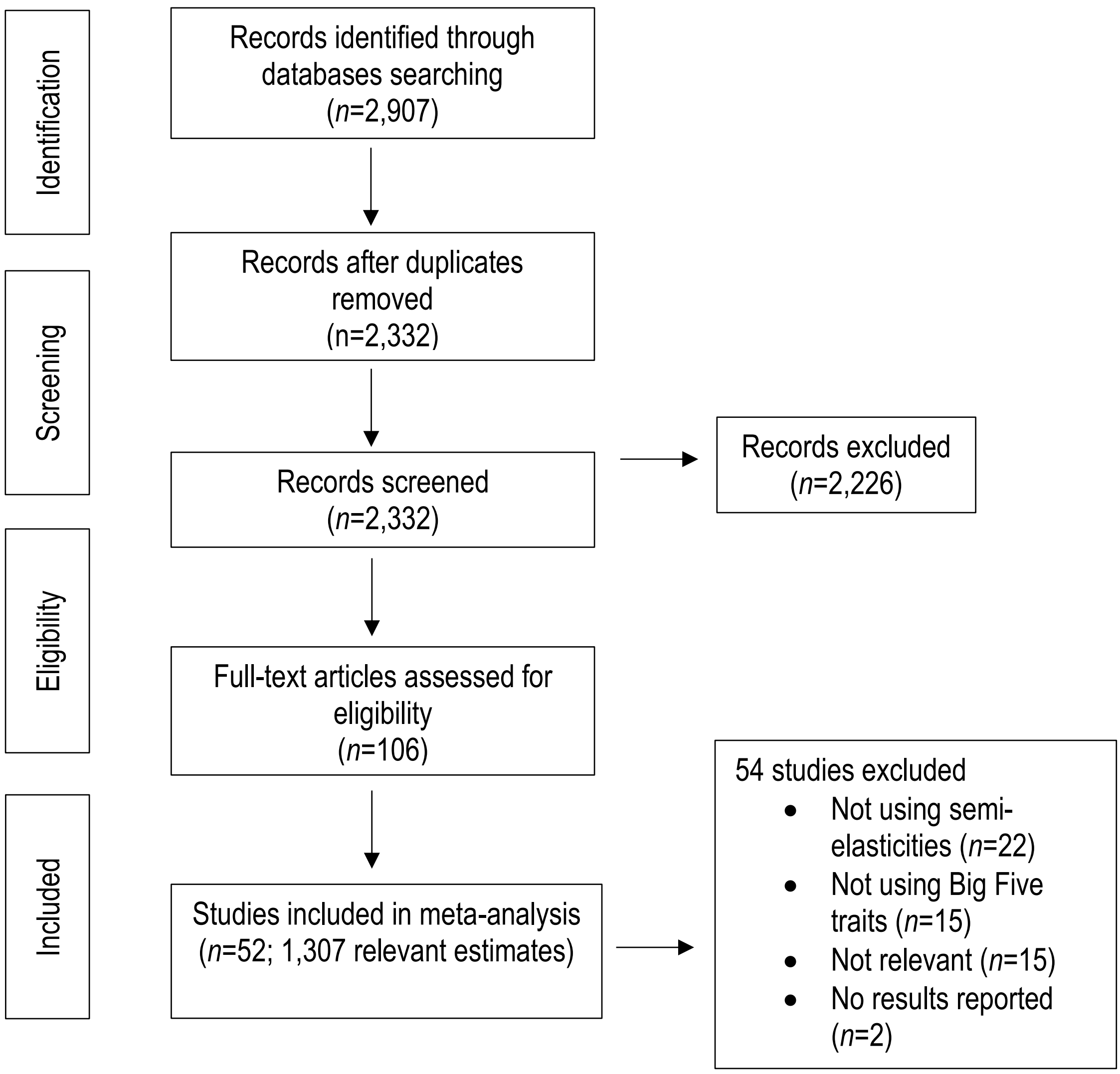
To create the dataset for the meta-analysis, I followed the established reporting guidelines (Moher *et al.*, 2009; Havránek *et al.*, 2020). The meta-analysis included studies that met seven specific criteria: a) the study had to examine the relationship between personality and earnings; b) it had to include at least one empirical estimate using econometric analysis to measure the effect of personality on the dependent variable, excluding theoretical studies or systematic reviews; c) it needed to report the standardised personality trait coefficient along with its corresponding standard error, t-statistic, or p-value[5]; d) only studies employing the log-transformed estimation strategy as described in Equation (2.1) were considered; e) only studies focusing on the Big Five personality traits were included, given their widespread use in both economics and personality research; and f) the study had to be written in English.

[5] Seven studies were included in the meta-analysis but do not report the relevant standard errors. The standard error is therefore obtained by dividing the value of the coefficient by the t-statistic. Another seven studies report the p-value along with the sample size and number of explanatory factors included in the regression so that the corresponding standard error could be calculated.

Due to the relatively limited number of available studies on earnings and the predefined inclusion criteria, I conducted a comprehensive literature review following a methodology similar to Havránek et al. (2020). This process involved searching eleven electronic databases: Business Source Complete, EconLit, Emerald, Google Scholar, JSTOR, RePEc, ScienceDirect, Scopus, ProQuest, PsychInfo, and Web of Science. Only peer-reviewed publications were considered to ensure quality control. I also employed reference pyramid schemes to identify relevant papers. The literature search was completed in April 2022, and the following search terms were used: “Big Five”, “income”, “earnings”, “labour market outcomes”, “noncognitive skills”, “noncognitive abilities”, “return to personality”, “personality”, “personality development”, “personality traits”, “salary”, and “wages”. The included studies are listed in the Appendix A and Figure 2.1 provides an overview of the literature search and screening process.

A total of 106 studies were initially identified, and this list was then narrowed down to 52 studies based on the defined inclusion criteria. Consequently, the final dataset comprises 1,307 estimates. Within this dataset, each study provides varying estimates for different personality traits, with estimates ranging from 1 to 120 per study. The inclusion of multiple estimates is due to the use of different techniques to ensure the validity of regression coefficients. Some studies also investigate systematic differences in coefficients among different groups or explore the impact of variables like family background on baseline results. For a detailed breakdown of the studies included in the dataset that meet the inclusion criteria, refer to the Table A1. This table

Figure 2.1: Flow chart of the search and screening process



includes information about the author(s), publication year, data collection year(s), countries covered, and the number of effect sizes collected for each study.[6]

The compiled dataset includes studies utilizing both cross-sectional and panel data, analysed with various econometric methods such as (pooled) OLS, random effects, and fixed effects. However, it is evident that some studies in the dataset do not

[6] To create the dataset, I categorised kindness and cooperation as agreeableness, constructiveness as conscientiousness, sociability as extraversion, withdrawal and aggression as negative values of emotional stability, and emotional instability as neuroticism.

adequately address omitted variable bias, while others examining endogeneity associated with personality employ instrumental variables (IV), correlated random effects, Hausman-Taylor IV, or within-group estimators. Additionally, some studies employ personality scores measured concurrently with earnings, while others gather personality scores from childhood or just before individuals enter the workforce. This is done to account for the possibility that personality traits are influenced by prior experiences. The time lag between the outcome variable and the personality scores in the dataset ranges from 0 to 65 years, although using lagged values can sometimes result in less precise data.

In addition to the standardised regression coefficient and its corresponding standard error, the constructed dataset includes information on sample size, degrees of freedom, data type (cross-sectional or panel data), econometric method used (OLS or otherwise), empirical settings (age cohort, country coverage, sex), year of data used for income and personality traits, as well as dummy variables for the inclusion of theoretically relevant factors (cognitive abilities, education, occupation, family background), publication characteristics, and methodological dummies, including endogeneity control and factor score personality measures.

Table 2.1 shows all explanatory variables included in the multi-regression approach, along with the mean of each personality trait. Notably, significant heterogeneity is observed in the averages. For instance, the earnings elasticity of openness to experience is positive for individuals aged 35 or over but negative for those under 35.

Table 2.1: Variable definitions, descriptive statistics and average size effect for every trait

	Definition	O	C	E	A	N
Age Category						
Above 35 (Base Category)	Study data is from a population aged more than 35	.028	.029	.011	-.029	-.033
Below 35	Study data is from a population aged less than 35	-.047	.117	.006	.003	-.061
Gender						
Not Controlled (Base Category)	Sample is mix	.024	.059	.014	-.024	-.052
Males	Sample is only males	.010	.021	.004	-.024	-.017
Females	Sample is only females	.010	.018	.008	-.022	-.030
Education Control						
No (Base Category)	No control for education	.033	.065	-.006	-.024	-.041
Yes	Controls for education	.014	.035	.016	-.024	-.037
Family Background Control						
No (Base Category)	No control for family background	.034	.050	.011	-.030	-.043
Yes	Controls for family background	.003	.035	.011	-.018	-.032
Occupation Control						
No (Base Category)	No control for occupation	.025	.054	.020	-.020	-.026
Yes	Controls for occupation	.011	.029	-.001	-.028	-.051
Cognition Control						
No (Base Category)	No control for cognitive ability	.027	.040	.015	-.021	-.047
Yes	Controls for cognitive ability	.007	.045	.006	-.027	-.026
Time Interval						
0 (Base Category)	No time lag	.021	.040	.010	-.026	-.039
1-65	With time lags	-.001	.055	.016	-.015	-.034
Unobserved Heterogeneity Controlled						
No (Base Category)	No control for unobserved heterogeneity	.020	.048	.016	-.026	-.040
Yes	Controls for unobserved heterogeneity	.007	.000	-.027	-.009	-.019

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. Standard errors are reported in parentheses. Statistics give equal weight to each study.

Table 2.1 (cont.): Variable definitions, descriptive statistics and average size effect for every trait

	Definition	O	C	E	A	N
Use of OLS						
No (Base Category)	No use of OLS	.042	.000	-.022	-.028	-.055
Yes	Use of OLS	.013	.051	.018	-.023	-.034
Use of Personality Factor Scores						
No (Base Category)	Uses average or sum of personality items	-.003	.038	-.003	-.026	-.037
Yes	Uses factor personality scores	.046	.049	.030	-.021	-.038
Data Type						
Cross-sectional Data (Base Category)	Uses cross-sectional data	.018	.043	.003	-.028	-.036
Panel Data	Uses panel data	.018	.041	.035	-.010	-.044
Country Coverage						
Europe, US (Base Category)	Country in Europe and US	.209	.407	.255	-.200	-.275
Australia	Australia	-.004	.021	.005	-.022	.000
Asia Pacific	Country in Asia Pacific region	.119	.018	-.025	-.051	-.187
World	Country, other than the above	-.041	.080	-.052	-.033	-.042
Publication Type						
Working Paper (Base Category)	Study published as a working paper	-.025	.053	-.024	-.026	-.031
Journal	Study published in a peer-reviewed journal	.033	.039	.022	-.023	-.040

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. Standard errors are reported in parentheses. Statistics give equal weight to each study.

2.4 RESULTS

Overall Effects

The estimation results for Equation (2.3) in Table 2.2 were obtained using the restricted maximum likelihood (REML) method to estimate the between-study variance.[7] These results clearly demonstrate that the overall regression coefficients for all personality traits are highly statistically significant (p-value < .0001).

For openness to experience, the true effect size is 0.019, indicating that a one standard deviation increase in openness to experience corresponds to a 1.92% increase in earnings. Similarly, conscientiousness (θ=0.016, 1.61%) and extraversion (θ=0.003, 0.30%) are positively correlated with earnings, while agreeableness (θ=-0.017, -1.69%) and neuroticism (θ=-0.018, -1.78%) show negative correlations. Despite being statistically significant, these effect sizes are considerably smaller than the returns to education found in other meta-analyses, which typically range from 8% to 10%

Table 2.2: Overall effect sizes, random-effects

	O	C	E	A	N
Effect Size	.019***	.016***	.003*	-.017***	-.018***
	(.002)	(.002)	(.001)	(.002)	(.002)
I^2 (%)	99.2%	99.3%	97.5%	98.3%	99.2%
Q-statistic	1926.60***	1216.05***	64.81***	1577.67***	7542.53***
N	216	231	245	246	246

*Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. The approach gives equal weight to each estimate. Standard errors are reported in parentheses and clustered at the study level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. I² value of 25% indicates low heterogeneity, while an I² value of 50% suggests moderate heterogeneity, and an I² value of 75% signifies high heterogeneity. A significant Q-statistic (p < 0.05) indicates that there is substantial variability in effect sizes across studies, suggesting the presence of heterogeneity.*

[7] Regression coefficients below the 5th percentile and above the 95th percentile are dropped in order to lessen the impact of outliers.

(Harmon, Oosterbeek and Walker, 2003; Horie and Iwasaki, 2023). However, the average effect can vary based on the context (Sianesi, Dearden and Blundell, 2003). In comparison, returns to cognitive skills are generally much higher, though they also depend on factors such as income level and gender, among others (Groves, 2005; Heineck and Anger, 2010; Lindqvist and Vestman, 2011).

The positive coefficient for openness suggests that attributes like creativity and willingness to learn new skills are highly valued in the labour market. Individuals who score high on openness are more likely to benefit from better educational attainment and training opportunities, which enhance their earnings potential, particularly in learning-intensive or cognitively demanding fields.

Conscientiousness is positively correlated with earnings, as expected. This trait is linked to job performance through attributes like reliability, diligence, and work ethic, all of which are rewarded by employers. The return on conscientiousness reflects its value in roles requiring persistence and careful planning, as well as its association with educational attainment, which further boosts earning capacity.

The positive but modest coefficient for extraversion implies that while extraverts may perform well in leadership, sales, or social interaction-based roles, its overall effect on earnings is relatively limited compared to other traits like conscientiousness. This effect likely depends on the occupation, being more valuable in specific fields such as sales, public relations, and management.

The negative coefficient for agreeableness suggests that while this trait may be beneficial in cooperative or team-oriented jobs, it can be a disadvantage in competitive environments. Agreeable individuals tend to avoid negotiation, assertiveness, and competitive situations, which can result in lower wages, particularly in occupations like teaching and nursing where wage negotiation is less common. This trait may be less advantageous in high-paying or leadership roles, where assertiveness is often required.

Finally, the negative effect of neuroticism is consistent with prior expectations. High levels of neuroticism are associated with lower productivity, poor performance under stress, and increased absenteeism, all of which negatively affect earnings. Employers may view neurotic individuals as less capable of handling high-pressure roles, which can limit their career progression and earnings potential, particularly in leadership or demanding positions.

To address the potential dependency of effect estimates within the same study, the robust variance estimation (RVE) approach was also used. Such dependency can arise from nested effect sizes or multiple measurements collected for the same individuals. The analysis showed that the overall earnings effects remained consistent with the main results across the Big Five personality traits, and no significant changes were observed when considering various within-study effect size correlations.[8] Additionally, four sensitivity analyses were conducted to validate the robustness of the REML results, and these analyses are available in Appendix B.

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[8] For the RVE method, τ^2 was estimated using the method-of-moments.

The summary statistics also reveal significant heteroskedasticity in the results, indicating that the reported personality effects lack consistency across studies. Indeed, the I^2 score demonstrates that over 99% of the total variation across studies can be attributed to between-study variability rather than sampling error.[9] The Q-statistic test, was also employed to assess whether the effect sizes are distributed around the mean, and this test underscores the presence of heterogeneity among the results (p-value < .0001).[10]

Publication Bias

In this study, Doi plots were employed to visually detect publication bias. Unlike funnel plots, where effect sizes are plotted against their precision score, Doi plots ranks coefficients of each study and plot them against a folded normal quantile (Z-score).[11] The main advantage of the Doi plot is that it facilitates the visualisation of asymmetry, with the lack of asymmetry indicating the absence of publication bias. The presence of publication bias is indicated by a disproportionate concentration of studies in either the bottom-right or bottom-left quadrants of the plot, indicating that studies with larger effect sizes and higher precision are more likely to be represented in the published literature. Additionally, Doi plot uses the Luis-Furuya-Kanamori (LFK) index to quantify this asymmetry. LFK index values between ±1 suggest no asymmetry, values

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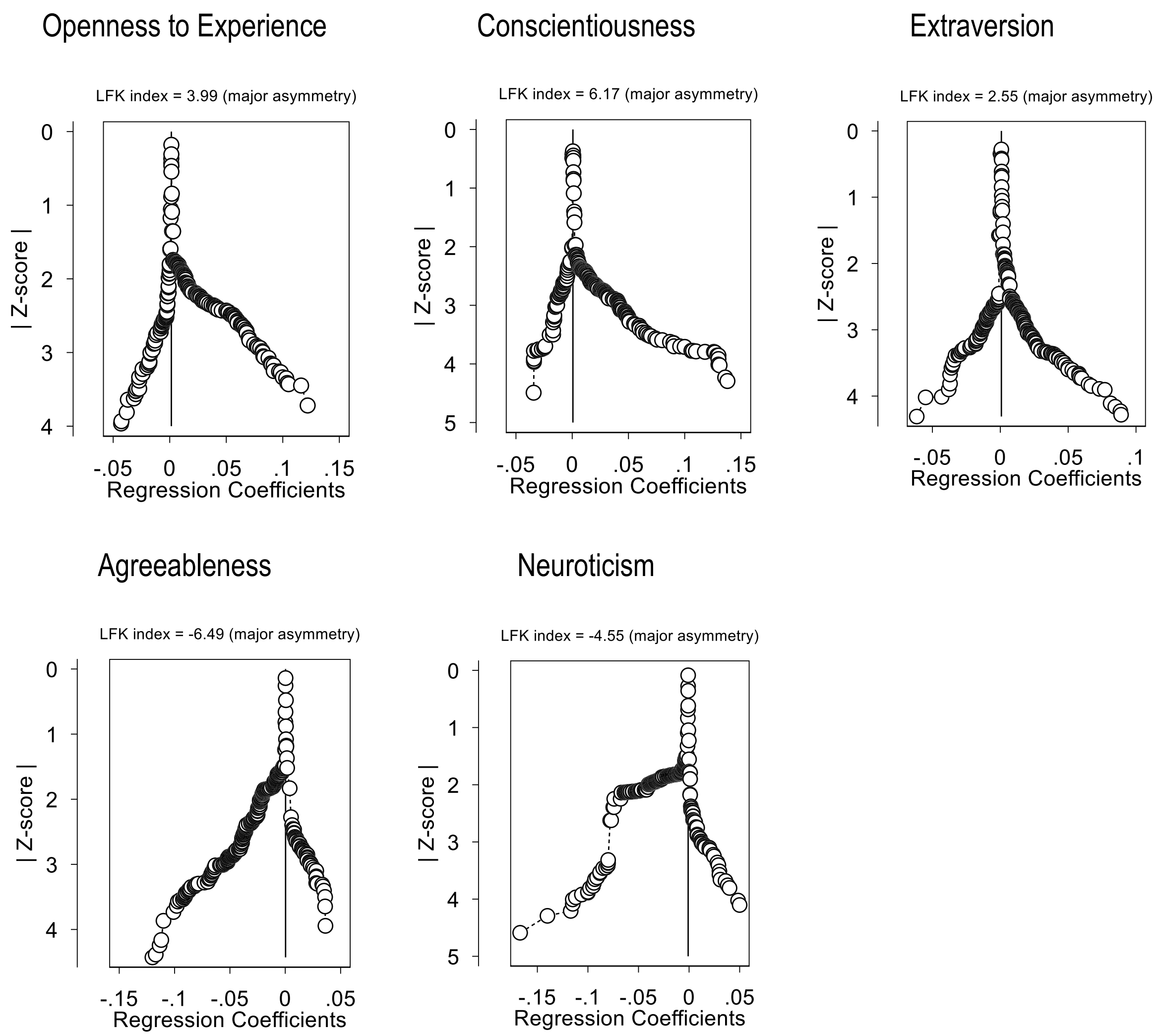
[9] I^2 statistic quantifies the percentage of total variation across studies in a meta-analysis that is attributable to heterogeneity rather than chance. Following Higgins et al. (2003), I^2 = 25% indicates low heterogeneity, I^2 = 50% indicates medium heterogeneity, and I^2 = 75% indicates high heterogeneity.
[10] The Q-statistic assesses the presence of heterogeneity among the studies included in the meta-analysis. A significant Q-statistic ($p < 0.05$) indicates that there is substantial variability in effect sizes across studies, suggesting the presence of heterogeneity.
[11] A detailed description of the Doi Plot is given in Furuya-Kanamori et al. (2018).

exceeding ±1 but within ±2 indicate minor asymmetry, and values greater than ±2 signify major asymmetry.

The Doi plots presented in Figure 2.2 reveal an uneven distribution of regression coefficients in the dataset. Moreover, the LFK index surpasses a value of 2 for all Big Five traits, indicating a strong presence of publication bias.

Figure 2.2: Doi plots



Note: The Doi plot features a folded normal quantile (Z-score) plotted against the effect size. In the absence of publication bias, a vertical line drawn from the tip of the Doi plot should divide the plot into two regions of roughly equal area.

Table 2.3 displays the results of the FAT-PET regression using Equation (2.4), initially without including $X_{i,k}$ covariates. The purpose of this test is to detect potential bias introduced typically by small studies. Smaller studies, which typically have larger standard errors, may only be published if they report sufficiently large effect sizes to reach statistical significance. Consequently, this selective reporting creates a correlation between the standard error and the reported effect size. If α_2 is statistically significant from zero, it indicates that the reported effect sizes systematically vary with the precision of the studies, suggesting the presence of publication bias.

The statistically different from zero coefficients for α_2 confirms the presence of publication bias for conscientiousness, agreeableness, and neuroticism. Consequently, the overall regression coefficients presented in Table 2.2 were overestimated due to this publication bias. For example, consider conscientiousness. Without accounting for publication bias, a one standard deviation increase in conscientiousness is associated with a 1.61% increase in earnings. However, the effect drops to 0.60% once publication bias is taken into account.

While it might appear that personality traits do not exert a significant influence on earnings once publication bias is considered, it is important to approach this conclusion with caution. The apparent insignificance of the coefficients does not necessarily imply that personality traits lack relevance in the labour market. There may be other factors at play that offset one another, making it difficult to determine the overall impact.

To further investigate potential publication bias, four additional tests were conducted in line with recent studies. These tests are particularly useful when significant heterogeneity is present (I^2 > 80%) (Stanley, 2017). The results of these tests are available in Appendix B. All of the methods employed indicate that the semi-elasticities essentially approach zero in magnitude. This suggests that, once publication bias is taken into account, there is minimal to no discernible correlation between personality traits and earnings.

Heterogeneity

Given the high I^2 value, the next step is to delve into the sources of the observed heterogeneity.[12] The results of Equation (2.4) estimation are summarised in Table 2.4, revealing several key insights.

Firstly, it has been confirmed that publication bias is indeed present, aligning with previous tests. This is evidenced by the statistical significance of the standard error coefficients for all Big Five traits at the 1% level.

Table 2.3: Publication Bias, FAT-PET

	O	C	E	A	N
Effect beyond bias (precision effect)	.015**	.006	.000	-.008**	-.006
	(.006)	(.004)	(.002)	(.004)	(.005)
Standard Error (publication bias)	.302	.906***	.386	-.786***	-1.007***
	(.201)	(.255)	(.231)	(.229)	(.275)
Adjusted R-sq	.275	.358	.063	.363	.366
N	216	231	245	246	245

*Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. The approach gives equal weight to each estimate. Standard errors are reported in parentheses and clustered at the study level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.*

[12] Ranges for interpreting I^2 are as follows: (i) 0% to 40%: heterogeneity may not be important; (ii) 30% to 60%; may represent moderate heterogeneity; (iii) 50% to 90% may represent substantial heterogeneity; and (iv) 75% to 100% considerable heterogeneity.

Table 2.4: Explaining Heterogeneity in the Estimated Effects of Personality on Wages

	O	C	E	A	N
Constant	55.803***	-15.594**	-.994	-27.385***	-3.629
	(9.039)	(7.416)	(4.695)	(7.204)	(6.400)
Standard Error	.361**	.838***	.535***	-.838***	-1.020***
	(.176)	(.150)	(.128)	(.148)	(.161)
Age Category	-.004	.015**	.017***	-.001	.014**
	(.013)	(.008)	(.004)	(.007)	(.006)
Males	-.000	-.000	-.005**	-.004	.009***
	(.005)	(.003)	(.002)	(.004)	(.003)
Females	.003	-.001	-.003	.000	.001
	(.005)	(.004)	(.002)	(.004)	(.003)
Education controlled	-.020***	-.002	.007***	-.002	.009***
	(.005)	(.004)	(.002)	(.004)	(.003)
Family Background controlled	-.011**	-.007**	.000	.002	.017***
	(.005)	(.003)	(.002)	(.003)	(.003)
Occupation controlled	.002	-.013***	-.005**	.001	-.002
	(.004)	(.003)	(.002)	(.003)	(.003)
Cognitive ability controlled	-.004	.011***	.001	-.004	.002
	(.004)	(.003)	(.002)	(.003)	(.003)
Time Lag	-.016*	-.005	-.019***	.024***	-.004
	(.009)	(.006)	(.004)	(.005)	(.005)
UH controlled	-.020***	-.007	-.001	.007	.002
	(.007)	(.006)	(.003)	(.006)	(.006)
OLS method	-.024***	-.009*	-.001	-.001	-.007
	(.007)	(.005)	(.003)	(.005)	(.005)
Use of Personality Factor Scores	.001	.008**	.001	-.001	.011***
	(.005)	(.003)	(.002)	(.004)	(.004)
Panel Data	.004	.007*	-.003	-.005	-.023***
	(.005)	(.004)	(.002)	(.004)	(.004)
Australia	.004	.004	-.004	-.013**	.001
	(.007)	(.006)	(.003)	(.006)	(.005)
Asia Pacific	-.001	.025***	.008	.023***	.022***
	(.009)	(.007)	(.005)	(.009)	(.007)
World (Other)	.036***	-.003	-.001	-.002	-.005
	(.007)	(.006)	(.004)	(.005)	(.005)
Journal	-.001	-.004	-.004*	.005	.006
	(.005)	(.004)	(.002)	(.004)	(.004)
Pub Year (logs)	-7.328***	2.051**	.132	3.599***	.477
	(1.188)	(.975)	(.617)	(.947)	(.841)
R-sq	.494	.560	.510	.527	.599
N	216	231	245	248	245

*Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. The approach gives equal weight to each estimate. Standard errors are reported in parentheses and clustered at the study level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.*

Secondly, the demographic variables shed light on the notion that the returns to personality traits vary throughout an individual's career. Specifically, individuals younger than 35 years old experience more significant effects on their earnings related to conscientiousness and extraversion. In contrast, neuroticism is associated with a greater decline in wages for those over 35 years old.

Furthermore, it appears that gender does not significantly influence the magnitude of most effect sizes. This suggests that, all else being equal, there are no systematic gender-related differences for most personality traits. More precisely, the results indicate that studies exclusively involving male respondents tend to report a smaller effect of neuroticism on earnings and a weaker effect of extraversion on wages compared to studies encompassing both genders.

The third set of variables pertains to an individual's socioeconomic status and family background. The meta-regression results indicate that studies failing to control for educational attainment tend to overstate the impact of openness to experience on earnings. Furthermore, studies considering education levels tend to report greater positive effects on earnings for individuals displaying extraverted traits, while those with neurotic tendencies tend to exhibit weaker effects on their earnings. These findings align with expectations, as openness to experience appears to be the most significant personality trait associated with educational achievement. Conversely, higher levels of neuroticism tend to correlate with lower performance on achievement tests.

The meta-analysis results highlight that an individual's family background can influence the relationship between the Big Five traits and their earnings. Studies omitting factors like parental education and household income may overestimate the effects of openness to experience, conscientiousness, and neuroticism on earnings. This suggests that individuals with higher socioeconomic status may have greater educational and career aspirations, along with more opportunities for advancement. Additionally, a person's family history can shape their personality development during their formative years, potentially impacting how their personality traits relate to their earnings.

The results of the meta-regression further support the idea that occupation plays a significant role in predicting the variation in reported personality effects on earnings, especially for traits like extraversion and conscientiousness. This underscores the intricate relationship between occupation and the returns associated with personality traits.

Cognitive ability emerges as another factor affecting the impact of personality traits on earnings. The results confirm that when cognitive ability is considered, the effect of conscientiousness on wages becomes even more significant. This finding aligns with prior research suggesting that individuals scoring high in conscientiousness may score lower on cognitive ability tests. Conversely, those with higher cognitive abilities may possess superior intelligence, memory, and attention skills but may not necessarily exhibit the same level of organization or diligence. Nevertheless, an individual's level of conscientiousness can still influence their motivation and engagement with tasks on an IQ test, indirectly affecting their IQ scores. Thus, accounting for cognitive ability is crucial to prevent potential bias from omitted factors.

In addition to what has been mentioned, I assess whether disparities in reported personality effects stem from variations in econometric techniques, data types, or publication characteristics. To commence this assessment, I compare studies that measure personality traits and their corresponding outcomes with and without a time lag. The results consistently demonstrate variations in the effects of openness to experience, extraversion, and agreeableness depending on the time lag employed.

Next, I compare studies employing different econometric techniques. The findings presented in the table indicate that differences in econometric methods do not explain the variations in reported effects for every personality trait. However, it is essential to approach these findings with caution, considering that nearly 80% of the studies in the dataset utilise an OLS approach. Additionally, the limited sample size in the meta-analysis poses challenges in fully evaluating the extent to which true effects may be influenced by the chosen econometric methods.

The results also indicate that studies using factor scores instead of simple summation or averaging of personality items yield different wage effects for conscientiousness and neuroticism. Comparing studies conducted on American, European, Asian, and Australian populations reveals variations in the impact of personality traits on earnings across different regions and populations. Additionally, the year of publication appears to influence reported effects, with more recent studies reporting higher effects for conscientiousness and agreeableness and lower effects for openness to experience and agreeableness.

In addition to the factors discussed above, it is also important to consider potential differences in how earnings are reported across studies. While efforts were made to ensure comparability, wage outcomes may still vary due to differences in the types of income reported. For instance, some studies focus on basic salary, while others include self-employment income, or total earnings (which may include benefits). Additionally, some studies may have used gross income, whereas others have used net earnings. These variations can pose challenges to comparability across analyses. To address this, I conducted a separate meta-regression to test whether the specific type of income measurement affects the overall results. The findings indicate that the measurement approach does not substantially affect the estimated regression coefficients effects, thus validating the results of the main model (see Appendix B). This finding is in line with the findings of Alderotti, Rapallini, and Traverso (2023). Additionally, as a sensitivity test, I also replaced the country selection variable with a dummy variable that equals one if the study utilises an anglophone sample (Great Britain, United States of America, or Australia). The findings reveal that studies utilising English-speaking samples report higher returns on conscientiousness and a more significant penalty on agreeableness.

Furthermore, Equation (2.4) was tested with seven different methods to check if the results from the main model were accurate and consistent. The results largely confirm what was found in Table 2.4, with the discrepancies being negligibly small. The sensitivity tests show that multicollinearity is not overly high. Appendix B provides a more detailed description of the findings.

2.5 CONCLUSION

This chapter explores the limited yet growing research on the relationship between personality and earnings. There has been an increased interest in studying personality traits as it has been recognised that noncognitive skills play an important role in shaping life outcomes. However, it is still unclear which personality traits have an effect on earnings, to what extent, and how. The complexity of personality traits, influenced by various factors and life events, contributes to this lack of clarity. Therefore, it is crucial to understand whether personality traits affect earnings and what factors explain the different reported effects across studies. The objective of this study was to use meta-analysis techniques to address this uncertainty and determine whether excluding certain explanatory variables from the model leads to a biased estimate of the true effect size.

The results of the meta-analysis reveal that individuals with higher levels of openness to experience and conscientiousness tend to earn more. While extraversion also has a positive correlation with earnings, it is not as strong. Conversely, individuals with higher levels of agreeableness and neuroticism tend to earn less. In addition, when accounting for publication bias, the influence of these traits on earnings diminishes, especially for conscientiousness, agreeableness, and neuroticism. These key findings are supported by various robustness tests.

This study also aimed to identify the factors contributing to differences in reported effects across studies, given the significant heterogeneity observed in outcomes. The results of the meta-regression analysis identify the factors responsible for variation in the estimated impact of each personality trait between studies. Notably, socioeconomic characteristics emerge as the most significant factors. Specifically, when education is omitted from the model, the effect of extraversion decreases while the effects of openness to experience and neuroticism increase. Similarly, excluding family-related variables leads to an increase in the returns associated with openness to experience and conscientiousness, but also an increase in the negative return of neuroticism. Furthermore, accounting for occupation reduces the return associated with conscientiousness, while omitting cognitive ability from the model increases the effect of conscientiousness. These results imply that personality traits may be susceptible to omitted variable bias, potentially leading to misleading estimates.

The meta-analysis results suggest several avenues for future research to gain a deeper understanding of the relationship between personality and labour market outcomes. First, a prevalent reliance on self-reported scores in many studies warrants looking for alternative measures, such as informant data or data collected earlier in one's career. This can enrich the analysis of personality trait returns. Additionally, this meta-analysis leans heavily on research from the United States and Europe, emphasising the need for more studies from other continents to provide valuable insights regarding the generalisability and universality of the findings.

Future studies can substantially benefit from exploring how levels of personality traits interact with socioeconomic factors and delving into the underlying mechanisms of personality formation. It remains unclear whether individuals shape their environments to align with their personalities or if environmental factors can alter their personalities. The role of past interactions in shaping personality is also pivotal, underscoring its importance as a factor to consider in future research. Consequently, further research into personality development is necessary, given its potential impact on the results.

REFERENCES

References included in the meta-analysis are marked with an asterisk.

*Acosta, P., Muller, N. and Sarzosa, M.A. (2015) ‘Beyond Qualifications: Returns to Cognitive and Socio-Emotional Skills in Colombia’, *IZA Discussion Paper Series* [Preprint]. Available at: https://papers.ssrn.com/abstract=2667984 (Accessed: 9 March 2024).

Alderotti, G., Rapallini, C. and Traverso, S. (2023) ‘The Big Five personality traits and earnings: A meta-analysis’, *Journal of Economic Psychology*, 94, p. 102570. Available at: https://doi.org/10.1016/j.joep.2022.102570.

Allemand, M. *et al.* (2023) *Conscientiousness and Labor Market Returns: Evidence from a Field Experiment in West Africa*. World Bank, Washington, DC. Available at: https://doi.org/10.1596/1813-9450-10378.

Almlund, M. *et al.* (2011) ‘Personality Psychology and Economics’, in E.A. Hanushek, S. Machin, and L. Woessmann (eds) *Handbook of the Economics of Education*. Elsevier (Handbook of The Economics of Education), pp. 1–181. Available at: https://doi.org/10.1016/B978-0-444-53444-6.00001-8.

Aloe, A.M. and Becker, B.J. (2012) ‘An Effect Size for Regression Predictors in Meta-Analysis’, *Journal of Educational and Behavioral Statistics*, 37(2), pp. 278–297. Available at: https://doi.org/10.3102/1076998610396901.

Andrews, I. and Kasy, M. (2019) ‘Identification of and Correction for Publication Bias’, *American Economic Review*, 109(8), pp. 2766–2794. Available at: https://doi.org/10.1257/aer.20180310.

Antecol, H. and Cobb-Clark, D.A. (2013) ‘Do psychosocial traits help explain gender segregation in young people’s occupations?’, *Labour Economics*, 21, pp. 59–73. Available at: https://doi.org/10.1016/j.labeco.2012.12.005.

Attanasio, O. *et al.* (2020) ‘Estimating the Production Function for Human Capital: Results from a Randomized Controlled Trial in Colombia’, *American Economic Review*, 110(1), pp. 48–85. Available at: https://doi.org/10.1257/aer.20150183.

*Averett, S.L., Bansak, C. and Smith, J.K. (2018) ‘Behind Every High Earning Man Is a Conscientious Woman: A Study of the Impact of Spousal Personality on Wages’, *IZA Discussion Paper Series* [Preprint]. Available at: https://www.econstor.eu/handle/10419/185216 (Accessed: 9 March 2024).

*Averett, S.L., Bansak, C. and Smith, J.K. (2021) ‘Behind Every High Earning Man is a Conscientious Woman: The Impact of Spousal Personality on Earnings and Marriage’, *Journal of Family and Economic Issues*, 42(1), pp. 29–46. Available at: https://doi.org/10.1007/s10834-020-09692-x.

Ayoub, M. *et al.* (2018) ‘The Relations Between Parental Socioeconomic Status, Personality, and Life Outcomes’, *Social Psychological and Personality Science*, 9(3), pp. 338–352. Available at: https://doi.org/10.1177/1948550617707018.

Becker, A. *et al.* (2012) ‘The Relationship Between Economic Preferences and Psychological Personality Measures’, *Annual Review of Economics*, 4(1), pp. 453–478. Available at: https://doi.org/10.1146/annurev-economics-080511-110922.

Bell, S.T. (2007) ‘Deep-level composition variables as predictors of team performance: A meta-analysis’, *Journal of Applied Psychology*, 92(3), pp. 595–615. Available at: https://doi.org/10.1037/0021-9010.92.3.595.

Bergold, S. and Steinmayr, R. (2018) ‘Personality and Intelligence Interact in the Prediction of Academic Achievement’, *Journal of Intelligence*, 6(2), p. 27. Available at: https://doi.org/10.3390/jintelligence6020027.

Bleidorn, W. *et al.* (2022) ‘Personality stability and change: A meta-analysis of longitudinal studies’, *Psychological Bulletin*, 148(7–8), pp. 588–619. Available at: https://doi.org/10.1037/bul0000365.

Block, J. (2010) ‘The Five-Factor Framing of Personality and Beyond: Some Ruminations’, *Psychological Inquiry*, 21(1), pp. 2–25. Available at: https://doi.org/10.1080/10478401003596626.

Bom, P.R.D. and Rachinger, H. (2019) ‘A kinked meta-regression model for publication bias correction’, *Research Synthesis Methods*, 10(4), pp. 497–514. Available at: https://doi.org/10.1002/jrsm.1352.

Borghans, L. *et al.* (2008) ‘The Economics and Psychology of Personality Traits’, *Journal of Human Resources*, 43(4), pp. 972–1059. Available at: https://doi.org/10.3368/jhr.43.4.972.

*Borghans, L. *et al.* (2011) ‘Identification problems in personality psychology’, *Personality and Individual Differences*, 51(3), pp. 315–320. Available at: https://doi.org/10.1016/j.paid.2011.03.029.

Bowles, S., Gintis, H. and Osborne, M. (2001) ‘The Determinants of Earnings: A Behavioral Approach’, *Journal of Economic Literature*, 39(4), pp. 1137–1176. Available at: https://doi.org/10.1257/jel.39.4.1137.

Brandt, N.D. *et al.* (2020) ‘Personality, cognitive ability, and academic performance: Differential associations across school subjects and school tracks’, *Journal of Personality*, 88(2), pp. 249–265. Available at: https://doi.org/10.1111/jopy.12482.

*Brenzel, H. and Laible, M.-C. (2016) ‘Does personality matter? : the impact of the big five on the migrant and gender wage gaps’, *IAB-Discussion Paper* [Preprint]. Available at: https://ideas.repec.org//p/iab/iabdpa/201626.html (Accessed: 9 March 2024).

*Bühler, D., Sharma, R. and Stein, W. (2020) ‘Occupational Attainment and Earnings in Southeast Asia: The Role of Non-cognitive Skills’, *Labour Economics*, 67, p. 101913. Available at: https://doi.org/10.1016/j.labeco.2020.101913.

Caspi, A., Roberts, B.W. and Shiner, R.L. (2005) 'Personality Development: Stability and Change', *Annual Review of Psychology*, 56(1), pp. 453–484. Available at: https://doi.org/10.1146/annurev.psych.55.090902.141913.

Cobb-Clark, D.A. and Schurer, S. (2012) 'The stability of big-five personality traits', *Economics Letters*, 115(1), pp. 11–15. Available at: https://doi.org/10.1016/j.econlet.2011.11.015.

Cobb-Clark, D.A. and Tan, M. (2011) 'Noncognitive skills, occupational attainment, and relative wages', *Labour Economics*, 18(1), pp. 1–13. Available at: https://doi.org/10.1016/j.labeco.2010.07.003.

*Collischon, M. (2020) 'The Returns to Personality Traits Across the Wage Distribution', *LABOUR*, 34(1), pp. 48–79. Available at: https://doi.org/10.1111/labr.12165.

*Cubel, M. *et al.* (2016) 'Do Personality Traits Affect Productivity? Evidence from the Laboratory', *The Economic Journal*, 126(592), pp. 654–681. Available at: https://doi.org/10.1111/ecoj.12373.

*Cunningham, W., Torrado, M. and Sarzosa, M. (2016) 'Cognitive and Non-Cognitive Skills for the Peruvian Labor Market: Addressing Measurement Error Through Latent Skills Estimations', *World Bank Policy Research Working Paper* [Preprint], (No. 7550). Available at: https://papers.ssrn.com/abstract=2726342 (Accessed: 9 March 2024).

*Dahmann, S.C. and Anger, S. (2014) 'The Impact of Education on Personality: Evidence from a German High School Reform', *IZA Discussion Paper Series* [Preprint]. Available at: https://doi.org/10.2139/ssrn.2432423.

*Damian, R.I. *et al.* (2015) 'Can personality traits and intelligence compensate for background disadvantage? Predicting status attainment in adulthood', *Journal of Personality and Social Psychology*, 109(3), pp. 473–489. Available at: https://doi.org/10.1037/pspp0000024.

Deckers, T. *et al.* (2015) 'How Does Socio-Economic Status Shape a Child's Personality?', *IZA Discussion Paper Series* [Preprint]. Available at: https://doi.org/10.2139/ssrn.2598917.

*Deming, D.J. (2017) 'The Growing Importance of Social Skills in the Labor Market', *The Quarterly Journal of Economics*, 132(4), pp. 1593–1640. Available at: https://doi.org/10.1093/qje/qjx022.

*Denissen, J.J.A. *et al.* (2018) 'Uncovering the Power of Personality to Shape Income', *Psychological Science*, 29(1), pp. 3–13. Available at: https://doi.org/10.1177/0956797617724435.

DeYoung, C.G. (2020) 'Intelligence and personality', in *The Cambridge handbook of intelligence, 2nd ed*. New York, NY, US: Cambridge University Press, pp. 1011–1047. Available at: https://doi.org/10.1017/9781108770422.043.

*Díaz, Juan José, Arias, Omar and Tudela, David Vera (2013) ‘Does Perseverance Pay as Much as Being Smart?: The Returns to Cognitive and Non-cognitive Skills in urban Peru’, in. *9th IZA/World Bank Conference on Employment and Development*, Peru: IZA/World Bank.

*Drydakis, N. (2013) ‘The Effect of Sexual Activity on Wages’, *IZA Discussion Paper Series* [Preprint]. Available at: https://doi.org/10.2139/ssrn.2314824.

*Duckworth, A. and Weir, D. (2010) ‘Personality, Lifetime Earnings, and Retirement Wealth’, *SSRN Electronic Journal* [Preprint]. Available at: https://doi.org/10.2139/ssrn.1710166.

*Duckworth, A.L. *et al.* (2012) ‘Who Does Well in Life? Conscientious Adults Excel in Both Objective and Subjective Success’, *Frontiers in Psychology*, 3, p. 356. Available at: https://doi.org/10.3389/fpsyg.2012.00356.

Egger, M. *et al.* (1997) ‘Bias in meta-analysis detected by a simple, graphical test’, *BMJ*, 315(7109), pp. 629–634. Available at: https://doi.org/10.1136/bmj.315.7109.629.

Eysenck, H.J. (1992) ‘Four ways five factors are not basic’, *Personality and Individual Differences*, 13(6), pp. 667–673. Available at: https://doi.org/10.1016/0191-8869(92)90237-J.

*Fletcher, J.M. (2013) ‘The effects of personality traits on adult labor market outcomes: Evidence from siblings’, *Journal of Economic Behavior & Organization*, 89, pp. 122–135. Available at: https://doi.org/10.1016/j.jebo.2013.02.004.

*Flinn, Christopher, Todd, Pedd and Zhang, Weilong (2020) ‘Personality Traits, Job Search and the Gender Wage Gap’, *HCEO Working Paper* [Preprint]. Available at: https://hceconomics.uchicago.edu/research/working-paper/personality-traits-job-search-and-gender-wage-gap (Accessed: 9 March 2024).

*Flinn, C.J., Todd, P.E. and Zhang, W. (2018) ‘Personality traits, intra-household allocation and the gender wage gap’, *European Economic Review*, 109, pp. 191–220. Available at: https://doi.org/10.1016/j.euroecorev.2017.11.003.

Furuya-Kanamori, L., Barendregt, J.J. and Doi, S.A.R. (2018) ‘A new improved graphical and quantitative method for detecting bias in meta-analysis’, *International Journal of Evidence-Based Healthcare*, 16(4), pp. 195–203. Available at: https://doi.org/10.1097/XEB.0000000000000141.

*Gelissen, J. and De Graaf, P.M. (2006) ‘Personality, social background, and occupational career success’, *Social Science Research*, 35(3), pp. 702–726. Available at: https://doi.org/10.1016/j.ssresearch.2005.06.005.

Gensowski, M. (2018) ‘Personality, IQ, and lifetime earnings’, *Labour Economics*, 51, pp. 170–183. Available at: https://doi.org/10.1016/j.labeco.2017.12.004.

Gertler, P. *et al.* (2014) ‘Labor market returns to an early childhood stimulation intervention in Jamaica’, *Science*, 344(6187), pp. 998–1001. Available at: https://doi.org/10.1126/science.1251178.

*Groves, M.O. (2005) ‘How important is your personality? Labor market returns to personality for women in the US and UK’, *Journal of Economic Psychology*, 26(6), pp. 827–841. Available at: https://doi.org/10.1016/j.joep.2005.03.001.

*Hagmann-von Arx, P. *et al.* (2016) ‘Testing Relations of Crystallized and Fluid Intelligence and the Incremental Predictive Validity of Conscientiousness and Its Facets on Career Success in a Small Sample of German and Swiss Workers’, *Frontiers in Psychology*, 7. Available at: https://doi.org/10.3389/fpsyg.2016.00500.

*Hamilton, B.H., Papageorge, N.W. and Pande, N. (2019) ‘The right stuff? Personality and entrepreneurship’, *Quantitative Economics*, 10(2), pp. 643–691. Available at: https://doi.org/10.3982/QE748.

Harmon, C., Oosterbeek, H. and Walker, I. (2003) ‘The Returns to Education: Microeconomics’, *Journal of Economic Surveys*, 17(2), pp. 115–156. Available at: https://doi.org/10.1111/1467-6419.00191.

Havránek, T. *et al.* (2020) ‘Reporting Guidelines for Meta-Analysis in Economics’, *Journal of Economic Surveys*, 34(3), pp. 469–475. Available at: https://doi.org/10.1111/joes.12363.

Higgins, J.P.T. *et al.* (2003) ‘Measuring inconsistency in meta-analyses’, *BMJ*, 327(7414), pp. 557–560. Available at: https://doi.org/10.1136/bmj.327.7414.557.

Heckman, J. and Kautz, T. (2013) *Fostering and Measuring Skills: Interventions That Improve Character and Cognition*. w19656. Cambridge, MA: National Bureau of Economic Research, p. w19656. Available at: https://doi.org/10.3386/w19656.

Heckman, J.J., Jagelka, T. and Kautz, T. (2021) ‘Some contributions of economics to the study of personality’, in *Handbook of personality: Theory and research*. 4th edn. New York, NY, US: The Guilford Press, pp. 853–892.

Heckman, J.J. and Rubinstein, Y. (2001) ‘The Importance of Noncognitive Skills: Lessons from the GED Testing Program’, *American Economic Review*, 91(2), pp. 145–149. Available at: https://doi.org/10.1257/aer.91.2.145.

Heckman, J.J., Stixrud, J. and Urzua, S. (2006) ‘The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior’, *Journal of Labor Economics*, 24(3), pp. 411–482. Available at: https://doi.org/10.1086/504455.

*Heineck, G. (2011) ‘Does it Pay to Be Nice? Personality and Earnings in the United Kingdom’, *ILR Review*, 64(5), pp. 1020–1038. Available at: https://doi.org/10.1177/001979391106400509.

*Heineck, G. and Anger, S. (2010) ‘The returns to cognitive abilities and personality traits in Germany’, *Labour Economics*, 17(3), pp. 535–546. Available at: https://doi.org/10.1016/j.labeco.2009.06.001.

Horie, N. and Iwasaki, I. (2023) ‘Returns to schooling in European emerging markets: a meta-analysis’, *Education Economics*, 31(1), pp. 102–128. Available at: https://doi.org/10.1080/09645292.2022.2036322.

*John, K. and Thomsen, S.L. (2014) 'Heterogeneous returns to personality: the role of occupational choice', *Empirical Economics*, 47(2), pp. 553–592. Available at: https://doi.org/10.1007/s00181-013-0756-8.

John, O.P. (2021) 'History, measurement, and conceptual elaboration of the Big-Five trait taxonomy: The paradigm matures', in *Handbook of personality: Theory and research, 4th ed*. New York, NY, US: The Guilford Press, pp. 35–82.

John, O.P., Naumann, L.P. and Soto, C.J. (2008) 'Paradigm shift to the integrative Big Five trait taxonomy: History, measurement, and conceptual issues', in *Handbook of personality: Theory and research*. 3rd edn. New York, NY, US: The Guilford Press, pp. 114–158.

*Judge, T.A., Livingston, B.A. and Hurst, C. (2012) 'Do nice guys--and gals--really finish last? The joint effects of sex and agreeableness on income', *Journal of Personality and Social Psychology*, 102(2), pp. 390–407. Available at: https://doi.org/10.1037/a0026021.

*Kajonius, P.J. and Carlander, A. (2017) 'Who gets ahead in life? Personality traits and childhood background in economic success', *Journal of Economic Psychology*, 59, pp. 164–170. Available at: https://doi.org/10.1016/j.joep.2017.03.004.

*Lechner, C.M., Anger, S. and Rammstedt, B. (2019) 'Socio-emotional skills in education and beyond: recent evidence and future research avenues', in *Research Handbook on the Sociology of Education*. Edward Elgar Publishing, pp. 427–453. Available at: https://china.elgaronline.com/edcollchap/edcoll/9781788110419/9781788110419.00034.xml (Accessed: 8 March 2024).

*Lee, S.Y. and Ohtake, F. (2018) 'Is being agreeable a key to success or failure in the labor market?', *Journal of the Japanese and International Economies*, 49, pp. 8–27. Available at: https://doi.org/10.1016/j.jjie.2018.01.003.

Lenton, P. (2014) 'Personality characteristics, educational attainment and wages: an economic analysis using the British cohort study', *The Sheffield Economic Research Paper Series*, 2014-01.

Lepine, J.A., Colquitt, J.A. and Erez, A. (2000) 'Adaptability to Changing Task Contexts: Effects of General Cognitive Ability, Conscientiousness, and Openness to Experience', *Personnel Psychology*, 53(3), pp. 563–593. Available at: https://doi.org/10.1111/j.1744-6570.2000.tb00214.x.

*Maczulskij, T. and Viinikainen, J. (2018) 'Is personality related to permanent earnings? Evidence using a twin design', *Journal of Economic Psychology*, 64, pp. 116–129. Available at: https://doi.org/10.1016/j.joep.2018.01.001.

Magnus, J.R. and De Luca, G. (2016) 'Weighted-Average Least Squares (wals): A Survey', *Journal of Economic Surveys*, 30(1), pp. 117–148. Available at: https://doi.org/10.1111/joes.12094.

Magnus, J.R., Powell, O. and Prüfer, P. (2010) ‘A comparison of two model averaging techniques with an application to growth empirics’, *Journal of Econometrics*, 154(2), pp. 139–153. Available at: https://doi.org/10.1016/j.jeconom.2009.07.004.

*Maksimova, M. (2019) ‘The return to non-cognitive skills on the Russian labor market’, *Applied Econometrics (Прикладная эконометрика)*, 53, pp. 55–72.

McCrae, R.R. and John, O.P. (1992) ‘An Introduction to the Five-Factor Model and Its Applications’, *Journal of Personality*, 60(2), pp. 175–215. Available at: https://doi.org/10.1111/j.1467-6494.1992.tb00970.x.

*Mohammed, I., Baffour, P.T. and Rahaman, W.A. (2021) ‘Gender Differences in Earnings Rewards to Personality Traits in Wage-employment and Self-employment Labour Markets’, *Management and Labour Studies*, 46(2), pp. 204–228. Available at: https://doi.org/10.1177/0258042X21989944.

Mohanty, M.S. (2010) ‘Effects of positive attitude and optimism on employment: Evidence from the US data’, *The Journal of Socio-Economics*, 39(2), pp. 258–270. Available at: https://doi.org/10.1016/j.socec.2009.12.004.

Moher, D. *et al.* (2009) ‘Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement’, *Annals of Internal Medicine*, 151(4), pp. 264–269. Available at: https://doi.org/10.7326/0003-4819-151-4-200908180-00135.

Mosca, I. and Wright, R. (2018) ‘Is Personality Endogenous? Evidence from Ireland’, *SSRN Electronic Journal* [Preprint]. Available at: https://doi.org/10.2139/ssrn.3153378.

Moutafi, J., Furnham, A. and Tsaousis, I. (2006) ‘Is the relationship between intelligence and trait Neuroticism mediated by test anxiety?’, *Personality and Individual Differences*, 40(3), pp. 587–597. Available at: https://doi.org/10.1016/j.paid.2005.08.004.

*Mueller, G. and Plug, E. (2006) ‘Estimating the Effect of Personality on Male and Female Earnings’, *ILR Review*, 60(1), pp. 3–22. Available at: https://doi.org/10.1177/001979390606000101.

*Nordman, C.J., Sarr, L.R. and Sharma, S. (2019) ‘Skills, personality traits, and gender wage gaps: evidence from Bangladesh’, *Oxford Economic Papers*, 71(3), pp. 687–708. Available at: https://doi.org/10.1093/oep/gpy043.

*Nyhus, E.K. and Pons, E. (2005) ‘The effects of personality on earnings’, *Journal of Economic Psychology*, 26(3), pp. 363–384. Available at: https://doi.org/10.1016/j.joep.2004.07.001.

*Nyhus, E.K. and Pons, E. (2012) ‘Personality and the gender wage gap’, *Applied Economics*, 44(1), pp. 105–118. Available at: https://doi.org/10.1080/00036846.2010.500272.

*O’Connell, M. and Sheikh, H. (2011) ‘“Big Five” personality dimensions and social attainment: Evidence from beyond the campus’, *Personality and Individual*

Differences, 50(6), pp. 828–833. Available at: https://doi.org/10.1016/j.paid.2011.01.004.

Ones, D.S. *et al.* (2007) 'In Support of Personality Assessment in Organizational Settings', *Personnel Psychology*, 60(4), pp. 995–1027. Available at: https://doi.org/10.1111/j.1744-6570.2007.00099.x.

Otten, S. (2020) 'Gender-specific personality traits and their effects on the gender wage gap: A correlated random effects approach using SOEP data', *SOEPpapers on Multidisciplinary Panel Data Research* [Preprint], (No. 1078). Available at: https://www.econstor.eu/handle/10419/218998 (Accessed: 9 March 2024).

*Palczyńska, M. (2021) 'Wage premia for skills: the complementarity of cognitive and non-cognitive skills', *International Journal of Manpower*, 42(4), pp. 556–580. Available at: https://doi.org/10.1108/IJM-08-2019-0379.

Peeters, M.A.G. *et al.* (2006) 'Personality and team performance: a meta-analysis', *European Journal of Personality*, 20(5), pp. 377–396. Available at: https://doi.org/10.1002/per.588.

Poropat, A.E. (2014) 'Other-rated personality and academic performance: Evidence and implications', *Learning and Individual Differences*, 34, pp. 24–32. Available at: https://doi.org/10.1016/j.lindif.2014.05.013.

*Prevoo, T. and Ter Weel, B. (2015) 'The importance of early conscientiousness for socio-economic outcomes: evidence from the British Cohort Study', *Oxford Economic Papers*, 67(4), pp. 918–948. Available at: https://doi.org/10.1093/oep/gpv022.

*Risse, L., Farrell, L. and Fry, T.R.L. (2018) 'Personality and pay: do gender gaps in confidence explain gender gaps in wages?', *Oxford Economic Papers*, 70(4), pp. 919–949. Available at: https://doi.org/10.1093/oep/gpy021.

Roberts, B.W. (2009) 'Back to the future: Personality and Assessment and personality development', *Journal of Research in Personality*, 43(2), pp. 137–145. Available at: https://doi.org/10.1016/j.jrp.2008.12.015.

Roberts, B.W., Walton, K.E. and Viechtbauer, W. (2006) 'Patterns of mean-level change in personality traits across the life course: a meta-analysis of longitudinal studies', *Psychological Bulletin*, 132(1), pp. 1–25. Available at: https://doi.org/10.1037/0033-2909.132.1.1.

*Sahn, D.E. and Villa, K. (2016) 'Labor Outcomes During the Transition from Adolescence to Adulthood: The Role of Personality, Cognition, and Shocks in Madagascar', *IZA Discussion Paper Series* [Preprint]. Available at: https://doi.org/10.2139/ssrn.2872616.

Salgado, J.F. *et al.* (2003) 'International Validity Generalization of Gma and Cognitive Abilities: A European Community Meta-Analysis', *Personnel Psychology*, 56(3), pp. 573–605. Available at: https://doi.org/10.1111/j.1744-6570.2003.tb00751.x.

*Schäfer, K.C. and Schwiebert, J. (2018) ‘The Impact of Personality Traits on Wage Growth and the Gender Wage Gap’, *Bulletin of Economic Research*, 70(1), pp. 20–34. Available at: https://doi.org/10.1111/boer.12115.

*Scholz, J.K. and Sicinski, K. (2015) ‘Facial Attractiveness and Lifetime Earnings: Evidence from a Cohort Study’, *The Review of Economics and Statistics*, 97(1), pp. 14–28. Available at: https://doi.org/10.1162/REST_a_00435.

*Seibert, S.E. and Kraimer, M.L. (2001) ‘The Five-Factor Model of Personality and Career Success’, *Journal of Vocational Behavior*, 58(1), pp. 1–21. Available at: https://doi.org/10.1006/jvbe.2000.1757.

*Semeijn, J. h., van der Heijden, B. i. j. m. and De Beuckelaer, A. (2020) ‘Personality Traits and Types in Relation to Career Success: An Empirical Comparison Using the Big Five’, *Applied Psychology*, 69(2), pp. 538–556. Available at: https://doi.org/10.1111/apps.12174.

Sianesi, B., Dearden, L. and Blundell, R. (2003) *Evaluating the impact of education on earnings in the UK: Models, methods and results from the NCDS*. Working Paper Series. IFS. Available at: https://doi.org/10.1920/wp.ifs.2003.0320.

*Shanahan, M.J. *et al.* (2014) ‘Personality and the Reproduction of Social Class’, *Social Forces*, 93(1), pp. 209–240. Available at: https://doi.org/10.1093/sf/sou050.

*Shi, Y. and Moody, J. (2017) ‘Most Likely to Succeed: Long-Run Returns to Adolescent Popularity’, *Social currents*, 4(1), pp. 13–33. Available at: https://doi.org/10.1177/2329496516651642.

Spengler, M. *et al.* (2013) ‘Personality is related to educational outcomes in late adolescence: Evidence from two large-scale achievement studies’, *Journal of Research in Personality*, 47(5), pp. 613–625. Available at: https://doi.org/10.1016/j.jrp.2013.05.008.

Spengler, M. *et al.* (2016) ‘The role of personality in predicting (change in) students’ academic success across four years of secondary school’, *European Journal of Psychological Assessment*, 32(1), pp. 95–103. Available at: https://doi.org/10.1027/1015-5759/a000330.

Stanley, T.D. (2017) ‘Limitations of PET-PEESE and Other Meta-Analysis Methods’, *Social Psychological and Personality Science*, 8(5), pp. 581–591. Available at: https://doi.org/10.1177/1948550617693062.

Stanley, T.D. and Doucouliagos, H. (2011) *Meta-Regression Analysis in Economics and Business*. London: Routledge. Available at: https://doi.org/10.4324/9780203111710.

Stanley, T.D. and Doucouliagos, H. (2014) ‘Meta-regression approximations to reduce publication selection bias’, *Research Synthesis Methods*, 5(1), pp. 60–78. Available at: https://doi.org/10.1002/jrsm.1095.

Stanley, T.D. and Doucouliagos, H. (2015) ‘Neither fixed nor random: weighted least squares meta-analysis’, *Statistics in Medicine*, 34(13), pp. 2116–2127. Available at: https://doi.org/10.1002/sim.6481.

Stanley, T.D., Jarrell, S.B. and Doucouliagos, H. (2010) ‘Could It Be Better to Discard 90% of the Data? A Statistical Paradox’, *The American Statistician*, 64(1), pp. 70–77. Available at: https://doi.org/10.1198/tast.2009.08205.

Vedel, A. and Poropat, A.E. (2017) ‘Personality and Academic Performance’, in V. Zeigler-Hill and T.K. Shackelford (eds) *Encyclopedia of Personality and Individual Differences*. Cham: Springer International Publishing, pp. 1–9. Available at: https://doi.org/10.1007/978-3-319-28099-8_989-1.

*Viinikainen, J. *et al.* (2010) ‘Personality and Labour Market Income: Evidence from Longitudinal Data’, *LABOUR*, 24(2), pp. 201–220. Available at: https://doi.org/10.1111/j.1467-9914.2010.00477.x.

*Viinikainen, J. *et al.* (2014) ‘Labor market performance of dropouts: the role of personality’, *Journal of Economic Studies*, 41(3), pp. 453–468. Available at: https://doi.org/10.1108/JES-02-2012-0022.

*Wichert, L. and Pohlmeier, W. (2010) ‘Female labor force participation and the big five’, *ZEW Discussion Papers* [Preprint]. Available at: https://ideas.repec.org//p/zbw/zewdip/10003.html (Accessed: 9 March 2024).

*Williams, M. and Gardiner, E. (2018) ‘The power of personality at work: Core self-evaluations and earnings in the United Kingdom’, *Human Resource Management Journal*, 28(1), pp. 45–60. Available at: https://doi.org/10.1111/1748-8583.12162.

*Yu, F. *et al.* (2017) ‘Effect of cognitive abilities and non-cognitive abilities on labor wages: empirical evidence from the Chinese Employer-Employee Survey’, *China Economic Journal*, 10(1), pp. 76–89. Available at: https://doi.org/10.1080/17538963.2016.1274005.

APPENDIX A

Studies included in the meta-analysis

Table A.1: Number of estimates for each study

Study (Author(s) and year of publication)	Study Title	Country	O	C	E	A	N
Acosta et al. (2015)	Beyond Qualifications: Returns to Cognitive and Socio-Emotional Skills in Colombia	Colombia	7	7	7	7	7
Averett et al. (2018)	Behind Every High Earning Man Is a Conscientious Woman: A Study of the Impact of Spousal Personality on Wages	Australia	20	20	20	20	20
Averett et al. (2021)	Behind Every High Earning Man is a Conscientious Woman: The Impact of Spousal Personality on Earnings and Marriage	Australia	4	4	4	4	4
Brenzel and Laible (2016)	Does Personality Matter? The Impact of the Big Five on the Migrant and Gender Wage Gaps	Germany	4	4	4	4	4
Bühler et al. (2020)	Occupational Attainment and Earnings in Southeast Asia: The Role of Noncognitive Skills	Thailand Vietnam	3	3	3	3	3
Collischon (2020)	The Returns to Personality Traits Across the Wage Distribution	Germany	3	3	3	3	3
Cubel et al. (2016)	Do personality traits affect productivity? evidence from the laboratory	UK	4	4	4	4	4
Cunningham et al. (2016)	Cognitive and Noncognitive Skills for the Peruvian Labor Market	Peru	1	1	1	2	1
Damian et al. (2015)	Can Personality Traits and Intelligence Compensate for Background Disadvantage? Predicting Status Attainment in Adulthood	United States of America	2	2	2	2	2
Denissen et al. (2018)	Uncovering the Power of Personality to Shape Income	Germany	1	1	1	1	1

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism

Table A.1 (cont.): Number of estimates for each study

Study (Author(s) and year of publication)	Study Title	Country	O	C	E	A	N
Díaz et al. (2013)	Does Perseverance Pay as Much as Being Smart?: The Returns to Cognitive and Noncognitive Skills in urban Peru	Peru	4	4	4	8	4
Drydakis (2013)	The Effect of Sexual Activity on Wages	Greece	3	3	3	3	3
Duckworth and Weir (2010)	Personality, lifetime earnings, and retirement wealth	United States of America	1	1	1	1	1
Duckworth et al. (2012)	Who does well in life? Conscientious adults excel in both objective and subjective success	United States of America	1	1	1	1	1
Fletcher (2013)	The effects of personality traits on adult labor market outcomes: Evidence from siblings	United States of America	7	7	7	7	7
Flinn et al. (2018)	Personality traits, intra-household allocation and the gender wage gap	Australia	2	2	2	2	2
Flinn et al. (2020)	Personality Traits, Job Search and the Gender Wage Gap	Germany	4	4	4	4	4
Gelissen and Graaf (2006)	Personality, social background, and occupational career success	Netherlands	3	3	3	3	3
Hagmann-von Arx et al. (2016)	Testing relations of crystallised and fluid intelligence and the incremental predictive validity of conscientiousness and its facets on career success in a small sample of German and Swiss workers	Germany/Switzerland	0	1	0	0	0
Hamilton et al. (2019)	The right stuff? Personality and entrepreneurship	United States of America	2	2	2	2	2
Heineck (2011)	Does it pay to be nice? personality and earnings in the united kingdom	United Kingdom	24	24	24	24	24
Heineck and Anger (2010)	The returns to cognitive abilities and personality traits in Germany	Germany	8	8	8	8	8
John and Thomsen (2014)	Heterogeneous returns to personality: the role of occupational choice	Germany	16	16	16	16	16
Judge et al. (2012)	Do Nice Guys—and Gals—Really Finish Last? The Joint Effects of Sex and Agreeableness on Income	United States of America	6	6	6	6	6

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism

Table A.1 (cont.): Number of estimates for each study

Study (Author(s) and year of publication)	Study Title	Country	O	C	E	A	N
Kajonius and Carlander (2017)	Who gets ahead in life? Personality traits and childhood background in economic success	Sweden	1	1	1	1	1
Lee and Ohtake (2018)	The Effect of Personality Traits and Behavioral Characteristics on Schooling, Earnings and Career Promotion	Japan	16	16	16	16	16
Lenton (2014)	Personality Characteristics, Educational Attainment and Wages: An Economic Analysis Using the British Cohort Study	United Kingdom	4	4	4	4	4
Maczulskij and Viinikainen (2018)	Is personality related to permanent earnings? evidence using a twin design	Finland	0	0	15	15	15
Maksimova (2019)	The return to noncognitive skills on the Russian labor market	Russia	12	12	12	12	12
Mohammed et al. (2021)	Gender Differences in Earnings Rewards to Personality Traits in Wage-employment and Self-employment Labour Markets	Ghana	9	9	9	9	9
Mueller and Plug (2006)	Estimating the effect of personality on male and female earnings	USA	12	12	12	12	12
Nordman et al (2019)	Skills, personality traits, and gender wage gaps: evidence from Bangladesh	Bangladesh	4	4	4	4	4
Nyhus and Pons (2005)	The effects of personality on earnings	Netherlands	0	6	6	6	6
Nyhus and Pons (2012)	Personality and the gender wage gap	Netherlands	4	4	4	4	4
O'Connell and Sheikh (2011)	'Big Five' personality dimensions and social attainment: Evidence from beyond the campus	United Kingdom	2	2	2	2	2
Osborne Groves (2005)	How important is your personality? labor market returns to personality for women in the US and UK	USA	0	0	0	0	2
Otten (2020)	Gender-Specific Personality Traits and Their Effects on the Gender Wage Gap: A Correlated Random Effects Approach using SOEP Data	Germany	4	4	4	4	4

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism

Table A.1 (cont.): Number of estimates for each study

Study (Author(s) and year of publication)	Study Title	Country	O	C	E	A	N
Palczyńska (2021)	Wage premia for skills: the complementarity of cognitive and noncognitive skills	Poland	6	6	6	6	6
Prevoo and ter Weel (2015)	The importance of early conscientiousness for socioeconomic outcomes: Evidence from the British Cohort Study	United Kingdom	0	8	8	8	8
Risse et al. (2018)	Personality and pay: Do gender gaps in confidence explain gender gaps in wages?	Australia	3	3	3	3	3
Sahn and Villa (2016)	Labor Outcomes during the Transition from Adolescence to Adulthood: The Role of Personality, Cognition, and Shocks in Madagascar	Madagascar	8	8	8	8	8
Schäfer and Schwiebert (2018)	The impact of personality traits on wage growth and the gender wage gap	Germany	4	4	4	4	4
Scholz and Sicinski (2015)	Facial attractiveness and lifetime earnings: Evidence from a cohort study	United States of America	4	4	4	4	4
Seibert and Kraimer (2001)	The Five-Factor Model of Personality and Career Success	United States of America	1	1	1	1	1
Semeijn et al. (2020)	Personality Traits and Types in Relation to Career Success: An Empirical Comparison Using the Big Five	Netherlands	1	1	1	1	1
Shanahan et al. (2014)	Personality and the reproduction of social class	United States of America	1	1	1	1	1
Shi and Moody (2017)	Most likely to succeed: Long-run returns to adolescent popularity	United States of America	1	1	1	1	1
Viinikainen et al. (2010)	Personality and labour market income: Evidence from longitudinal data	Finland	4	6	8	4	4
Viinikainen et al. (2014)	Labor market performance of dropouts: the role of personality	Finland	0	0	0	0	2
Wichert and Pohlmeier (2010)	Female labor force participation and the big five	Germany	3	3	3	3	3

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism

Table A.1 (cont.): Number of estimates for each study

Study (Author(s) and year of publication)	Study Title	Country	O	C	E	A	N
Williams and Gardiner (2018)	The power of personality at work: Core self-evaluations and earnings in the United Kingdom	UK	1	1	1	1	1
Yu et al. (2017)	Effect of cognitive abilities and noncognitive abilities on labor wages: empirical evidence from the Chinese Employer-Employee Survey	China	3	3	3	3	3
Total			238	255	271	272	271

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism

APPENDIX B

Robustness Tests for Overall Effects

Table A.1 presents two extra heterogeneity tests that complement the results obtained from the restricted maximum likelihood (REML) method, as shown in Table 2.2 of the main text. The two tests are the Cochran's Q test and the prediction interval.

The Q test is commonly used for assessing if effect sizes are symmetrically or asymmetrically distributed. This test assumes that there is no heterogeneity and helps to determine if the variability in effect size estimates is due to differences between studies or sample variations. The reported effect sizes in studies demonstrate significant heterogeneity.

A second indicator called the prediction interval is used to evaluate potential heterogeneity. This interval refers to the range in which the effect size of a hypothetical new study would fall if it were randomly selected from the same population of studies included in the meta-analysis. If there is significant heterogeneity, then the prediction intervals are expected to be wider than the 95% confidence interval of the summary effect size. The extracted results indicate that the larger range in the prediction interval supports the presence of heterogeneous effects caused by factors other than within-study variance.

To ensure the reliability of the REML results, an additional three sensitivity analyses were performed to calculate the collective effect size of each personality trait, namely Sidik-Jonkman, DerSimonian-Laird, and Paule-Mandel. Each method utilised different algorithms for estimating the between-study variance, τ^2. The iterative methods REML and Paule-Mandel assume that the distribution of random effects is normally distributed, while no distributional assumptions about random effects are made by the Sidik-Jonkman and DerSimonian-Laird estimators. The Sidik-Jonkman and Paule-Mandel estimators are the best estimators in terms of bias for large between-study variance. However, when variability is high, and the small size is small, the DerSimonian-Laird estimator may underestimate τ^2. Despite this, the DerSimonian-Laird estimator is more efficient than Sidik-Jonkman when the variability is not large, and the sample size is not small. Overall, all three sensitivity tests support the existence of substantial heterogeneity between studies.

In addition to the above, the Hartung-Knapp adjustment to the standard error of the effect size was also used to confirm the overall effect size for all traits. The Hartung-Knapp adjustment uses the t-distribution rather than the standard normal distribution when assessing the overall effect sizes and their confidence intervals. Despite this, my conclusion remains the same that the overall effect sizes obtained are statistically significant.

Table B.1: Summary statistics of the overall estimation results

	Restricted Maximum Likelihood (1)	Sidik-Jonkman (2)	DerSimonian and Laird (3)	Paule-Mandel (4)
Openness to Experience				
Effect size (SE) [p-value]	.019 (.002) [.000]	.019 (.002) [.000]	.015 (.001) [.000]	.019 (.002) [.000]
95% Confidence Interval	[.015, .023]	[.015, .023]	[.010, .028]	[.015, .023]
Q-statistic [p-value]	1926.60 [.000]	1926.60 [.000]	1926.60 [.000]	1926.60 [.000]
I2 (%)	99.23	99.23	88.84	99.13
95% Prediction interval	[-.032, .070]	[-.035, .073]	[.001, .028]	[-.032, .070]
Conscientiousness				
Effect size (SE) [p-value]	.016 (.002) [.000]	.017 (.002) [.000]	.007 (.001) [.000]	.016 (.002) [.000]
95% Confidence Interval	[.013, .020]	[.013, .021]	[.006, .008]	[.013, .020]
Q-statistic [p-value]	1216.05 [.000]	1216.05 [.000]	1216.05 [.000]	1216.05 [.000]
I2 (%)	99.28	99.57	81.12	99.38
95% Prediction interval	[-.024, .056]	[-.034, .069]	[-.000, .014]	[-.027, .059]
Extraversion				
Effect size (SE) [p-value]	.003 (.001) [.001]	.004 (.001) [.004]	.002 (.000) [.000]	.004 (.001) [.001]
95% Confidence Interval	[.001, .005]	[.001, .007]	[.001, .003]	[.001, .006]
Q-statistic [p-value]	64.81 [.000]	64.81 [.000]	64.81 [.000]	64.81 [.000]
I2 (%)	97.5	99.17	62.05	98.41
95% Prediction interval	[-.016, .022]	[-.029, .037]	[-.002, .006]	[-.020, .028]
Agreeableness				
Effect size (SE) [p-value]	-.017 (.002) [.000]	-.018 (.002) [.000]	-.013 (.001) [.000]	-.018 (.002) [.000]
95% Confidence Interval	[-.021, -.014]	[-.022, -.014]	[-.015, -.012]	[-.021, -.014]
Q-statistic [p-value]	1577.67 [.000]	1577.67 [.000]	1577.67 [.000]	1577.67 [.000]
I2 (%)	98.26	98.94	84.31	98.53
95% Prediction interval	[-.057, .022]	[-.069, .032]	[-.025,-.001]	[-.060, .025]
Neuroticism				
Effect size (SE) [p-value]	-.018 (.002) [.000]	-.026 (.004) [.000]	-.016 (.001) [.000]	-.018 (.002) [.000]
95% Confidence Interval	[-.023, -.017]	[-.023, -.015]	[-.018, -.014]	[-.022, -.015]
Q-statistic [p-value]	7542.53 [.000]	7542.53 [.000]	7542.53 [.000]	7542.53 [.000]
I2 (%)	99.16	99.45	96.78	99.3
95% Prediction interval	[-.062, .026]	[-.073, .035]	[-.038, .007]	[-.066, .030]

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. REML is the method of estimation of the between-study component of variance τ^2. The Q-statistic follows a χ^2 distribution with N-1 degrees of freedom with N being the number of effect sizes. Hartung-Knapp standard errors are reported in round parentheses, and p-value in square brackets.

Robustness Tests for Publication Bias

In the first sensitivity test, the Weighted Average of Adequately Powered (WAAP) estimator (Stanley, 2017) was applied. This method computes the unrestricted WLS-weighted average of estimates that have reasonable statistical power. When the standard error of the estimates is smaller than the WLS estimate divided by 2.8, then the statistical power of the estimates is considered reasonable (80% or higher). However, the major drawback of this approach is that many meta-analyses often lack studies with sufficient power. In this case, except for openness to experience and neuroticism, no studies with adequate validity were identified.

The second approach only uses the fixed effect method for the top 10% of reported estimates that exhibit the highest level of precision, as indicated by the standard error. The rationale behind this method, as postulated by Stanley, Jarrell, and Doucouliagos (2010), is that the most precise estimates are less susceptible to selection bias or bias stemming from small sample sizes. According to the Top 10% method, the overall effect sizes for all personality traits are essentially negligible.

The third approach used is the Endogenous Kink (EK) method (Bom and Rachinger, 2019). The purpose of the EK estimator is to more accurately consider the non-linear connection between the estimated impact and the standard error when publication bias is present. The rationale for adopting this methodology is rooted in the observation that minimal standard errors correspond to limited publication bias, whereas this bias becomes increasingly pronounced as the standard error exceeds a certain threshold, estimated by the endogenous cut-off value. After accounting for publication bias in the meta-regression analysis, the findings presented in Table B.2 confirm that there exists almost no discernible correlation between personality traits and earnings in the broader context. This signifies that the association between personality traits and wages is, for all intents and purposes, nearly negligible.

In addition to the above, the AK estimator, introduced by Andrews and Kasy (2019), is also incorporated. This estimator accommodates publication bias through two distinct approaches. The first approach, known as the symmetric estimator (AK1), considers the likelihood of an estimate being published based on its statistical significance. Conversely, the second approach, the asymmetric estimator (AK2), addresses selective publication influenced by both statistical significance and the direction of the estimates. According to the results presented in Table B.2, all personality traits exhibit a very small overall effect size when subjected to analysis using either of the two methods.

Furthermore, a comparison of two sets of specifications is conducted. The first set assigns equal weight to each estimate, while the second set assigns equal weight to each study. Interestingly, the outcomes remain largely consistent in both scenarios, even when studies reporting a greater number of estimates are accorded greater weight.

Table B.2: Bias-Adjusted Mean Effects with Modern Methods

	Mean Effect	Standard Error
Openness to Experience		
WAAP	.001***	.000
Top 10%	.001***	.000
EK	.001***	.000
AK (symmetric)	.012	.019
AK (asymmetric)	.001***	.000
Conscientiousness		
WAAP	N/A	N/A
Top 10%	.000	.001
EK	.000	.000
AK (symmetric)	.008***	.003
AK (asymmetric)	.000	.000
Extraversion		
WAAP	N/A	N/A
Top 10%	.000	.000
EK	.000	.000
AK (symmetric)	.001	.001
AK (asymmetric)	-.002	.003
Agreeableness		
WAAP	N/A	N/A
Top 10%	-.000	.001
EK	.001**	.000
AK (symmetric)	-.012***	.002
AK (asymmetric)	-.003	.003
Neuroticism		
WAAP	-.001***	.000
Top 10%	-.001***	.000
EK	-.002	.002
AK (symmetric)	-.001***	.000
AK (asymmetric)	-.001***	.000

*Notes: *, **, and *** denote statistical significance at 10, 5, and 1%, respectively.*

Robustness Tests for Meta-Regression

The random effects meta-regression operates under the assumption that control variables can account for only a portion of the variation, with a random-effects component introduced to accommodate the remaining variability. Existing research has suggested that the Weighted Least Squares (WLS) method, which assigns weights equal to the inverse of each estimate's standard error, is a preferable choice over the random effects method when there is evidence of publication bias and substantial heterogeneity (Stanley and Doucouliagos, 2015). The outcomes obtained through the WLS method generally align with those acquired through the Restricted Maximum Likelihood (REML) estimation method.

In a second check, I conducted a sensitivity analysis on the REML results by calculating the standard errors using the Hartung-Knapp method. In the context of estimating a confidence interval for the true effect size, the Hartung-Knapp technique substitutes quantiles from the t-distribution for the conventional normal distribution. This approach is considered a substantial improvement as it provides a more accurate confidence interval for the average effect size. Notably, the results remain essentially unchanged when employing the Hartung-Knapp approach.

To address uncertainties surrounding accurate model specification, Bayesian Model Averaging (BMA) and Weighted Average Least Squares (WALS) methods were employed to eliminate such ambiguities. BMA assesses the degree of uncertainty related to the model specification and ranks various model specifications in terms of relevance. It then assigns weights to these models based on how well they align with the data, enabling it to determine which model specifications lack support from the data. BMA estimates the model specification by considering all possible combinations of control variables. The weights used in BMA, known as posterior model probabilities (PIP), evaluate the significance of each control variable. Additionally, the WALS estimator, introduced by Magnus, Powell, and Patricia (2010), represents a Bayesian combination of frequentist estimators and offers advantages over other model averaging methods.[13] In general, the results of the main model strongly corroborate those obtained through BMA and WALS (refer to Table B.3).

[13] See Magnus and De Luca (2016) for more details.

Table B.3: Robustness Tests

	BMA					WALS				
	O	C	E	A	N	O	C	E	A	N
Standard Error	.252	.737***	.363***	-.389***	-.920***	.245**	.619***	.282***	-.327***	-.814***
	(.166)	(.108)	(.081)	(.084)	(.151)	(.103)	(.105)	(.078)	(.081)	(.146)
	[.779]	**[1]**	**[.999]**	**[.999]**	**[1]**	**(2.390)**	**(5.910)**	**(3.633)**	**(-4.036)**	**(-5.571)**
Age Category	-.001	.005	.017***	.000	.009	-.000	.008	.013***	-.000	.017**
	(.005)	(.006)	(.004)	(.002)	(.011)	(-.038)	(1.094)	(3.245)	(-.066)	(2.552)
	[.085]	**[.493]**	**[.996]**	[.054]	**[.462]**	(.050)	**(1.133)**	**(3.240)**	(-.140)	**(2.536)**
Only male sample	-.000	.000	-.001	-.000	.001	-.001	.001	-.002	-.001	.004*
	(.001)	(.001)	(.001)	(.001)	(.002)	(.003)	(.002)	(.002)	(.002)	(.002)
	[.055]	[.056]	[.225]	[.09]	[.286]	(-.201)	(.225)	**(-1.256)**	(-.523)	**(1.733)**
Only female sample	.000	-.000	.000	.000	-.001	.000	-.001	-.000	.001	-.002
	(.001)	(.001)	(.000)	(.001)	(.002)	(.003)	(.002)	(.002)	(.002)	(.002)
	[.058]	[.062]	[.057]	[.06]	[.164]	(.162)	(-.354)	(-.166)	(.542)	(-.755)
Education	-.022***	-.000	.000	.000	.014***	-.019***	-.003	.004*	.002	.014***
	(.004)	(.001)	(.001)	(.001)	(.004)	(.004)	(.003)	(.002)	(.003)	(.003)
	[1]	[.083]	[.125]	[.069]	**[.993]**	(-4.367)	**(-1.044)**	**(1.884)**	(.688)	**(4.236)**
Family Background	-.004	-.000	-.000	-.000	.018***	-.008**	-.002	.000	.001	.013***
	(.005)	(.001)	(.001)	(.001)	(.004)	(.004)	(.003)	(.002)	(.003)	(.003)
	[.445]	[.065]	[.07]	[.054]	**[1]**	**(-2.071)**	(-.541)	(.084)	(.274)	**(4.220)**
Occupation	.000	-.012***	-.000	.000	-.001	.003	-.011***	-.004	.001	-.001
	(.001)	(.003)	(.001)	(.001)	(.002)	(.004)	(.003)	(.002)	(.003)	(.003)
	[.066]	**[.993]**	[.079]	[.06]	[.128]	(.803)	**(-3.903)**	**(-1.610)**	(.199)	(-.496)
Cognitive ability	-.000	.010***	.000	.000	.000	-.002	.009***	.001	-.000	.002
	(.001)	(.003)	(.000)	(.001)	(.001)	(.003)	(.003)	(.002)	(.003)	(.003)
	[.078]	**[.976]**	[.062]	[.054]	[.08]	(-.690)	**(3.584)**	(.628)	(-.157)	(.888)
Time Interval	-.015	.000	-.019***	.019***	-.006	-.013	-.002	-.016***	.016***	-.011**
	(.010)	(.003)	(.004)	(.004)	(.007)	(.008)	(.006)	(.004)	(.005)	(.004)
	[.786]	[.135]	**[.998]**	**[.999]**	[.452]	**(-1.548)**	(-.350)	**(-3.720)**	**(3.382)**	**(-2.521)**
UH controlled	-.018**	-.000	-.000	.001	.002	-.018***	-.003	.001	.006	.004
	(.009)	(.002)	(.001)	(.003)	(.004)	(.006)	(.005)	(.004)	(.005)	(.005)
	[.897]	[.066]	[.053]	[.225]	[.284]	**(-2.922)**	(-.626)	(.231)	**(1.248)**	(.836)
OLS method	-.024***	-.001	.000	-.000	-.004	-.022***	-.007	-.000	-.001	-.005
	(.007)	(.003)	(.001)	(.001)	(.005)	(.006)	(.005)	(.003)	(.004)	(.004)
	[.996]	[.152]	[.054]	[.084]	**[.414]**	**(-3.769)**	**(-1.454)**	(-.026)	(-.140)	**(-1.106)**
Measurement error	-.000	.001	.000	.000	.004	-.001	.003	.001	.002	.007**
	(.001)	(.003)	(.001)	(.002)	(.005)	(.004)	(.003)	(.002)	(.003)	(.003)
	[.056]	[.238]	[.067]	[.116]	**[.464]**	(-.229)	(.976)	(.288)	(.750)	**(2.389)**
Panel Data	-.000	.004	-.000	-.000	-.025***	.003	.004	-.002	-.004	-.018***
	(.001)	(.004)	(.001)	(.002)	(.004)	(.005)	(.003)	(.002)	(.003)	(.003)
	[.061]	**[.478]**	[.072]	[.114]	**[1]**	(.732)	**(1.146)**	(-.984)	**(-1.175)**	**(-5.227)**

*Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. Standard errors are reported in parentheses, and clustered at the study level. *, **, and *** denote statistical significance at 10, 5, and 1%, respectively. PIP scores are reported in squared brackets for BMA. t-values are recorded in the parentheses just below the standard errors for WALS. If a variable's PIP is greater than 0.5, it is regarded to have a strong effect in BMA; but, for WALS, the t-value must be bigger than one. PIPs greater than 0.5 and t-values greater than 1 are in bold.*

Table B.3 (cont.): Robustness Tests

	BMA					WALS				
	O	**C**	**E**	**A**	**N**	**O**	**C**	**E**	**A**	**N**
Australia	.001	.003	-.000	-.018***	.000	.008	.005	-.005	-.016***	.004
	(.002)	(.005)	(.001)	(.005)	(.002)	(.006)	(.005)	(.003)	(.005)	(.005)
	[.091]	[.268]	[.089]	**[.991]**	[.085]	**(1.452)**	(.926)	**(-1.571)**	**(-3.213)**	(.913)
Asia Pacific	.000	.028***	.002	.003	.015	.001	.023***	.007	.011	.015*
	(.002)	(.010)	(.004)	(.008)	(.012)	(.008)	(.008)	(.005)	(.008)	(.008)
	[.059]	**[.97]**	[.199]	[.223]	**[.693]**	(.142)	**(2.927)**	**(1.279)**	**(1.372)**	**(1.949)**
World (Other)	.018***	-.008	-.000	-.000	.006	.019***	-.007	-.005	.000	.006*
	(.004)	(.007)	(.000)	(.001)	(.005)	(.005)	(.005)	(.003)	(.004)	(.004)
	[.998]	**[.639]**	[.057]	[.063]	**[.632]**	**(3.514)**	**(-1.536)**	**(-1.484)**	(.098)	**(1.757)**
Journal	-.000	-.001	-.000	.001	.000	-.002	-.002	-.002	.006*	.004
	(.002)	(.002)	(.001)	(.002)	(.002)	(.004)	(.004)	(.002)	(.003)	(.003)
	[.079]	[.115]	[0.054]	[0.15]	[0.105]	(-0.614)	(-0.554)	(-0.670)	**(1.911)**	**(1.033)**
Pub Year (logs)	-6.452***	1.785	-.002	4.222***	.098	-6.361***	2.024**	.409	3.480***	.476
	(.914)	(1.437)	(.095)	(.559)	(.382)	(1.083)	(.885)	(.562)	(.859)	(.756)
	[1]	**[.684]**	[.054]	**[1]**	[.112]	**(-5.875)**	**(2.286)**	(.728)	**(4.050)**	(.629)
Constant	49.141***	-13.578	.018	-32.135***	-.742	48.445***	-15.387**	-3.106	-26.489***	-3.625
	(6.954)	(1.930)	(.724)	(4.255)	(2.908)	(8.238)	(6.738)	(4.273)	(6.537)	(5.754)
	[1]	**[1]**	**[1]**	**[1]**	**[1]**	**(5.881)**	**(-2.284)**	(-.727)	**(-4.052)**	(-.630)
N	216	231	245	246	245	216	231	245	246	245

*Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. Standard errors are reported in parentheses, and clustered at the study level. *, **, and *** denote statistical significance at 10, 5, and 1%, respectively. PIP scores are reported in squared brackets for BMA. t-values are recorded in the parentheses just below the standard errors for WALS. If a variable's PIP is greater than 0.5, it is regarded to have a strong effect in BMA; but, for WALS, the t-value must be bigger than one. PIPs greater than 0.5 and t-values greater than 1 are in bold.*

Table B.4: Robustness Test, only for studies reporting wage outcomes

	O	C	E	A	N
Constant	64.960***	-22.856**	1.415**	-21.378**	-3.805***
	(11.190)	(1.025)	(4.160)	(8.612)	(8.554)
Standard Error	.916***	.687***	.281*	-1.202***	-.919***
	(.243)	(.221)	(.148)	(.219)	(.228)
Age Category	-.047	.033	.002	.046*	-.007
	(.044)	(.051)	(.051)	(.026)	(.022)
Males	-.004	-.001	-.000	-.001	.008**
	(.005)	(.004)	(.000)	(.003)	(.004)
Females	-.007	-.003	.000	.006*	-.001
	(.005)	(.004)	(.000)	(.004)	(.004)
Education controlled	-.015***	.002	.010***	.002	.000
	(.006)	(.005)	(.002)	(.004)	(.004)
Family Background controlled	-.012**	-.002	-.009***	.009**	.018***
	(.006)	(.005)	(.002)	(.004)	(.004)
Occupation controlled	-.004	-.011**	-.001	.002	.003
	(.005)	(.005)	(.002)	(.004)	(.004)
Cognitive ability controlled	-.007	.012**	.003	-.000	-.003
	(.006)	(.006)	(.002)	(.005)	(.004)
Time Lag	.015	-.014	-.001	-.021	.015
	(.045)	(.051)	(.051)	(.026)	(.022)
UH controlled	-.009	-.007	-.002	.001	.003
	(.006)	(.005)	(.002)	(.005)	(.005)
OLS method	-.022***	-.011**	-.001	-.004	.004
	(.006)	(.005)	(.002)	(.004)	(.005)
Use of Personality Factor Scores	-.002	.017***	.004	-.005	.000
	(.005)	(.005)	(.003)	(.004)	(.004)
Panel Data	.011*	.010*	-.000	-.014***	-.009*
	(.006)	(.006)	(.002)	(.005)	(.005)
Australia	.011	.001	-.001	-.012**	.000
	(.007)	(.007)	(.003)	(.006)	(.006)
Asia Pacific	.007	.017*	-.012**	.030***	.021**
	(.011)	(.010)	(.006)	(.010)	(.009)
World (Other)	.034***	.002	-.001	.003	-.009*
	(.006)	(.006)	(.003)	(.005)	(.005)
Journal	-.001	-.001	-.008***	.001	.007*
	(.004)	(.004)	(.002)	(.003)	(.004)
Pub Year (logs)	-8.533***	3.004**	-1.368**	2.810**	4.046***
	(1.470)	(1.318)	(.547)	(1.132)	(1.124)
N	143	150	156	157	157

3. CHAPTER TWO: THE IMPACT OF PARENTAL BACKGROUND ON THE BIG FIVE TRAITS AND INTELLIGENCE: EVIDENCE FROM A TWIN-BASED STUDY

3.1 INTRODUCTION

Personality traits have been repeatedly shown to predict significant life outcomes, such as academic success, earnings, health, stress, and relationship quality (e.g., Heckman, Stixrud and Urzua, 2006; Almlund *et al.*, 2011). Defined as "relatively enduring patterns of thoughts, feelings, and behaviours that differentiate individuals from one another" (Roberts, 2009, p. 2), these traits shape how individuals navigate various aspects of life. However, the factors that interact with these traits remain not well-understood.

This chapter aims to bridge this gap by examining the relationship between parental factors and children's personality traits. "Parental factors" refer to various influences originating from parents that shape the child's personality development, including cognitive skills, personality traits, and the opportunities they provide, the latter known as parental investment. This includes the parenting styles the child is exposed to and the time parents spend actively involved in the child's life. Additionally, parental socioeconomic status (SES) – which includes income, education, and occupational prestige – directly and indirectly influences a child's personality and cognitive outcomes by shaping the level of investment and its effectiveness, ultimately shaping the environment in which a child develops.

Existing research has established links between parental SES and children's personality traits (Deckers *et al.*, 2015; Ayoub *et al.*, 2018; Lechner *et al.*, 2021) and between one's own SES and personality traits in adulthood (Hughes *et al.*, 2021; Luo *et al.*, 2024). Nonetheless, the number of studies is limited and often descriptive, lacking a comprehensive understanding of these relationships.

This chapter also contributes to the literature by comparing the influence of parental factors on personality traits versus cognitive skills. While it is well-established that parental factors influence a child's intelligence (e.g., Falk *et al.*, 2021), less is known about their impact on personality traits. Instead of using complex and difficult-to-interpret one-dimensional noncognitive measures, this study employs the well-established Big Five personality traits.

The chapter explores two pathways through which parental SES can influence a child's personality: (a) parental SES predicts the *level of parental investment*, which in turn predicts the child's intelligence and personality; and (b) parental SES predicts the *effectiveness of both parental investment and parents' personality*, which then affects the child's intelligence and personality. The research utilises data from twins aged 10 to 12 years from the first wave of the German Twin Family Panel (TwinLIFE), which includes detailed socio-economic measurements, personality traits (Big Five), family background information, and cognitive ability (fluid intelligence).[14] This study uses fluid intelligence as a proxy for academic ability or potential, as it is less influenced by sociocultural factors and individual effort compared to academic performance

[14] Fluid intelligence and crystallised intelligence are the two components of general intelligence. Fluid intelligence refers to the ability to reason, solve problems, and learn new information and skills. Crystallised intelligence refers to the accumulation of knowledge, facts, and skills that are acquired throughout life. Both forms of intelligence are thought of as two distinct but related forms of intelligence. In this study, fluid intelligence and cognitive skills are used interchangeably.

measures (Cliffordson and Gustafsson, 2008; Rindermann, Flores-Mendoza and Mansur-Alves, 2010; Carlsson *et al.*, 2015).

The use of twin data offers an important advantage over other types of household datasets. Twin studies are commonly used to address endogeneity concerns in developmental and behavioural research. MZ (Monozygotic) twins share nearly 100% of their genetic material, while DZ (Dizygotic) twins share about 50%, which allows for a more controlled comparison of environmental factors, like parental investments. If the estimates remain similar in both groups, it indicates that the results are not driven by unobserved genetic factors and other latent variables that would otherwise bias the analysis.

A distinctive feature of this study is the use of a Constant Elasticity of Substitution (CES) production function approach to link a child's personality traits to parental inputs. This method, unlike traditional linear models, estimates the elasticity of substitution parameter, providing a nuanced analysis of parental influences.

Additionally, the chapter explores whether offspring personality traits correlate with unobserved developmental shocks resulting from parental investments. If parents positively reinforce their children's development, a correlation between parental investment and unobserved shocks could arise, potentially leading to an upward bias in the estimated effects of parental investment on personality traits.

The findings suggest that although personality traits are generally considered stable over time, parental experiences and opportunities can introduce systematic variations.

This implies that personality, which influences both observable and unobservable heterogeneity, may not be strictly time-invariant. However, the disparities in Big Five personality traits across children from different SES are relatively minor when compared to the more pronounced SES-related differences in fluid intelligence.

Lastly, the chapter explores policy implications, proposing that interventions aimed at enhancing both cognitive and personality development can help mitigate early-life inequities. Existing literature shows that children from higher SES families typically achieve more education, higher wages, and better job status, while those from lower SES backgrounds face greater health risks and cognitive impairments that persist into adulthood (Luo and Waite, 2005). If personality traits, like fluid intelligence, can be nurtured from a young age, such interventions could have lasting positive impacts. This supports the notion that personality can mitigate the disadvantages of an unfavourable upbringing (Shanahan *et al.*, 2014; Damian *et al.*, 2015). That said, Lechner et al. (2021) caution that promoting personality traits to reduce inequality may not be entirely effective, as traits conducive to achievement are unevenly distributed, favouring high SES students, and returns to personality traits are higher among high SES students than low SES students.

The rest of the chapter is structured as follows. Section 2 discusses the main literature on the relationship between personality traits and SES. Section 3 provides a brief description of the methods used to measure personality traits, intelligence, and parental investments, along with a descriptive analysis of the survey data. Section 4 presents the identification strategy, with the main results discussed in Section 5. Section 6 concludes.

3.2 LITERATURE REVIEW

Personality Traits

The Big Five model of personality is widely recognised as the standard framework in psychology that describes human personality. This model includes five traits: openness to experience (creativity, curiosity, intellectual engagement, honesty, humility, and inquisitiveness), conscientiousness (self-discipline, punctuality, organisation, and general competence), extraversion (talkativeness, friendliness, energy, and sociability), agreeableness (kindness, charity, warmth, and generosity), and neuroticism (fear, worry, paranoia, and stress). For contextual appropriateness, this chapter uses the term “emotional stability”, which is the opposite of neuroticism.

A growing body of research underscores the importance of the Big Five traits in the job market (Alderotti, Rapallini and Traverso, 2023; Vella, 2024). Findings from industrial and organisational psychology suggest that personality affects outcomes through individual actions, demands placed on employees by their employers, and job performance. Thus, variations in these traits may explain why some individuals are more successful or valued in the workforce than others.

Individuals high in openness to experience tend to excel in tasks requiring training due to their curiosity and eagerness for new experiences and ideas (Lepine, Colquitt and Erez, 2000). Conscientiousness is consistently linked to favourable labour market outcomes as it drives productivity and motivation at work (Barrick, Mount and Judge, 2001; Salgado *et al.*, 2003; Ones *et al.*, 2007). Extraversion is particularly beneficial in roles involving significant interpersonal interaction, such as job interviews and collaborative tasks (Caldwell and Burger, 1998; Chi *et al.*, 2011; Zeigler-Hill *et al.*, 2015).

Agreeableness enhances interpersonal interactions and team performance, making it valuable in some occupations (Peeters *et al.*, 2006; Bell, 2007). However, less agreeable personalities may be preferred in managerial or higher-paying positions (Wells, Ham and Junankar, 2016). More agreeable individuals are often found in lower-paying caregiving occupations, such as teaching and nursing, are less effective at negotiating wages and tend to hold more egalitarian views on work and pay (Nyhus and Pons, 2005).

Emotional stability, the opposite of neuroticism, is valuable for job performance and stability. According to Judge, Heller, and Mount (2002), in many organisations and situations, emotional stability is associated with a higher likelihood of employment and better job performance (Wichert and Pohlmeier, 2010), which in turn increases an individual's ability to perform their job (Ones *et al.*, 2007), making them well-suited for challenging and high-stress roles.

Parental SES Gaps in Offspring Personality

Parental SES, quantified by education, income, and occupational prestige, represents the resources available to parents and access to opportunities. SES is a well-established determinant of both cognitive and non-cognitive development, as well as the intergenerational transmission of wealth (de Neubourg *et al.*, 2018). Research from various disciplines consistently shows that children from low SES backgrounds face numerous disadvantages (Bradley and Corwyn, 2002; Cunha *et al.*, 2006; Heckman, Stixrud and Urzua, 2006; Kalil, 2015). While much of the literature has focused on the links between parental SES, parenting practices, and the cognitive development of offspring, relatively fewer studies have examined the impact of parental SES on offspring personality traits as the primary outcome.

Several theories provide insight into why parental SES might affect child personality. One explanation involves genetic inheritance: children may inherit both personality traits and SES-related genes from their parents, influencing their personality. Studies in behavioural genetics indicate that personality traits have a substantial genetic component, with nearly 50% heritability (Briley and Tucker-Drob, 2017). Specific genes may also influence the development of certain personality traits. For instance, de Zeeuw et al. (2019) found that parents who provide a good socioeconomic environment also pass on genetic variants favourable for learning. Similarly, Demange et al. (2021) found that non-cognitive genetic variants are associated with longevity, socioeconomic success, and better educational outcomes. This genetic transmission helps explain the association between personality traits and life outcomes.

Another explanation focuses on the developmental environment. Children from high SES families are more likely to grow up in more stable and nurturing environments, which foster the development of positive personality traits. For example, Ayoub et al. (2018) found that children from higher SES families tend to exhibit higher levels of emotional stability, openness to experience, conscientiousness, extraversion, and agreeableness, albeit with small effect sizes.

The social investment principle of the neo-socioanalytic model further emphasises the role of experiences in shaping personality. According to this principle, social relationships and experiences (e.g., families and occupational roles) mould personality over time (Roberts and Nickel, 2021). Consequently, children exposed to conflict or exclusion in their family relationships may develop negative personality traits, such as neuroticism and hostility, leading to disparities in Big Five traits among children from different socio-economic backgrounds.

Despite the considerable evidence linking parental SES to factors correlated with personality, the underlying mechanisms are complex. Bradley and Corwyn (2002) categorise these factors into three groups: resources, stress reactions, and parental health and lifestyles.

In terms of resources, high SES families are typically able to invest more financially and spend time with their children, which directly influences child outcomes (e.g., Bernal and Keane, 2011; Bono *et al.*, 2016; Francesconi and Heckman, 2016; Conger, Martin and Masarik, 2021). Indeed, Schneider et al. (2018) add to this by showing that growing income gaps in the US have been accompanied by growing class differences in parental time and financial investments. As several Big Five traits are associated with cognitive functioning (DeYoung, 2015, 2020), it is expected that family SES also impacts personality development.

Conversely, families from lower SES backgrounds are more susceptible to financial hardship (Bradley and Whiteside-Mansell, 1997), unhealthy lifestyles (Baum, Garofalo and Yali, 1999), and parental behavioural issues that can negatively affect child development. For example, parenting style differences among identical twins reveal that the twin exposed to more negative parenting and less maternal warmth exhibited more behavioural problems and less social interaction (Mullineaux *et al.*, 2009).

However, higher SES families do not always result in positive personality development. Contrary to Ayoub et al. (2018), Sutin et al. (2017) found a negative association between parental educational attainment and offspring conscientiousness in younger cohorts (14-30 years). They suggest that highly educated parents may adopt parenting styles that adversely affect offspring conscientiousness. For instance, increased parental involvement in upbringing and education during the late 20th century may have unintentionally hindered the development of children's conscientiousness (Schaub, 2010).

Based on genetic and environmental links between parental SES and offspring personality, it can be hypothesized that higher parental SES is associated with more favourable personality development, characterized by higher scores on traits like openness, conscientiousness, extraversion, agreeableness, and emotional stability. Furthermore, higher SES is expected to correlate with more positive parenting styles and greater parental investment, giving children from high SES families a potential advantage in developing these traits and creating early disparities in the Big Five traits among children from different socioeconomic backgrounds.

3.3 DATA

This study utilises data from the German Twin Family Panel (TwinLIFE), a comprehensive, ongoing 12-year behavioural genetic study focused on social inequality development. TwinLIFE collects data through face-to-face and Computer-Assisted Telephone Interviews (CATI) with same-sex twins and their families. The study targets twins raised in the same family across four age cohorts: 2009/2010 (Cohort 1), 2003/2004 (Cohort 2), 1997/1998 (Cohort 3), and 1990-1993 (Cohort 4). The initial wave, conducted in 2015, included 4,097 twin families with twins aged 4 to 25. The sample was selected using a probability-based sampling design, ensuring representation across socio-demographic indicators such as education, occupation, and income structures, as detailed by Lang and Kottwitz (2020) and Mönkediek et al. (2019).

For this study, data from Cohort 2 (twins aged 10 to 12) were used, including cognitive testing, personality assessments, and parenting questionnaires. After excluding missing and invalid responses, the final sample comprised 392 monozygotic (MZ) twins and 648 dizygotic (DZ) twins. The analysis is based on data from the first wave, which was collected via face-to-face interviews, with all data standardised for consistency.

The reason for choosing twins aged between 10 to 12 stems from the fact that the Big Five personality traits were only measured for this cohort and the other two cohorts of greater age. This age range was selected to evaluate fluid intelligence and personality traits early in life, as evidence from social and biological sciences highlights the important role of early years in fostering skills essential for human development. Families contribute far more than just genetic inheritance, such that skills development is a dynamic interaction between nature and nurture. By starting at a younger age, the study reduces endogeneity issues related to feedback from experiences, such as education attainment, labour market status. However, it cannot fully eliminate other potential sources of endogeneity, such as the influence of parental investment interacting with unobserved factors like resources and wealth.

Socioeconomic Status Measurement

SES is often measured using a variety of factors, such as level of education, financial situation, and occupational status. In this study, a family was classified as low SES if either of the following conditions was met: (i) the highest educational level of the parents was ISCED Level 3, not qualifying for higher education, or (ii) the household's equivalised disposable income was below the 30th percentile of the German income distribution (e.g., Falk *et al.*, 2021).[15] Families not meeting these criteria were classified as high SES.

As a robustness check, parental occupational status, household income, and educational level were also analysed separately. Parental education, often considered a stable SES indicator, strongly correlates with income and human capital, whereas household disposable income reflects resource accessibility for children. Overall, there was a moderate correlation between the two, with 55% of low-income households having parents with ISCED Level 3 or lower education.

Personality Traits Measurements

Personality traits were assessed using the 15-item Big Five Inventory (BFI-S) (Hahn, Gottschling and Spinath, 2012), developed for the German SOEP study. Respondents

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[15] The 30th percentile of the household equivalised disposable income is closely aligned with the poverty line used by European institutions.

rated how well a series of statements (e.g., “I see myself as someone who is original, comes up with new ideas”) represented them on a seven-point Likert scale (1 = "does not apply to me at all" to 7 = "applies to me perfectly"). The inventory includes three items each for conscientiousness, extraversion, agreeableness, and neuroticism, and four items for openness to experience.[16]

To derive an index for each of the Big Five personality traits, I applied factor analysis to the responses. This method identifies the underlying “factor” that influences the rating scores of all the measured items, and reduce the dimensionality of the data, making it easier to interpret. This “factor” is then interpreted as representing one of the Big Five personality traits. The appealing feature of this technique is that factor analysis can be useful in dealing with measurement error under the assumption that the error is random and uncorrelated with the true values of the items, and it helps address multicollinearity issues.

Fluid Intelligence Measurement

Fluid intelligence, defined as the ability to reason and solve problems independently of prior experience (Horn and Cattell, 1966), was measured using the short version of the Culture Fair Test 20R (Weiß, 2006; Weiß and Osterland, 2012). The fluid intelligence test was conducted under a detailed procedure to reduce noise and allow for more accurate and reliable data.[17]

[16] The full wording of the statements is provided in the Appendix A.
[17] The details of the procedure, subsets and the factor analysis are given in the Appendix A.

In general, the test consisted of puzzles, shape comparisons, and spatial reasoning tasks. The test is divided into four different subtests: figural reasoning, figural classification, matrices, and reasoning (Weiß and Osterland, 2012). The first three subtests consist of 15 items, and the fourth subtest consists of 11 items. Factor analysis was used to consolidate these subtests into a single fluid intelligence score.

Parental Investment Measurements

Parental investment, reflecting parental support and involvement in a child's development, was measured using two indicators: parenting styles and parental time spent with children.

i. Parenting Style

Parenting style, which sets the emotional context for parental behaviour (Leung and Tsang Kit Man, 2014), was evaluated using adapted scales from the Panel Analysis of Intimate Relationships and Family Dynamics (Huinink *et al.*, 2011).

This study focused on four dimensions: emotional warmth, psychological control, negative communication, and monitoring. Seven parenting style variables were used, namely: (i) a measure of parental warmth (includes praise and emotional warmth), (ii) a measure of monitoring (knowing one's children's friends), (iii) a measure of negative communications (yelling at the child and scolding the name of the child when the parent is angry at them), (iv) a measure of parental psychological control (punishment), and (v) a measure of inconsistent parenting (empty threats).

Like fluid intelligence and personality, a pure measure of parenting style is difficult because it is unobserved to the researcher. I follow Falk et al. (2021) and many others by extracting a latent variable from the set of questionnaire items using structural equation modelling. This strategy is parsimonious compared to multi-factor models.

Emotional warmth and monitoring are expected to positively correlate with the parenting style score derived from the measurement model, while negative communication and psychological control are anticipated to have a negative correlation. Thus, a higher score on the parenting style scale indicates a more positive parenting approach.

The measurement model assumes that the observed parenting style items are influenced by factors such as parental IQ, parental personality, household characteristics, and an underlying latent parenting style. This approach is designed to account for unobserved heterogeneity, allowing for a more accurate extraction of the parenting style measure.

Given that the questionnaire collects separate self-reports from mothers and fathers, the parenting styles of both parents are assessed separately. Then, to obtain an overall parenting style score, a principal component analysis is performed to reduce the dimensionality of the data. A full description of the measurement model is provided in Appendix A.

Table 3.1: SES Gaps in Offspring Fluid Intelligence and Personality Scores

	FI	O	C	E	A	ES
Baseline (Low SES)						
High SES	.209***	.044	.017	.055*	.016	.112***
	(.0033)	(.0035)	(.033)	(.033)	(.033)	(.032)
N	1,040	1,040	1,040	1,040	1,040	1,040

Notes: FI – Fluid Intelligence, O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, E – Emotional Stability. Each coefficient indicates difference between baseline category low SES and each high SES group. Standard errors (in parentheses) are bootstrapped using 1,000 bootstrap replications and are clustered by family.
*Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.*

ii. Parental Time

Parental time was measured through the frequency of family activities. This index approximates the amount of interaction time parents spend with their children. The activities are singing/playing music, reading/talking about books, sports, walks and day trips, and visiting the theatre or museum. By using this index, one can make an approximation of the amount of time that family members spend engaging in interaction activities with the child.

Parental SES Gaps in Children's Personality Traits

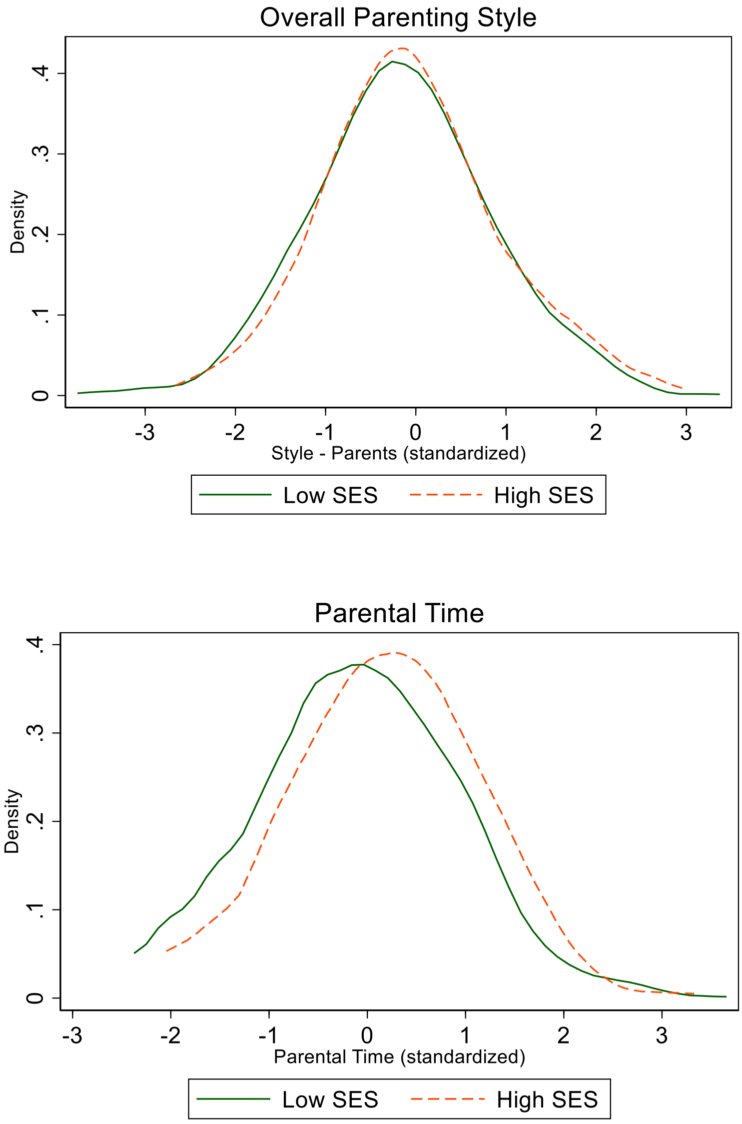
This section describes the data used to quantify the production function equation in the next section.

Table 3.1 displays the regression coefficients for the high SES dummy variable, indicating that children from high SES backgrounds exhibit higher scores in fluid intelligence and emotional stability, with a more modest effect on extraversion.

Specifically, children from high SES households show an increase of 0.21 standard deviations in fluid intelligence and 0.11 standard deviations in emotional stability. Although the extraversion score rises by 0.06 standard deviations, this change is statistically significant at the 10% level. For the other personality traits, however, there is mixed descriptive evidence, making it difficult to draw any strong conclusions given that the coefficients are not statistically significant from zero.

Figure 3.1 depicts the kernel density estimate of standardised scores, illustrating the distribution characteristics of parenting style and parental time. The distribution for

Figure 3.1: Parental SES Gaps in Parenting Investments



Notes: Kernel density plots of standardised investment measures by parental SES. Parental scores are defined as the principal component analysis of maternal and paternal scores.

parenting style indicates that parents from high SES families are almost indistinguishable from low SES background. However, a mean-comparison test shows that low-SES families score significantly lower on parenting style, with a small effect size of -0.097 standard deviations at 5% level. This difference is primarily driven by variation in mothers' parenting styles across SES groups, with no significant difference observed between fathers.

Furthermore, children from lower SES families report that their parents spend less time with them, scoring 0.256 standard deviations lower than children from high SES families. This difference is statistically significant at the 1% level and more pronounced than differences in parenting style across SES ranks.

To further explore SES effects, an alternative measure divides families into three different groups: (i) low-income families, (ii) families with low educational attainment, and (iii) families with multiple risks, i.e., low-income and low-educated parents. Table

Table 3.2: Components of Parental SES Gaps in Offspring Fluid Intelligence and Personality Scores

	FI	O	C	E	A	ES
Base Category (High SES)						
Low Income	-.111***	-.010	.011	-.032	.016	.046
	(.036)	(.031)	(.036)	(.029)	(.029)	(.037)
Low Education	-.149***	-.038	-.018	-.039	-.008	-.093***
	(.035)	(.036)	(.0033)	(.033)	(.037)	(.036)
Low Income and Education	-.240***	-.050	-.029	-.061*	-.056	-.110***
	(.037)	(.033)	(.040)	(.036)	(.036)	(.045)
N	1,040	1,040	1,040	1,040	1,040	1,040

*Notes: FI – Fluid Intelligence, O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, E – Emotional Stability. Each coefficient indicates differences between baseline category high SES and each respective low-SES subgroup. Each column is a regression of intelligence or personality on the three low-SES subgroup dummies. Standard errors (in parentheses) are bootstrapped using 1,000 bootstrap replications and are clustered by family. Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.*

3.2 presents the disparities between the children by these three categories, and each coefficient compares each group to the high-income group (base category). It shows that children from high SES families outperform those from low SES backgrounds in fluid intelligence and are more extroverted, and emotionally stable. The overall data also show that all SES groups have a negative sign, underscoring the importance of parental education and income as risk factors.

Table 3.1 and Table 3.2 highlight significant distinctions between cognitive ability and personality traits. The gaps in fluid intelligence are more pronounced than those in personality scores, and this pattern persists when analysing MZ and DZ twins separately (refer to Appendix A). This finding aligns with previous research, which indicates that about half of the variation in cognitive ability is attributable to a shared early childhood environment, whereas genetic factors more likely influence personality variation (Briley and Tucker-Drob, 2017). In essence, family-environmental factors have a greater impact on cognitive ability during early childhood than on personality traits.

To delve deeper into the role of SES, I replicated the descriptive analysis using the European Socio-Economic Classification (ESeC) by Rose and Harrison (2007). The ESeC classification assesses an individual's market position within the professional division of labour – a key driver of inequality – by categorising occupations based on the required knowledge level and the complexity of monitoring job performance. Unlike traditional occupational scales, this classification divides occupations into ten distinct classes, capturing qualitative differences in employment relationships.[18]

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[18] For more information on socio-economic classifications and the benefits of using ESeC see Rose (2005) and Rose and Harrison (2007).

Table 3.3: Parental Occupational Gaps in Offspring Fluid Intelligence and Personality Traits Scores

	FI	O	C	E	A	ES
Base Category (Inactive, unemployed)						
Semi-/unskilled, skilled manual, lower shite collar	.052	-.020	-.077	-.027	-.064	-.012
	(.061)	(.062)	(.062)	(.061)	(.063)	(.066)
Higher grade blue collar and white collar	.218***	-.017	.037	-.010	.031	.025
	(.067)	(.063)	(.063)	(.065)	(.064)	(.068)
Lower salariat, higher salariat	.309***	-.023	-.078	-.012	-.055	.016
	(.072)	(.074)	(.073)	(.074)	(.076)	(.083)
N	974	974	974	974	974	974

*Notes: FI – Fluid Intelligence, O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, E – Emotional Stability. Each coefficient indicates differences between baseline category inactive or long-term unemployed and each respective occupational group. Each column is a regression of intelligence or personality on the three low-SES subgroup dummies. Standard errors (in parentheses) are bootstrapped using 1,000 bootstrap replications and are clustered by family. Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.*

A linear regression analysis examined the correlation between parental occupational status and offspring fluid intelligence and personality scores. The reference category comprised individuals who had never worked or were long-term unemployed. As shown in Table 3.3, children with at least one parent in the highest skilled occupation class report significantly higher fluid intelligence scores than children of inactive or unemployed parents (0.31 of a standard deviation). Furthermore, the gap in fluid intelligence scores widens as one moves up the occupational ladder.

In contrast, the data reveal no significant differences in personality trait scores between children from high-status and low-status occupational backgrounds. This finding suggests that parental social roles have a limited impact on shaping offspring personality traits. However, it also underscores the complexity of the relationship, given the numerous variables that can influence personality development. This complexity highlights the need for further analysis to understand the mechanisms at play better.

3.4 EMPIRICAL STRATEGY

The Formation of Child's Intelligence and Personality Traits

To analyse the relationship between a child's outcomes and various parental inputs, such as parental personality traits and investments, the following specification is used:

$$M_i^\ell = \Pi^{\ell^{SES_i}} \left[\gamma_P P_i^{\ell^\phi} + \gamma_S S_i^{\ell^\phi} + \gamma_T T_i^{\ell^\phi}\right]^{\nu/\phi} e^{\eta_i^\ell} \tag{3.1}$$

Here, M_i represents the child's outcome, where ℓ denotes the specific trait being studied: fluid intelligence, openness to experience, conscientiousness, extraversion, agreeableness, or emotional stability. P_i^ℓ represents the parental characteristic, S_i^ℓ denotes parenting style, and T_i^ℓ signifies parental time. SES_i is a binary indicator, equal to one for high SES households and zero for low SES households. The error term is denoted by η_i^ℓ.

The productivity parameter, Π, captures systematic differences in how effective parental inputs are in shaping child outcomes across different SES. In essence, Π reflects the total factor productivity (TFP), reflecting how the same parental effort or input might yield different results depending on whether a family is high SES or low SES. If $\Pi > 1$, parental factors are more effective for high SES families than for low SES families. This implies that, for example, a unit increase in parental time or effort in a high SES family lead to a more than proportional improvement in the child's outcomes (e.g., intelligence or personality traits). This could be due to better resources, more stimulating environments, or other unobserved advantages in high SES families. If $\Pi = 1$, it suggests that the effectiveness of parental inputs is the same across SES levels. If $\Pi < 1$, it suggests that parental inputs are actually more effective in low SES families. This might occur because the marginal benefit of each additional unit of input is greater.

The substitution parameter, ϕ, determines how easily one parental input – such as parental traits, parenting style, and parental time with children – can substitute for another in the development of child outcomes, like intelligence or personality traits. ϕ is related to the elasticity of substitution (ε) between different inputs, where $\varepsilon = 1/(1-\phi)$. ε measures how easily one input can be replaced with another without affecting the outcome. For example, it indicates to what extent more parental time can compensate for less favourable parenting style, or whether a more favourable parenting style can compensate for less time spent with children. ϕ ranges from $-\infty$ to 1. If $\phi = 0$, the inputs are imperfect substitutes with a constant elasticity of substitution equal to one. This scenario is common in economic models, referred to as a Cobb–Douglas production function. In the CES production function as $\phi \rightarrow 1$ and consequently $\varepsilon \rightarrow \infty$, the inputs can perfectly substitute for each other. Whereas, as $\phi \rightarrow -\infty$ and $\varepsilon \rightarrow 0$, the inputs are perfect complements.

The distribution parameter, γ, for each input measures the contribution of different parental inputs toward the overall outcome of a child's development, with the sum of the three parameters constrained to one. In other words, this parameter determines the relevant importance of each input in the production process of child outcomes. A higher value for a particular input means that this input has a larger contribution to the child's outcome, while a lower value indicates a lesser contribution.

The homogeneity parameter, ν, measures the degree of returns to scale: $\nu = 1$ implies constant returns, $\nu < 1$ implies decreasing returns, and $\nu > 1$ implies increasing returns. For instance, in the context of child's development, if $\nu = 1$, it means that increasing all parental inputs by a certain factor will result in a proportional increase in the child's outcomes.

Drawing on Falk et al. (2021), the factor inputs put an emphasis on family caregivers, as underscored in psychological literature. Other factors, such as home chaos, health, and parental religious affiliation, also play a role in personality development but are likely partially accounted for by parental characteristics, primarily due to genetic influences.

Expressing Equation (3.1) in log form gives:

$$\ln M_i^{\ell} = SES_i \ln\left(\Pi^{\ell}\right) + \frac{\nu}{\phi} \ln\left[\gamma_P P_i^{\ell^{\phi}} + \gamma_S S_i^{\ell^{\phi}} + \gamma_T T_i^{\ell^{\phi}}\right] + \eta_i^{\ell} \tag{3.2}$$

Following the approaches of Cunha, Heckman, and Schennach (2010) and Falk et al. (2021), it is assumed that the data measurements of parental IQ, personality traits, and investment serve as proxies for their natural logarithms, ensuring that these measures remain nonnegative.

This functional form has its caveats. First, it assumes a common elasticity of substitution between the three parental inputs, implying that the ease of substituting one parent's input for the other is uniform. Additionally, the CES framework treats parental inputs as homogenous in their effect on outcomes, which may not hold in practice. For example, it assumes that maternal and paternal personality traits have similar effects. However, these traits might influence a child's personality development differently depending on factors such as the child's gender or the specific traits being analysed. Finally, estimating the CES production function can be computationally intensive and may present challenges with model convergence, and the estimation becomes even more complex when including the heterogeneity effects.

Parental Investments and SES

It is anticipated that SES influences a child's development in two ways. First, as suggested by Equation (3.2), SES can affect cognitive and personality development through the productivity effect captured by Π^{ℓ}. Additionally, SES may indirectly affect a child's development through parental investments. Higher-educated parents are more likely to monitor their children and spend more time with them. High SES families can also invest more time and resources in positive interactions. The investment function is specified as:

$$I_i^j = \alpha_0^j + \alpha_P^j P_i^{\ell} + \alpha_{SES}^j SES_i + \alpha_X^j X_i + \epsilon_i^j \tag{3.3}$$

In this equation, I_i^j represents parental investment in dimension j, which includes parenting style S_i and time spent with the child T_i. X_i is a vector of household characteristics, P_i^{ℓ} and SES_i are as previously defined, and ϵ_i^j is the error term. α_{SES}^j is expected to be positive, indicating that parental investment typically increases in high SES backgrounds, assuming all other factors remain constant.

Investment Endogeneity

Parental investments I_i^j are likely to be responsive to unobserved developmental shocks (e.g., innate child abilities or unexpected events), potentially causing biased estimates of the effect of parental investments on child outcomes found in Equation (3.1). For example, parents might adjust investments in response to observed deficiencies or strengths in their children, leading to a correlation between I_i^j and unobserved factors influencing child development. This can result in an upward bias in the estimated effect of investment in Equation (3.2).[19]

Moreover, parental investments I_i^j are also likely to be endogenous to child outcomes M_i^ℓ, particularly if child outcomes and investments are jointly determined rather than being independent. For example, variables such as SES_i and P_i^ℓ influence I_i^j through Equation (3.3), and in turn affects M_i^ℓ in Equation (3.2). This interdependence may result in a feedback loop, complicating causal interpretation of the effect of parental investments on cognitive abilities and personality traits.

To address this, a valid exclusion restriction requires variables that influence parental resource allocation exogenously but are not directly related to the child’s intelligence or personality traits. Some scholars model the unobserved heterogeneity using dynamic latent factor models (Cunha, Heckman and Schennach, 2010), while others use a control function approach (Attanasio *et al.*, 2020). Due to data limitations, we

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[19] While parenting is conceptualised in terms of its effects on offspring development, children can also play an active role in influencing the parental investment they receive. For example, Ayoub et al. (2019) found that considerable variance in parental warmth and stress were due to child genetic influences on parenting style. This suggests that parents adapt their parenting style to their child's personality.

follow Falk et al. (2021), assuming that the error terms in Equations (3.1) and (3.3) are additively separable as follows:

$$\eta_i^{\ell} = \chi_Z^{\ell} Z_i + \mu_i^{\ell},$$

$$\epsilon_i^{j} = \delta_Z^{j} Z_i + \xi_i^{j},$$

where $\mu_i \sim N\left(0, \sigma^{2^{\ell}}\right)$ and $\xi_i \sim N(0, s^{2^j})$. The exponents χ_Z^{ℓ} and δ_Z^{j} capture parental reactions to shocks affecting the child, while μ_i^{ℓ} and ξ_i^{j} represent idiosyncratic random shocks. These shocks are assumed to be orthogonal to Z_i, meaning that the error terms between investment and production functions are related only because of Z_i.

Given the constraints of the available data, we include parental satisfaction with family life into the CES production function to address potential endogeneity issues. This approach, inspired by Falk et al. (2021), assumes that parental satisfaction mediates family responses to developmental shocks, thereby linking Equations (3.1) and (3.3) through a common determinant of family responses. This approach reduces, though may not entirely eliminate, endogeneity, as parental satisfaction itself may be endogenous – since parents might increase their investments to enhance their satisfaction rather than the other way around. However, the risk is mitigated by controlling for various parent and child characteristics in the investment measurement model. Robustness tests suggest that excluding parental satisfaction affects the precision of the estimates but does not significantly alter the point estimates.

3.5 EMPIRICAL RESULTS

Main Results

Table 3.4 presents the overall results of the parental investment specification in Equation (3.3). The findings indicate that, after accounting for the potential endogeneity related to family life satisfaction, SES significantly influences the amount of time parents invest in their children. However, there is no statistically significant difference between high and low SES parents in terms of their investment in parenting style. This suggests that when other factors are controlled for, SES does not directly impact parenting style.

Examining the mechanism by which SES affects parental investment, we find that parents' education and household income do not influence parenting style, they influence parental time. This likely reflects the fact that income affects parental investments in multiple ways. On one hand, higher income allows parents to allocate more resources to their children. However, the substitution effect of increased income

Table 3.4: The relationship between SES and parental investments

	Parenting Style	Parental Time	Parenting Style	Parental Time
High SES	.030	.129***		
	(.044)	(.038)		
Parents' Education			.068	.107***
			(.046)	(.040)
Poor			.067	.026
			(.046)	(.039)
Satisfaction with family life	.112***	.128***	.112***	.129***
	(.043)	(.035)	(.042)	(.035)
Observations	1,040	1,040	1,040	1,040

Notes: Standard errors (in parentheses) are bootstrapped using 1,000 *bootstrap replications and clustered by family. Control variables comprise paternal personalities and IQ, child age, household size, and a measure of parental satisfaction with family life. Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table 3.5: Estimates of the CES production function for fluid intelligence and personality traits

	FI	O	C	E	A	ES
Distribution Parameters						
Parental Traits	.570***	.384***	.357***	.427***	.362***	.360***
	(.037)	(.032)	(.034)	(.031)	(.032)	(.033)
Parenting Style	.256***	.214***	.321***	.246***	.292***	.356***
	(.031)	(.033)	(.032)	(.031)	(.033)	(.033)
Parental Time	.174***	.402***	.322***	.327***	.346***	.284***
	(.027)	(.032)	(.032)	(.032)	(.032)	(.033)
Productivity Parameters						
SES	.920	.938	.992	1.019	.937	1.097
	(.053)	(.064)	(.069)	(.068)	(.070)	(.084)
Satisfaction	.935	1.006	.989	.993	.998	1.026
	(.006)	(.007)	(.007)	(.007)	(.008)	(.008)
Substitution Parameters						
Substitution parameter	.108	.309*	.126	.269*	.249	.068
	(.151)	(.136)	(.125)	(.122)	(.132)	(.124)
Elasticity of substitution	1.121	1.448†	1.144	1.367†	1.332	1.073
	(.190)	(.285)	(.164)	(.229)	(.235)	(.143)
N	1,040	1,040	1,040	1,040	1,040	1,040

*Notes: The reported standard errors (in parentheses) were bootstrapped using 1,000 bootstrap replications and clustered by family. Parental scores were then calculated using principal component analysis, combining the maternal and paternal scores into a single composite measure. Significance at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. † Significantly different from one at the 10% level. SES, Parental Satisfaction, and Elasticity of Substitution parameters are tested for statistical difference from one.*

may lead parents to sacrifice time off in favour of longer working hours, thereby reducing the time they spend with their children (Agostinelli and Sorrenti, 2022).

Table 3.5 shows the estimates of the CES production function as specified in Equation (3.2). These estimates account for the endogeneity of investments through parental satisfaction with family life. The overall estimates suggest that parents play an important role in explaining individual differences in cognitive ability and personality traits, and that the estimates for cognitive ability are broadly consistent with those of Falk et al. (2021), which provides support that the findings are reliable and can be replicated across different samples.

Several key insights emerge regarding cognitive development and personality formation, as all distribution parameters are found to be statistically different from zero. First, the findings suggest that parental traits significantly predict both fluid intelligence and personality traits in children, either genetically or through role modelling. Parental traits have a stronger impact on fluid intelligence than on personality traits, aligning with Briley and Tucker-Drob’s (2017) finding that shared environmental factors contribute more to cognitive ability variation than to personality trait variation.

Second, the results support the hypothesis that parenting style and parental time investments significantly influence variability in children’s fluid intelligence and personality traits. Positive parenting styles and increased parental time positively affect cognitive development and personality formation, highlighting the importance of shared environmental factors.

The estimated SES coefficient is close to one for both fluid intelligence and personality traits, suggesting that the effectiveness of parental inputs is the same across SES levels. In other words, for a given level of parental traits, parenting style, and parental time, the effect on child outcomes is similar regardless of whether the family has high or low SES background. We also test whether the SES parameter is statistically different from 1, and the results indicate it is not, further supporting that the estimated model effectively captures the most important aspects of parental inputs.

Additionally, the substitution parameters suggest that parental inputs are neither perfect substitutes nor perfect complements. However, for openness to experience and extraversion, the substitution parameter is statistically different from 0, with the elasticity of substitution is greater than 1 at the 10% level. This implies that the production function for fluid intelligence and the majority of the personality traits has a Cobb-Douglas form. This implies that a slight reduction in one parental input (e.g., time with children) could be compensated, though not perfectly, by enhancing another parental input (e.g., creating a more supportive atmosphere for learning) without negatively affecting the child's outcomes.

To interpret the magnitude of the parameters, Table 3.6 presents the average marginal effects, showing the effect of increasing factor inputs by one standard deviation on children's fluid intelligence and personality traits. The marginal effects suggest that the heritability of parental traits primarily affects fluid intelligence, extraversion, and emotional stability. Conscientiousness is equally influenced by parenting style and parental time, while traits such as openness to experience, extraversion, and agreeableness are more affected by parental time than by parenting style.

Figure 3.2 illustrates the marginal effects of a one standard deviation increase in parenting style and parental time investments on offspring's fluid intelligence and personality traits across different deciles of the respective parental traits. The findings

Table 3.6: Average Marginal Effects of the CES production function

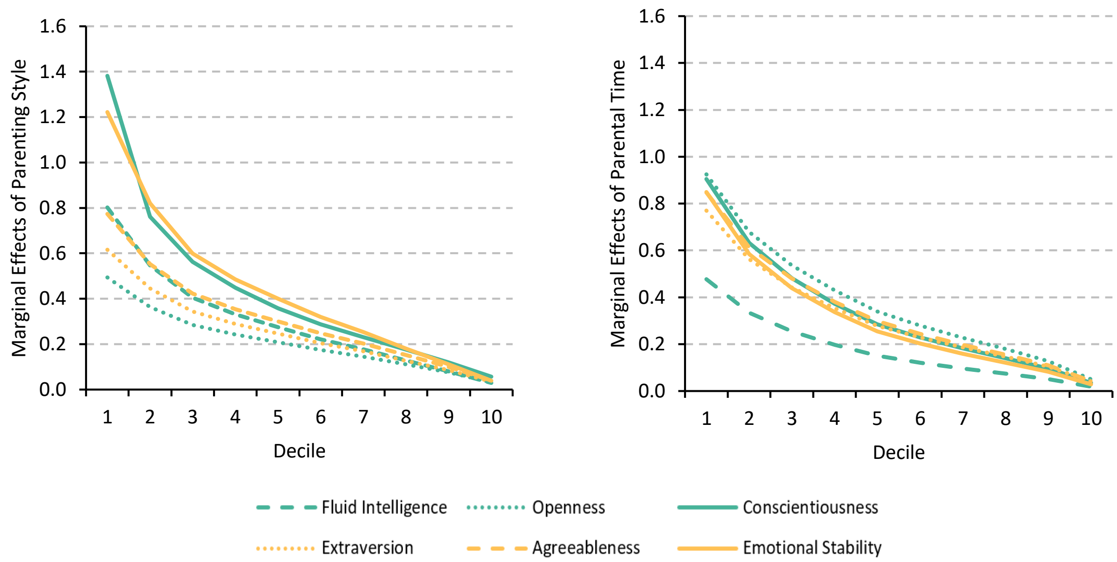
	FI	O	C	E	A	ES
AME: Parental Traits	.523***	.404***	.414***	.507***	.407***	.564***
	(.044)	(.041)	(.042)	(.051)	(.041)	(.064)
AME: Parenting Style	.399***	.287***	.508***	.343***	.421***	.594***
	(.056)	(.054)	(.075)	(.055)	(.072)	(.071)
AME: Parental Time	.246***	.519***	.467***	.431***	.464***	.428***
	(.048)	(.063)	(.062)	(.057)	(.054)	(.059)
N	1,040	1,040	1,040	1,040	1,040	1,040

*Notes: The reported standard errors (in parentheses) were bootstrapped using 1,000 bootstrap replications and clustered by family. Parental scores were then calculated using principal component analysis, combining the maternal and paternal scores into a single composite measure. Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.*

indicate that children from parents with lower scores in intelligence and personality traits benefit more from increased parental investments. For instance, the impact of parenting style and parental time on offspring's emotional stability is three times stronger in the third decile than in the eighth decile of parents' emotional stability scores. This supports the view that early, high-quality interventions benefit children from disadvantaged backgrounds the most (Elango *et al.*, 2015). Moreover, for some personality traits, the marginal effects of parental investments surpass those of fluid intelligence, particularly for traits like conscientiousness and emotional stability, when parents have low scores of fluid intelligence and personality traits.

It is important to note that endogeneity issues likely persist due to the estimation strategy, as the cross-sectional data did not allow for sufficient control of reverse causality. However, the close proximity of the productivity parameters to one indicates

Figure 3.2: Marginal effects on offspring fluid intelligence and personality traits, by decile of respective parents' fluid intelligence and personality traits



Notes: The marginal product of parenting style and involvement in the production function of skill of type k are given by: $\gamma_P P_i^{\phi-1}/\gamma_P P_i^{\phi}+\gamma_S S_i^{\phi}+\gamma_T T_i^{\phi}$ *and* $\gamma_S S_i^{\phi-1}/\gamma_P P_i^{\phi}+\gamma_S S_i^{\phi}+\gamma_T T_i^{\phi}$*. Parental scores were then calculated using principal component analysis, combining the maternal and paternal scores into a single composite measure.*

that the estimated production functions effectively account for the most important inputs. This suggests that incorporating parental satisfaction with family life has mitigated some of the endogeneity concerns.

Robustness Tests

Table 3.7 presents production function estimates without controlling for parental satisfaction with family life. The estimates remain largely stable, indicating no obvious bias. However, when parental satisfaction is included, the SES coefficient for fluid intelligence increases while it decreases for emotional stability, suggesting potential bias in the original SES parameter. This discrepancy may result from compensatory parental responses: higher SES families might focus on enhancing fluid intelligence, while lower SES families might compensate for emotional stability through other mechanisms not accounted for in the model.

Additionally, Equation (3.2) was re-estimated to examine if the SES parameter varies with occupation, as parents with higher social status might more effectively influence their children's personality traits. This was tested by replacing the SES parameter with the ESeC parameter, which accounts for disparities associated with top occupational classes. The ESeC parameter was set to one if the parents' top occupation was in the upper or lower salariat classes and zero otherwise. Parents who have never worked or are long-term unemployed were excluded from the analysis. The estimated productivity parameters are close to one in all cases, except for fluid intelligence (refer to Table 3.8). This suggests no significant differences in the efficiency of parental inputs to personality development across different parental occupations.

Table 3.7: Estimates of the CES production function for fluid intelligence and personality traits, without parental satisfaction

	FI	O	C	E	A	ES
Distribution Parameters						
Parental Traits	.578***	.386***	.346***	.422***	.361***	.357***
	(.043)	(.032)	(.034)	(.031)	(.032)	(.034)
Style	.239***	.212***	.326***	.249***	.293***	.359***
	(.032)	(.033)	(.032)	(.031)	(.032)	(.035)
Time	.183***	.402***	.327***	.329***	.347***	.284***
	(.026)	(.032)	(.032)	(.032)	(.032)	(.033)
Productivity Parameters						
SES	.638†	.968	.933	.981	.926	1.265†
	(.033)	(.054)	(.052)	(.052)	(.057)	(.080)
Substitution Parameters						
Substitution parameter	-.575***	.367**	.0224	.202	.229*	.303**
	(.158)	(.120)	(.107)	(.104)	(.113)	(.115)
Elasticity of substitution	.635†	1.580†	1.023	1.253	1.297	1.435†
	(.064)	(.299)	(.111)	(.163)	(.190)	(.238)

*Notes: The reported standard errors (in parentheses) were bootstrapped using 1,000 bootstrap replications clustered at family level. Parental scores were then calculated using principal component analysis, combining the maternal and paternal scores into a single composite measure. Significance at * p < 0.1, ** p < 0.05, *** p < 0.01. † Significantly different from one at the 10% level. SES, Parental Satisfaction, and Elasticity of Substitution parameters are tested for statistical difference from one.*

Furthermore, the productivity parameter might be influenced by parents' intelligence, as more knowledgeable parents can potentially foster better development in their children. To test this hypothesis, an additional parameter was introduced into the model alongside SES, assigning a value of one to parents with an intelligence score above the median and zero otherwise. The estimation results show that this additional parameter is close to and not significantly different from one in all cases except for intelligence. This suggests that there are no significant productivity differences between high and low IQ parents regarding their influence on personality traits.

Table 3.8: Estimates of the CES production function for fluid intelligence and personality traits, using ESeC as an indicator for SES

	FI	O	C	E	A	ES
Distribution Parameters						
Parental Traits	.567***	.389***	.359***	.426***	.384***	.365***
	(.037)	(.033)	(.036)	(.032)	(.035)	(.035)
Parenting Style	.249***	.206***	.295***	.252***	.277***	.360***
	(.033)	(.034)	(.034)	(.032)	(.034)	(.037)
Parental Time	.185***	.405***	.346***	.322***	.339***	.275***
	(.029)	(.032)	(.033)	(.032)	(.033)	(.035)
Productivity Parameters						
SES	.891†	.961	.909	1.024	.887	1.042
	(.057)	(.070)	(.069)	(.071)	(.072)	(.081)
Satisfaction	.940	1.004	.994	.990	1.003	1.032
	(.006)	(.008)	(.009)	(.008)	(.009)	(.009)
Substitution Parameters						
Substitution parameter	.102	.312*	.122	.341*	.210	.0476
	(.143)	(.143)	(.156)	(.134)	(.147)	(.133)
Elasticity of substitution	1.113	1.453	1.139	1.517	1.266	1.050
	(.177)	(.301)	(.202)	(.308)	(.235)	(.147)
N	913	913	913	913	913	913

*Notes: The reported standard errors (in parentheses) were bootstrapped using 1,000 bootstrap replications and clustered by family. Parental scores were then calculated using principal component analysis, combining the maternal and paternal scores into a single composite measure. Significance at * p < 0.1, ** p < 0.05, *** p < 0.01. † Significantly different from one at the 10% level. SES, Parental Satisfaction, and Elasticity of Substitution parameters are tested for statistical difference from one.*

Finally, two additional robustness tests were conducted by dividing the sample into MZ (monozygotic) and DZ (dizygotic) twins. MZ twins are genetically identical, while DZ twins share an average of 50% of their genetic makeup. The within-twins fixed-effects technique, extensively used in empirical research, controls for genetic endowment to examine the effect of environmental factors on social and economic outcomes.[20] However, if the within-twins difference does not completely eliminate all unobserved heterogeneity, it may exacerbate bias caused by omitted variables. Additionally, the

[20] The differences between twins would account for genetic and other unobserved confounders if the twins have similar family background and have the same genes. The drawback of this strategy is that it loses efficiency by relying on variables that do not change sufficiently within the family. Loss of efficiency can provide extremely unreliable point estimates as well as greater standard errors, which, like biased estimators, can produce incorrect inferences.

influence of SES cannot be estimated within families, as it remains constant across family members.

To address these concerns, a sensitivity analysis of the production function estimates was conducted to assess stability and robustness across MZ and DZ twin families. If the bias from omitted variables explained by genes is substantial, the results are expected to be unstable and unreliable. However, the estimated parameters remained largely consistent with the major specification estimations, suggesting the robustness of the findings. Specifically, when considering only DZ twin families, the distribution parameters remain broadly consistent with the main results. However, the SES parameters for fluid intelligence, openness to experience, and emotional stability are statistically significantly different from 1, at the 10% level, except for openness to experience, which is significant at the 5% level (refer to Appendix A). This suggests that factors beyond the identified parental inputs may contribute to the differences in children's outcomes between high and low SES families. As a result, excluding MZ twin pairs could exacerbate endogeneity issues due to unobserved genetic factors.

3.6 CONCLUSION

This study extends previous research on economic preferences by Falk et al. (2021), and, in contrast to other studies, it emphasises how individual personality characteristics depend on biological and familial contextual factors. Unlike one-dimensional noncognitive measures, which lack a clear definition in personality psychology, this study focuses on the Big Five traits and compares the results with fluid intelligence. The findings support the hypothesis that family socioeconomic background influences offspring's fluid intelligence and personality traits. As might be expected, children from high SES families score higher in fluid intelligence, emotional stability, and extraversion. However, the SES gaps in personality traits are smaller than those for fluid intelligence, suggesting that these traits are influenced by factors beyond genetics, aligning with the social investment principle (Roberts and Wood, 2006; Roberts and Damian, 2019; Roberts and Nickel, 2021). Additionally, the study reveals that low parental education negatively impacts parental time investments, contributing to differences in fluid intelligence and personality traits across children from varying socioeconomic backgrounds.

Despite higher SES families having more resources, there is no evidence that investment productivity differs across socioeconomic classes. Parental characteristics and investments are equally effective for both high and low SES backgrounds in developing personality traits. This suggests that children from low SES families could develop similar personality traits to those from high SES families if given the same parental investments.

The productivity parameter estimates do not significantly depend on whether investments are considered endogenous, except in two cases. Ignoring endogeneity results in a downward bias in the productivity parameter for fluid intelligence, indicating reinforcing parental responses to intelligence among high SES parents. In contrast, the productive parameter for emotional stability is biased upward, indicating that families with low SES tend to have compensatory parental responses to this trait.

The findings have significant implications for the development of children’s cognitive skills and personality traits. Parents from low socioeconomic backgrounds often have lower levels of fluid intelligence and emotional stability, which they may pass on to their children, perpetuating cycles of disadvantage. Moreover, children from high SES families benefit from more parental time and resources, while those from low SES families face greater time and financial constraints, with limited access to social capital. These disparities contribute to the persistence of intergenerational immobility.

The intergenerational immobility opens the debate on how best to close SES gaps in fluid intelligence and personality development. Given that parental SES is very unlikely to change, children born into low-income families are unlikely to do better than their parents. In addition, changes in SES may be too slow to produce significant changes in the lives of children. Social interventions that encourage parental investments are crucial for the child's development. Closing SES gaps necessitates policy efforts that enhance early childhood development and support parents from low socioeconomic backgrounds in raising their children. To name a few, programs that invest in children's cognitive and noncognitive skills, such as the General Educational Development (GED) Program (Heckman and Rubinstein, 2001), the Perry Preschoolers Program (Heckman, Stixrud and Urzua, 2006), the Jamaican Study (Gertler *et al.*, 2014) and the Columbia study (Attanasio *et al.*, 2020), have been shown to be effective in reducing gap in outcomes. In certain contexts, particularly at a young age, investing in personality traits such as conscientiousness, the trait most relevant to academic achievement, and openness to experience, the trait most associated with cognitive function, and emotional stability, offers a promising avenue to help children from disadvantaged backgrounds overcome or at least counteract the associated negative effects originating from low SES.

Future studies are needed to understand the role effects of SES. First, studies can look at the relationship between SES and personality traits from a young age to adulthood to see if the estimated production function parameters are likely to change over the course of the person's life. Second, longitudinal data models can be better used to account for endogenous effects when estimating the contribution of parental investments to the development of fluid intelligence and personality traits. Third, additional research is required to determine whether the findings are generally replicable across different samples.

REFERENCES

Agostinelli, F. and Sorrenti, G. (2022) ‘Money vs. Time: Family Income, Maternal Labor Supply, and Child Development’, *HCEO* [Preprint]. Available at: https://ideas.repec.org//p/hka/wpaper/2018-017.html (Accessed: 12 March 2024).

Alderotti, G., Rapallini, C. and Traverso, S. (2023) ‘The Big Five personality traits and earnings: A meta-analysis’, *Journal of Economic Psychology*, 94, p. 102570. Available at: https://doi.org/10.1016/j.joep.2022.102570.

Almlund, M. *et al.* (2011) ‘Personality Psychology and Economics’, in E.A. Hanushek, S. Machin, and L. Woessmann (eds) *Handbook of the Economics of Education*. Elsevier (Handbook of The Economics of Education), pp. 1–181. Available at: https://doi.org/10.1016/B978-0-444-53444-6.00001-8.

Attanasio, O. *et al.* (2020) ‘Estimating the Production Function for Human Capital: Results from a Randomized Controlled Trial in Colombia’, *American Economic Review*, 110(1), pp. 48–85. Available at: https://doi.org/10.1257/aer.20150183.

Ayoub, M. *et al.* (2018) ‘The Relations Between Parental Socioeconomic Status, Personality, and Life Outcomes’, *Social Psychological and Personality Science*, 9(3), pp. 338–352. Available at: https://doi.org/10.1177/1948550617707018.

Ayoub, M. *et al.* (2019) ‘Genetic and Environmental Associations Between Child Personality and Parenting’, *Social Psychological and Personality Science*, 10(6), pp. 711–721. Available at: https://doi.org/10.1177/1948550618784890.

Barrick, M.R., Mount, M.K. and Judge, T.A. (2001) ‘Personality and Performance at the Beginning of the New Millennium: What Do We Know and Where Do We Go Next?’, *International Journal of Selection and Assessment*, 9(1–2), pp. 9–30. Available at: https://doi.org/10.1111/1468-2389.00160.

Baum, A., Garofalo, J.P. and Yali, A.M. (1999) ‘Socioeconomic Status and Chronic Stress: Does Stress Account for SES Effects on Health?’, *Annals of the New York Academy of Sciences*, 896(1), pp. 131–144. Available at: https://doi.org/10.1111/j.1749-6632.1999.tb08111.x.

Bell, S.T. (2007) ‘Deep-level composition variables as predictors of team performance: A meta-analysis’, *Journal of Applied Psychology*, 92(3), pp. 595–615. Available at: https://doi.org/10.1037/0021-9010.92.3.595.

Bernal, R. and Keane, M.P. (2011) ‘Child Care Choices and Children’s Cognitive Achievement: The Case of Single Mothers’, *Journal of Labor Economics*, 29(3), pp. 459–512. Available at: https://doi.org/10.1086/659343.

Bono, E.D. *et al.* (2016) ‘Early Maternal Time Investment and Early Child Outcomes’, *The Economic Journal*, 126(596), pp. F96–F135. Available at: https://doi.org/10.1111/ecoj.12342.

Bradley, R.H. and Corwyn, R.F. (2002) 'Socioeconomic Status and Child Development', *Annual Review of Psychology*, 53(1), pp. 371–399. Available at: https://doi.org/10.1146/annurev.psych.53.100901.135233.

Bradley, R.H. and Whiteside-Mansell, L. (1997) 'Children in poverty', in *Handbook of prevention and treatment with children and adolescents: Intervention in the real world context*. Hoboken, NJ, US: John Wiley & Sons, Inc., pp. 13–58.

Briley, D.A. and Tucker-Drob, E.M. (2017) 'Comparing the Developmental Genetics of Cognition and Personality over the Life Span', *Journal of Personality*, 85(1), pp. 51–64. Available at: https://doi.org/10.1111/jopy.12186.

Caldwell, D.F. and Burger, J.M. (1998) 'Personality Characteristics of Job Applicants and Success in Screening Interviews', *Personnel Psychology*, 51(1), pp. 119–136. Available at: https://doi.org/10.1111/j.1744-6570.1998.tb00718.x.

Carlsson, M. *et al.* (2015) 'The Effect of Schooling on Cognitive Skills', *Review of Economics and Statistics*, 97(3), pp. 533–547. Available at: https://doi.org/10.1162/REST_a_00501.

Carneiro, P., Hansen, K.T. and Heckman, J.J. (2003) 'Estimating Distributions of Treatment Effects with an Application to the Returns to Schooling and Measurement of the Effects of Uncertainty on College Choice', *International Economic Review*, 44(2), pp. 361–422.

Chi, N.-W. *et al.* (2011) 'Want a tip? Service performance as a function of emotion regulation and extraversion', *Journal of Applied Psychology*, 96(6), pp. 1337–1346. Available at: https://doi.org/10.1037/a0022884.

Cliffordson, C. and Gustafsson, J.-E. (2008) 'Effects of age and schooling on intellectual performance: Estimates obtained from analysis of continuous variation in age and length of schooling', *Intelligence*, 36(2), pp. 143–152. Available at: https://doi.org/10.1016/j.intell.2007.03.006.

Conger, R.D., Martin, M.J. and Masarik, A.S. (2021) 'Dynamic associations among socioeconomic status (SES), parenting investments, and conscientiousness across time and generations', *Developmental Psychology*, 57(2), pp. 147–163. Available at: https://doi.org/10.1037/dev0000463.

Cunha, F. *et al.* (2006) 'Chapter 12 Interpreting the Evidence on Life Cycle Skill Formation', in E. Hanushek and F. Welch (eds) *Handbook of the Economics of Education*. Elsevier, pp. 697–812. Available at: https://doi.org/10.1016/S1574-0692(06)01012-9.

Cunha, F., Heckman, J.J. and Schennach, S.M. (2010) 'Estimating the Technology of Cognitive and Noncognitive Skill Formation', *Econometrica*, 78(3), pp. 883–931. Available at: https://doi.org/10.3982/ECTA6551.

Damian, R.I. *et al.* (2015) 'Can personality traits and intelligence compensate for background disadvantage? Predicting status attainment in adulthood', *Journal of Personality and Social Psychology*, 109(3), pp. 473–489. Available at: https://doi.org/10.1037/pspp0000024.

Deckers, T. *et al.* (2015) ‘How Does Socio-Economic Status Shape a Child’s Personality?’, *IZA Discussion Paper Series* [Preprint]. Available at: https://doi.org/10.2139/ssrn.2598917.

Dehne, M. and Schupp, J. (2007) ‘Persönlichkeitsmerkmale im Sozio-oekonomischen Panel (SOEP)–Konzept, Umsetzung und empirische Eigenschaften’, *DIW Research Notes*, 26.

Demange, P.A. *et al.* (2021) ‘Investigating the genetic architecture of noncognitive skills using GWAS-by-subtraction’, *Nature Genetics*, 53(1), pp. 35–44. Available at: https://doi.org/10.1038/s41588-020-00754-2.

DeYoung, C.G. (2015) ‘Openness/intellect: A dimension of personality reflecting cognitive exploration’, in *APA handbook of personality and social psychology, Volume 4: Personality processes and individual differences*. Washington, DC, US: American Psychological Association (APA handbooks in psychology®), pp. 369–399. Available at: https://doi.org/10.1037/14343-017.

DeYoung, C.G. (2020) ‘Intelligence and personality’, in *The Cambridge handbook of intelligence, 2nd ed*. New York, NY, US: Cambridge University Press, pp. 1011–1047. Available at: https://doi.org/10.1017/9781108770422.043.

Diewald, M. *et al.* (2021) ‘TwinLife’. [Research data]. Available at: https://doi.org/10.4232/1.13747.

Donnellan, M.B. and Lucas, R.E. (2008) ‘Age differences in the big five across the life span: Evidence from two national samples’, *Psychology and Aging*, 23(3), pp. 558–566. Available at: https://doi.org/10.1037/a0012897.

Elango, S. *et al.* (2015) *Early Childhood Education*. w21766. Cambridge, MA: National Bureau of Economic Research, p. w21766. Available at: https://doi.org/10.3386/w21766.

Falk, A. *et al.* (2021) ‘Socioeconomic Status and Inequalities in Children’s IQ and Economic Preferences’, *Journal of Political Economy*, 129(9), pp. 2504–2545. Available at: https://doi.org/10.1086/714992.

Francesconi, M. and Heckman, J.J. (2016) ‘Child Development and Parental Investment: Introduction’, *The Economic Journal*, 126(596), pp. F1–F27. Available at: https://doi.org/10.1111/ecoj.12388.

Gagne, P. and Hancock, G.R. (2006) ‘Measurement Model Quality, Sample Size, and Solution Propriety in Confirmatory Factor Models’, *Multivariate Behavioral Research*, 41(1), pp. 65–83. Available at: https://doi.org/10.1207/s15327906mbr4101_5.

Gerlitz, J.-Y. and Schupp, J. (2005) ‘Zur Erhebung der Big-Five-basierten Persönlichkeitsmerkmale im SOEP’, *DIW Research Notes*, 4.

Gertler, P. *et al.* (2014) ‘Labor market returns to an early childhood stimulation intervention in Jamaica’, *Science*, 344(6187), pp. 998–1001. Available at: https://doi.org/10.1126/science.1251178.

Gottschling, J. (2017) ‘Documentation TwinLife Data: Cognitive Abilities’, (TwinLife Technical Report Series).

Hahn, E. *et al.* (2016) ‘What Drives the Development of Social Inequality Over the Life Course? The German TwinLife Study’, *Twin Research and Human Genetics: The Official Journal of the International Society for Twin Studies*, 19(6), pp. 659–672. Available at: https://doi.org/10.1017/thg.2016.76.

Hahn, E., Gottschling, J. and Spinath, F.M. (2012) ‘Short measurements of personality—Validity and reliability of the GSOEP Big Five Inventory (BFI-S)’, *Journal of Research in Personality*, 46(3), pp. 355–359. Available at: https://doi.org/10.1016/j.jrp.2012.03.008.

Heckman, J., Pinto, R. and Savelyev, P. (2013) ‘Understanding the Mechanisms through Which an Influential Early Childhood Program Boosted Adult Outcomes’, *American Economic Review*, 103(6), pp. 2052–2086. Available at: https://doi.org/10.1257/aer.103.6.2052.

Heckman, J.J. and Rubinstein, Y. (2001) ‘The Importance of Noncognitive Skills: Lessons from the GED Testing Program’, *American Economic Review*, 91(2), pp. 145–149. Available at: https://doi.org/10.1257/aer.91.2.145.

Heckman, J.J., Stixrud, J. and Urzua, S. (2006) ‘The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior’, *Journal of Labor Economics*, 24(3), pp. 411–482. Available at: https://doi.org/10.1086/504455.

Horn, J.L. and Cattell, R.B. (1966) ‘Refinement and test of the theory of fluid and crystallized general intelligences’, *Journal of Educational Psychology*, 57(5), pp. 253–270. Available at: https://doi.org/10.1037/h0023816.

Hughes, B.T. *et al.* (2021) ‘The Big Five Across Socioeconomic Status: Measurement Invariance, Relationships, and Age Trends’, *Collabra: Psychology*, 7(1), p. 24431. Available at: https://doi.org/10.1525/collabra.24431.

Huinink, J. *et al.* (2011) ‘Panel analysis of intimate relationships and family dynamics (pairfam): conceptual framework and design’, *Zeitschrift für Familienforschung*, 23(1), pp. 77–101.

Judge, T.A., Heller, D. and Mount, M.K. (2002) ‘Five-factor model of personality and job satisfaction: A meta-analysis’, *Journal of Applied Psychology*, 87(3), pp. 530–541. Available at: https://doi.org/10.1037/0021-9010.87.3.530.

Kalil, A. (2015) ‘Inequality begins at home: The role of parenting in the diverging destinies of rich and poor children’, in *Families in an era of increasing inequality: Diverging destinies*. Cham, Switzerland: Springer International Publishing/Springer Nature (National symposium on family issues), pp. 63–82. Available at: https://doi.org/10.1007/978-3-319-08308-7_5.

Lang, F. *et al.* (2011) ‘Short assessment of the Big Five: Robust across survey methods except telephone interviewing’, *Behavior research methods*, 43, pp. 548–67. Available at: https://doi.org/10.3758/s13428-011-0066-z.

Lang, V. and Kottwitz, A. (2020) 'The Socio-demographic Structure of the First Wave of the TwinLife Panel Study: A Comparison with the Microcensus', *methods, data, analyses*, 14(1), p. 28. Available at: https://doi.org/10.12758/mda.2020.02.

Lechner, C.M. *et al.* (2021) 'Two Forms of Social Inequality in Students' Socio-Emotional Skills: Do the Levels of Big Five Personality Traits and Their Associations With Academic Achievement Depend on Parental Socioeconomic Status?', *Frontiers in Psychology*, 12. Available at: https://doi.org/10.3389/fpsyg.2021.679438.

Lepine, J.A., Colquitt, J.A. and Erez, A. (2000) 'Adaptability to Changing Task Contexts: Effects of General Cognitive Ability, Conscientiousness, and Openness to Experience', *Personnel Psychology*, 53(3), pp. 563–593. Available at: https://doi.org/10.1111/j.1744-6570.2000.tb00214.x.

Lucas, R.E. and Donnellan, M.B. (2009) 'Age differences in personality: Evidence from a nationally representative Australian sample', *Developmental Psychology*, 45(5), pp. 1353–1363. Available at: https://doi.org/10.1037/a0013914.

Luo, J. *et al.* (2024) 'The effects of socioeconomic status on personality development in adulthood and aging', *Journal of Personality*, 92(1), pp. 243–260. Available at: https://doi.org/10.1111/jopy.12801.

Luo, Y. and Waite, L.J. (2005) 'The impact of childhood and adult SES on physical, mental, and cognitive well-being in later life', *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, 60(2), pp. S93–S101. Available at: https://doi.org/10.1093/geronb/60.2.s93.

McCrae, R.R. and Costa, P.T. (1985) 'Updating Norman's "adequacy taxonomy": Intelligence and personality dimensions in natural language and in questionnaires', *Journal of Personality and Social Psychology*, 49(3), pp. 710–721. Available at: https://doi.org/10.1037/0022-3514.49.3.710.

Mönkediek, B. *et al.* (2019) 'The German Twin Family Panel (TwinLife)', *Twin Research and Human Genetics: The Official Journal of the International Society for Twin Studies*, 22(6), pp. 540–547. Available at: https://doi.org/10.1017/thg.2019.63.

Mullineaux, P.Y. *et al.* (2009) 'Parenting and child behaviour problems: a longitudinal analysis of non-shared environment', *Infant and Child Development*, 18(2), pp. 133–148. Available at: https://doi.org/10.1002/icd.593.

de Neubourg, E. *et al.* (2018) 'Explaining Children's Life Outcomes: Parental Socioeconomic Status, Intelligence and Neurocognitive Factors in a Dynamic Life Cycle Model', *Child Indicators Research*, 11(5), pp. 1495–1513. Available at: https://doi.org/10.1007/s12187-017-9481-8.

Nyhus, E.K. and Pons, E. (2005) 'The effects of personality on earnings', *Journal of Economic Psychology*, 26(3), pp. 363–384. Available at: https://doi.org/10.1016/j.joep.2004.07.001.

Ones, D.S. *et al.* (2007) 'In Support of Personality Assessment in Organizational Settings', *Personnel Psychology*, 60(4), pp. 995–1027. Available at: https://doi.org/10.1111/j.1744-6570.2007.00099.x.

Peeters, M.A.G. *et al.* (2006) ‘Personality and team performance: a meta-analysis’, *European Journal of Personality*, 20(5), pp. 377–396. Available at: https://doi.org/10.1002/per.588.

Rammstedt, B. and John, O.P. (2007) ‘Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German’, *Journal of Research in Personality*, 41(1), pp. 203–212. Available at: https://doi.org/10.1016/j.jrp.2006.02.001.

Rindermann, H., Flores-Mendoza, C. and Mansur-Alves, M. (2010) ‘Reciprocal effects between fluid and crystallized intelligence and their dependence on parents’ socioeconomic status and education’, *Learning and Individual Differences*, 20(5), pp. 544–548. Available at: https://doi.org/10.1016/j.lindif.2010.07.002.

Roberts, B.W. (2009) ‘Back to the future: Personality and Assessment and personality development’, *Journal of Research in Personality*, 43(2), pp. 137–145. Available at: https://doi.org/10.1016/j.jrp.2008.12.015.

Roberts, B.W. and Damian, R.I. (2019) ‘The Principles of Personality Trait Development and Their Relation to Psychopathology’, in Roberts, B. W. and Damian, R. I., *Using Basic Personality Research to Inform Personality Pathology*. Edited by D. B. Samuel and D. R. Lynam. Oxford University Press, pp. 153–168. Available at: https://doi.org/10.1093/med-psych/9780190227074.003.0007.

Roberts, B.W. and Nickel, L.B. (2021) ‘Personality development across the life course: A neo-socioanalytic perspective’, in *Handbook of personality: Theory and research, 4th ed*. New York, NY, US: The Guilford Press, pp. 259–283.

Roberts, B.W. and Wood, D. (2006) ‘Personality Development in the Context of the Neo-Socioanalytic Model of Personality’, in *Handbook of personality development*. Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers, pp. 11–39.

Rose, D. (2005) ‘Socio-economic classifications: classes and scales, measurement and theories’, in *First Conference of the European Survey Research Association, Pompeu Fabra University, Barcelona*, pp. 18–22.

Rose, D. and Harrison, E. (2007) ‘The European Socio-Economic Classification: A New Social Class Schema for Comparative European Research’, *European Societies*, 9(3), pp. 459–490. Available at: https://doi.org/10.1080/14616690701336518.

Salgado, J.F. *et al.* (2003) ‘International Validity Generalization of Gma and Cognitive Abilities: A European Community Meta-Analysis’, *Personnel Psychology*, 56(3), pp. 573–605. Available at: https://doi.org/10.1111/j.1744-6570.2003.tb00751.x.

Schaub, M. (2010) ‘Parenting for cognitive development from 1950 to 2000: The institutionalization of mass education and the social construction of parenting in the United States’, *Sociology of Education*, 83(1), pp. 46–66. Available at: https://doi.org/10.1177/0038040709356566.

Schneider, D., Hastings, O.P. and LaBriola, J. (2018) 'Income inequality and class divides in parental investments', *American Sociological Review*, 83(3), pp. 475–507. Available at: https://doi.org/10.1177/0003122418772034.

Shanahan, M.J. *et al.* (2014) 'Personality and the Reproduction of Social Class', *Social Forces*, 93(1), pp. 209–240. Available at: https://doi.org/10.1093/sf/sou050.

Sutin, A.R. *et al.* (2017) 'Parental Educational Attainment and Adult Offspring Personality: An Intergenerational Lifespan Approach to the Origin of Adult Personality Traits', *Journal of personality and social psychology*, 113(1), pp. 144–166. Available at: https://doi.org/10.1037/pspp0000137.

Taylor, M., Brice, J. and Buck, N. (2001) *British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices*. Colchester: University of Essex.

Vella, M. (2024) 'The relationship between the Big Five personality traits and earnings: Evidence from a meta-analysis', *Bulletin of Economic Research*, n/a(n/a). Available at: https://doi.org/10.1111/boer.12437.

Weiß, von R.H. (2006) *CFT 20-R mit WS/ZF-R - Grundintelligenztest Skala 2 – Revision (CFT 20-R) mit Wortschatztest (WS) und Zahlenfolgentest (ZF) – Revision (WS/ZF-R) | Testzentrale*. Germany: Hogrefe Verlag. Available at: https://www.testzentrale.de/shop/grundintelligenztest-skala-2-revision-cft-20-r-mit-wortschatztest-ws-und-zahlenfolgentest-zf-revision-ws-zf-r-90116.html (Accessed: 12 March 2024).

Weiß, von R.H. and Osterland, J. (2012) *CFT 1-R - Grundintelligenztest Skala 1 | Testzentrale*. Germany: Hogrefe Verlag. Available at: https://www.testzentrale.de/shop/grundintelligenztest-skala-1-44125.html (Accessed: 12 March 2024).

Wells, R., Ham, R. and Junankar, P.N. (Raja) (2016) 'An examination of personality in occupational outcomes: antagonistic managers, careless workers and extraverted salespeople', *Applied Economics*, 48(7), pp. 636–651. Available at: https://doi.org/10.1080/00036846.2015.1085636.

Wichert, L. and Pohlmeier, W. (2010) 'Female labor force participation and the big five', *ZEW Discussion Papers* [Preprint]. Available at: https://ideas.repec.org//p/zbw/zewdip/10003.html (Accessed: 9 March 2024).

Winkelmann, L. and Winkelmann, R. (2008) 'Personality, work, and satisfaction: evidence from the German Socio-Economic Panel', *The Journal of Positive Psychology*, 3(4), pp. 266–275. Available at: https://doi.org/10.1080/17439760802399232.

de Zeeuw, E.L. *et al.* (2019) 'The moderating role of SES on genetic differences in educational achievement in the Netherlands', *npj Science of Learning*, 4(1), pp. 1–8. Available at: https://doi.org/10.1038/s41539-019-0052-2.

Zeigler-Hill, V. *et al.* (2015) 'Would you like fries with that? The roles of servers' personality traits and job performance in the tipping behavior of customers', *Journal of Research in Personality*, 57, pp. 110–118. Available at: https://doi.org/10.1016/j.jrp.2015.05.001.

APPENDIX A

Measures of Personality Traits, Fluid Intelligence and Parenting Style

Sections A.1 and A.2 contain detailed information on each of the instruments used to measure fluid intelligence and personality traits. Section A.3 describes the procedure used to measure the standardised measure of parenting style.

A.1 Measures of personality traits

The Big Five Inventory (BFI) model is commonly used framework for describing the structure of the personality traits. According to the BFI, personality traits can be described by five different dimensions: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (McCrae and Costa, 1985). The Big Five traits have been widely used in other surveys, including the BHPS (Taylor, Brice and Buck, 2001) and the HILDA study (Lucas and Donnellan, 2009).

Despite the fact that psychologists typically use longer questionnaires, shorter versions of the Big Five traits, such as 15-item or even shorter versions of personality questionnaires, have gained popularity in recent years. Despite their brevity, these shorter versions of the Big Five traits have shown to retain a high level of validity and reliability. Indeed, the BFI-S has been validated against longer inventories (Dehne and Schupp, 2007; Donnellan and Lucas, 2008; Winkelmann and Winkelmann, 2008). A potential drawback of using shortened inventories is that they may compromise the richness of the Big Five constructs, reducing their usefulness in factor modelling. In fact, three items per construct are thought to be the bare minimum for factor analysis to find a common factor (Gagne and Hancock, 2006).

The first wave of TwinLife contains self-reported items to measure the Big Five personality traits. The TwinLife survey adopts the 15-item Big Five Inventory (BFI-S) (Hahn, Gottschling and Spinath, 2012) developed for the German SOEP study, with a 7-item Likert scale (1 ‘does not apply to me at all’ to 7 ‘applies to me perfectly’). It is recognised that BFI-S retains a considerable level of validity and reliability (Gerlitz and Schupp, 2005; Dehne and Schupp, 2007; Rammstedt and John, 2007) across different assessment methods for young and middle-aged individuals (Lang *et al.*, 2011).

Table A.1: BFI-S Items, pre-selected set of items

Openness	*per0103*	*. . . is original, comes up with new ideas.*	
	per0108	*. . . is artistic, values aesthetic experiences.*	
	per0113	*. . . has a lively imagination, perception.*	
	per0115	*. . . is eager to learn.*	
Conscientiousness	*per0100*	*. . . does a thorough job.*	
	per0106	*. . . tends to be lazy.*	*R*
	per0110	*. . . does things efficiently and efficiently.*	
Extraversion	*per0101*	*. . . is communicative, is talkative.*	
	per0107	*. . . is outgoing, sociable.*	
	per0111	*. . . is reserved.*	*R*
Agreeableness	*per0102*	*. . . is sometimes somewhat rude to others.*	*R*
	per0105	*. . . can forgive.*	
	per0112	*. . . is considerate and kind to others.*	
Neuroticism	*per0104*	*. . . worries a lot.*	
	per0109	*. . . gets nervous easily.*	
	per0114	*. . . is relaxed, handles stress well.*	*R*

Table A.1 presents the items used for the BFI-S scale ratings, with “R” indicating reversed items. Four negatively phrased items were reverse-coded prior to factor analysis to reduce acquiescence bias – the tendency of respondents to consistently agree or disagree with survey items regardless of their content.

To calculate personality scale scores for each individual in the sample, most studies in the economics literature rely on either the mean or total score of preselected item sets. While these methods are widely accepted, there are notable advantages to using simple factor analysis. First, the mean and summation approaches assume that all items contribute equally to the underlying personality construct, known as the *tau-equivalent condition*. However, when this assumption does not hold, factor scores from factor analysis provide more accurate measures, as they relax the equal-loading constraint.

Factor analysis decomposes observed survey items into two components: a common factor, representing the true underlying construct, and a unique error term, capturing measurement error. This method assigns different weights to each item based on their interrelations, offering a more nuanced understanding of the personality traits.

Table A.2 displays the correlation matrices for the 15 items, with larger values highlighted in bold. These bold values suggest five distinct construct groups: {per0103, per0108, per0113}, {per0100, per0106, per0110}, {per0101, per0107, per0111}, {per0102, per0105, per0112}, and {per0104, per0109, per0114}. For each of these groups, a unique factor score can be expected, reflecting the commonality among the items within each set. This factor score represents the underlying personality trait.

Table A.2 Correlation Table

	per0103	per0108	per0113	per0100	per0106	per0110	per0101	per0107	per0111	per0102	per0105	per0112	per0104	per0109	per0114
per0103	1														
per0108	**.27***	1													
per0113	**.32***	**.29***	1												
per0100	.18*	.09*	.01	1											
per0106	.05*	.08*	-.02	**.28***	1										
per0110	.23*	.09*	.04*	**.48***	**.21***	1									
per0101	.32*	.12*	.20*	.13*	.05*	.14*	1								
per0107	.31*	.15*	.18*	.07*	-.01	.14*	**.48***	1							
per0111	.10*	-.03*	.01	-.08*	.04*	-.07*	**.35***	**.26***	1						
per0102	-.11*	.05*	-.02	.08*	.19*	.07*	-.09*	-.02	-.05*	1					
per0105	.12*	.13*	.12*	.13*	.04*	.17*	.13*	.17*	-.06*	**.10***	1				
per0112	.16*	.12*	.15*	.28*	.14*	.26*	.12*	.18*	-.11*	**.27***	**.30***	1			
per0104	.08*	.07*	.07*	.09*	-.08*	.07*	.04*	.03*	-.18*	-.09*	.07*	.14*	1		
per0109	-.03*	.07*	.04*	.02	-.13*	-.01	-.05*	-.07*	-.26*	-.08*	.01	.05*	**.37***	1	
per0114	-.18*	-.06*	-.15*	-.13*	-.05*	-.23*	-.12*	-.17*	-.03	-.01	-.14*	-.11*	**.16***	**.22***	1

Consider a set of m survey items $j = 1, \ldots, m$ each with scores $x_1, \ldots x_m$ and pairwise covariances σ_{jk} in the population of interest. Assuming that these survey items share a common factor, such as a personality trait, each item score can be expressed as:

$$P_j = T + E_j, \tag{A.1}$$

where T represents the common attribute across items (the true underlying construct), and E_j are the unique components specific to each item. For this study, the appropriate model using cross-sectional data and a common factor for a pre-selected set of items is:

$$x_j = \mu_j + \lambda_j f + e_j, \tag{A.2}$$

Here, x_j is the score for the jth item, f represents the common factor part, and e_j captures the unique error components. The factor loadings λ_j are the correlation coefficients between each observed item and the latent factor. Larger values of λ_j indicate a stronger relationship between the item and the factor. By definition, the unique component e_j is uncorrelated with the common factor f, and all unique components are independent of each other. The scale of f is standardised with mean of zero and variance of one.

Since the covariance between f and e_j is zero, the implied covariance of two item scores x_j and x_k is the product of their factor loadings:

$$\sigma_{jk} = \lambda_j \lambda_k.$$

The variance σ_{jj} of the jth item is expressed as:

$$\sigma_{jj} = \lambda_j^2 + \psi_j^2,$$

where σ_{jj} is the sum of the squared loading λ_j^2 (known as communality, h_j^2) and the unique variance ψ_j^2. The parameters λ_j and Ψ_i are the parameters to be estimated from the model. The square loadings represent the correlations of the survey items with the factor, indicating the proportion of variance due to communality in standardised variables.

Before conducting the factor analysis on the survey items, we calculated the omega measure of sampling adequacy and performed Bartlett's test of sphericity, both of which supported the factorability of the personality data at the 5% significance level.[21] The ratios were as follows: ω=0.79 (openness to experience), ω=0.84 (conscientiousness), ω=0.89 (extraversion), ω=0.77 (agreeableness), and ω=0.80 (neuroticism). Based on these results, an Exploratory Factor Analysis (EFA) was applied to reduce the multiple items into common factors. The EFA was conducted

[21] The omega measure of sample adequacy indicates the proportion of variance in items that could be caused by underlying factors. High scores (close to 1.0) generally indicate that factor analysis on the data may be useful. A value below 0.50 indicates that factor analysis may not produce useful results. Bartlett's test of sphericity tests the hypothesis that the correlation matrix is an identity matrix, which would suggest that the items are unrelated and therefore unsuitable for factor analysis. Small values (less than 0.05) of the significance level indicate that a factor analysis on the data may be useful.

using principal factor components and Bartlett scores, with the results presented in Tables A.3–A.7.

Table A.3: The factor loadings for Openness to Experience

	Children			Parents		
Variable	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j
per0103	.74	.54	.46	.74	.55	.45
per0108	.68	.46	.54	.69	.48	.52
per0113	.72	.52	.48	.74	.55	.45
per0115	.67	.44	.56	.65	.42	.58
Variance accounted for	1.964	1.964		2.012	2.012	
Proportion of total variance	.491	.491		.503	.503	
Cumulative proportion	.491			.503		

Table A.4: The factor loadings for Conscientiousness

	Children			Parents		
Variable	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j
per0100	.84	.70	.30	.86	.73	.27
per0106	.63	.40	.60	.70	.50	.50
per0110	.81	.65	.35	.81	.66	.34
Variance accounted for	1.759	1.759		1.885	1.885	
Proportion of total variance	.586	.586		.628	.628	
Cumulative proportion	.586			.628		

Table A.5: The factor loadings for Extraversion

	Children			Parents		
Variable	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j
per0101	.84	.71	.29	.85	.73	.27
per0107	.79	.63	.37	.83	.69	.31
per0111	.69	.47	.53	.72	.52	.48
Variance accounted for	1.817	1.817		1.945	1.945	
Proportion of total variance	.606	.606		.648	.648	
Cumulative proportion	.606			.648		

Table A.6: The factor loadings for Agreeableness

	Children			Parents		
	Loadings	Communalities	Specific Variance	Loadings	Communalities	Specific Variance
Variable	λ_j	h_j^2	ψ_j	λ_j	h_j^2	ψ_j
per0102	.67	.45	.55	.67	.45	.55
per0105	.66	.44	.56	.67	.45	.55
per0112	.82	.68	.32	.82	.68	.32
Variance accounted for	1.565	1.565		1.579	1.579	
Proportion of total variance	.522	.522		.526	.526	
Cumulative proportion	.522			.526		

Table A.7: The factor loadings for Neuroticism

	Children			Parents		
	Loadings	Communalities	Specific Variance	Loadings	Communalities	Specific Variance
Variable	λ_j	h_j^2	ψ_j	λ_j	h_j^2	ψ_j
per0104	.76	.58	.42	.73	.54	.46
per0109	.80	.64	.36	.81	.65	.35
per0114	.59	.35	.65	.68	.46	.54
Variance accounted for	1.571	1.571		1.648	1.648	
Proportion of total variance	.524	.524		.549	.549	
Cumulative proportion	.524			.549		

A.2 Measures of fluid intelligence

To assess cognitive ability, this study utilised the short version of the German adaptation of the Culture Fair Test 20R (Weiß, 2006; Weiß and Osterland, 2012) as as a proxy for fluid intelligence. The test comprises four subtests: Figural Reasoning, Figural Classification, Matrices, and Reasoning. The first three subtests contain 15 items each, while the fourth subtest includes 11 items. This test makes use of figures so that it avoids the use of language or other cultural cues that may be unfamiliar to certain groups of test-takers. An exploratory one-factor analysis was conducted on the scores from each subtest to create an index of fluid intelligence.

To reduce noise and enhance the precision and reliability of measurements, the test was administered under a structured control system. This protocol included supervised test administration, simultaneous testing of all children in a family whenever possible, and strict timing protocols. Each test session, including instructions, was limited to 30 minutes. The test was administered in both a short version (three minutes) and a long version (one additional minute). If a test-taker did not finish within the allotted time, the extra minute was automatically provided. During this additional time, respondents were allowed to revise their answers, whether correct or incorrect. If the interviewer determined that the test environment compromised validity – due to factors such as behavioural issues, random responses, parental influence, or lack of motivation – the results were deemed invalid.

Each correct answer was coded as one, and each incorrect answer as zero. For each subtest, three distinct scores were computed: the total number of correct answers during the short test period, the total number of correct answers during the additional time, and the total number of correct answers across the entire test. A detailed overview of the cognitive test battery and the handling of invalid cases is provided by Gottschling (2017). This study exclusively uses the short version of the test.

To construct an index for fluid intelligence, an EFA was performed on the four subtest scores. As outlined in Section A.1, the EFA identifies an underlying factor that influences all measured items, extracting the shared variance of all test items into a single score. Formally, the variance for any measure of fluid intelligence can be expressed as:

$$\sigma = \lambda^2 + \psi^2$$

where λ^2 represents the common variance shared by all fluid intelligence subtests, and ψ^2 represents the unique variance specific to each subset. The EFA process involves estimating the parameters λ and ψ . This analysis was conducted using principal factor components and Bartlett scores.

Prior to conducting the EFA, the reliability ratios of sample adequacy and Bartlett's test of sphericity were calculated to assess the quality of the latent structure. These tests confirmed that the data were suitable for factor analysis. The results indicated that the variables loaded heavily on a single factor, with an eigenvalue greater than one.

Table A.8: The factor loadings for Fluid Intelligence

	Children			Parents		
	Loadings	Communalities	Specific Variance	Loadings	Communalities	Specific Variance
Variable	λ_j	h_j^2	ψ_j	λ_j	h_j^2	ψ_j
Figural Reasoning	.79	.62	.38	.81	.65	.35
Figural Classification	.79	.63	.37	.78	.61	.39
Matrices	.81	.65	.35	.81	.66	.34
Reasoning	.66	.44	.56	.67	.45	.55
Variance accounted for	2.338	2.338		2.373	2.373	
Proportion of total variance	.585	.585		.593	.593	
Cumulative proportion	.585			.593		

Figure A.1: Children's eigenvalue size for each factor

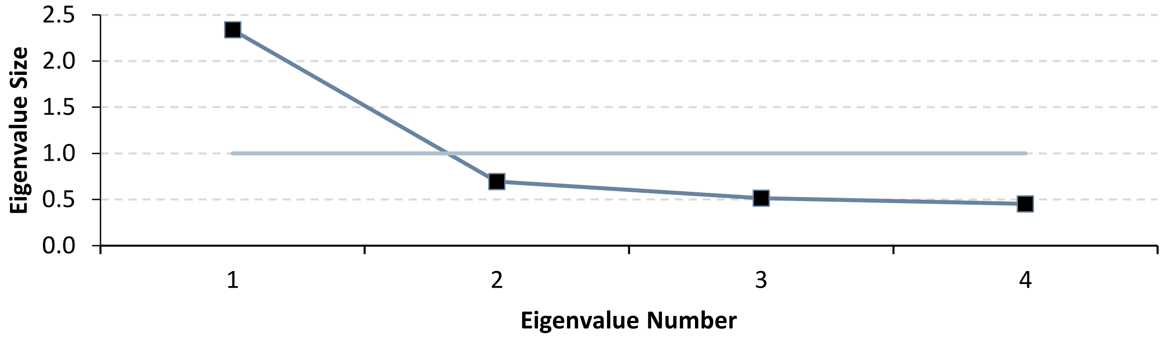
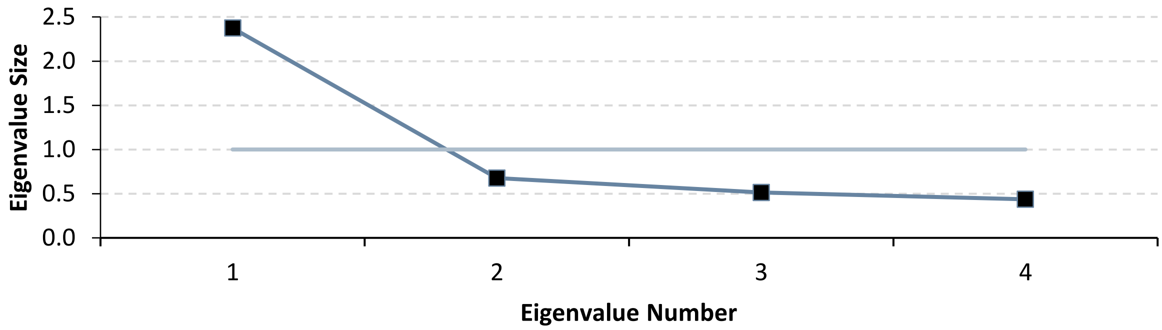


Figure A.2: Parent's eigenvalue size for each factor



A.3 Parenting Style

The researcher cannot observe the parenting style directly. Because of this, asking parents to rate their parenting style might be the most effective approach. To capture a comprehensive perspective, in TwinLife, questions were posed separately to both mothers and fathers. As discussed in sections A.1 and A.2, this survey approach is based on two key assumptions. First, the survey items serve as a reliable substitute for the variable that cannot be assessed directly. Second, there must be a meaningful relationship between these survey items and the factor score that will be constructed for parenting style. The specific survey items used to assess parenting style are detailed in Table A.9. These items, derived from the TwinLife study and adapted from

Huinink et al. (2011), employ a seven-point Likert scale ranging from 1 ("Never") to 5 ("Very Often").

Table A.9: Parenting style items

Positive Parenting Style (Emotional Warmth, Surveillance)	You show/ed [name of child] with words and gestures that you like him/her
	You give/gave [name of child] advice regarding his/her personal problems
	When [name of child] makes/made new friends, you get/got to know them soon thereafter
Negative Parenting Style (Psychological control)	If [name of child] does something against your will, you punish him/her
	You threaten/ed [name of child] with a punishment but don't/didn't actually follow through
	You find/found it hard to set and keep consistent rules for [name of child]

Following the approach of Falk et al. (2021) and many other researchers, a latent variable is extracted from these questionnaire items. This parsimonious approach is preferred over multi-factor models. It is expected that higher scores on emotional warmth and surveillance will positively correlate with the inferred parenting style, while higher scores on psychological control will negatively correlate with it. Consequently, a higher overall parenting style score indicates a more positive parenting style, and vice versa.

The measurement model assumes that observed parenting style items are functions of parental IQ, parental personality, household characteristics, and a latent parenting structure. This structure aligns with models proposed by Carneiro et al. (2003), Heckman et al. (2006), Heckman et al., (2013) or Falk et al., (2021).

For individual i and measurement k, the model is as follows:

$$\mathbf{Q} = \mathbf{X}_Q \beta_Q + \mathbf{\Lambda_Q} S + \mathbf{e_Q}$$

where $\mathbf{Q}$ is a $L \times 1$ vector of measurements (e.g., emotional warmth, monitoring scores, etc.), $\mathbf{X}_Q$ is an $L \times K$ matrix with all observable controls for each measurement, $\alpha^{\mathbf{Q}}$ is a K$\times$ 1 matrix of factor loadings of the latent parenting variable ($\boldsymbol{S^A}$), and $\mathbf{e^Q}$ is an $L \times 1$ vector of measurement errors.

This equation states that the values for variable $\mathbf{Q}$ are a function of the variable's factor loading ($\boldsymbol{\Lambda}_\mathbf{Q}$) on the latent variable (S), a vector of control variables $\mathbf{X}_Q$, and a vector of error terms, $\mathbf{e_Q}$. It is assumed that $\mathbf{e_Q}$ is orthogonal to S and $\mathbf{X}_Q$ and follows a normally distribution. Furthermore, the factor S is assumed to be normally distributed with a mean of zero.

To estimate the model parameters, the variance-covariance matrix of the data is replicated by minimising the difference between the predicted and observed sample values using a maximum likelihood fitting function. The measurement model also accounts for the ordinal nature of the outcome variables.

The detailed results of the confirmatory factor analysis (CFA), for both mothers and fathers, are presented in Tables A.10 and A.11. Parental scores were then calculated using principal component analysis, combining the maternal and paternal scores into a single composite measure.

The structural model results indicate, as expected, that both fluid intelligence and the respondent's personality influence the scores on the parenting style survey items. For example, there is a negative correlation between parenting style and the parent's fluid intelligence and the number of people living in the household. With the exception of neuroticism, all of the Big Five personality traits of the parents are positively correlated with survey items related to a positive parenting style.

Table A.10 Mother's Parenting Style, Confirmatory Factor Analysis

	Coef.	Std. Error.	z	P>|z|	[95% Conf. Interval]	
Shows twin affection						
Fluid Intelligence	-0.01	0.01	-0.79	0.43	-0.03	0.01
Openness	0.13	0.02	5.67	0.00	0.09	0.18
Consciousnesses	0.16	0.03	5.62	0.00	0.11	0.22
Extraversion	0.20	0.02	9.16	0.00	0.16	0.24
Agreeableness	0.31	0.03	11.55	0.00	0.26	0.36
Neuroticism	-0.03	0.02	-1.51	0.13	-0.07	0.01
# of persons in household	-0.16	0.02	-7.97	0.00	-0.20	-0.12
Gender	0.17	0.05	3.52	0.00	0.08	0.26
Birth Cohort	-0.44	0.02	-18.35	0.00	-0.49	-0.39
Style	1.00					
Supports twin						
Fluid Intelligence	0.00	0.01	0.40	0.69	-0.02	0.03
Openness	0.17	0.02	7.25	0.00	0.13	0.22
Consciousnesses	0.18	0.03	6.11	0.00	0.12	0.23
Extraversion	0.13	0.02	5.86	0.00	0.09	0.17
Agreeableness	0.21	0.03	8.01	0.00	0.16	0.27
Neuroticism	-0.01	0.02	-0.27	0.79	-0.05	0.03
# of persons in household	-0.07	0.02	-3.45	0.00	-0.11	-0.03
Gender	0.09	0.05	1.77	0.08	-0.01	0.18
Birth Cohort	-0.22	0.02	-9.37	0.00	-0.27	-0.18
Style	0.74	0.15	4.94	0.00	0.44	1.03
Punishes twin						
Fluid Intelligence	-0.02	0.01	-1.38	0.17	-0.04	0.01
Openness	-0.09	0.02	-3.82	0.00	-0.14	-0.04
Consciousnesses	-0.04	0.03	-1.40	0.16	-0.10	0.02
Extraversion	0.03	0.02	1.49	0.14	-0.01	0.07
Agreeableness	-0.18	0.03	-6.88	0.00	-0.24	-0.13
Neuroticism	0.11	0.02	5.70	0.00	0.08	0.15
# of persons in household	-0.08	0.02	-3.97	0.00	-0.12	-0.04
Gender	-0.37	0.05	-7.82	0.00	-0.47	-0.28
Birth Cohort	-0.44	0.02	-18.49	0.00	-0.49	-0.39
Style	-3.20	0.45	-7.17	0.00	-4.07	-2.32
Yells at twin						
Fluid Intelligence	-0.04	0.01	-3.32	0.00	-0.07	-0.02
Openness	-0.07	0.03	-2.96	0.00	-0.12	-0.03
Consciousnesses	-0.14	0.03	-4.61	0.00	-0.20	-0.08
Extraversion	0.08	0.02	3.47	0.00	0.03	0.12
Agreeableness	-0.41	0.03	-14.37	0.00	-0.46	-0.35

	Coef.	Std. Error.	z	P>|z|	[95% Conf. Interval]	
Neuroticism	0.29	0.02	13.55	0.00	0.25	0.34
# of persons in household	0.02	0.02	0.85	0.40	-0.02	0.06
Gender	-0.28	0.05	-5.50	0.00	-0.38	-0.18
Birth Cohort	-0.24	0.02	-9.78	0.00	-0.29	-0.19
Style	-4.24	0.57	-7.40	0.00	-5.36	-3.11
Gets to know new friends						
Fluid Intelligence	0.01	0.01	1.08	0.28	-0.01	0.03
Openness	0.17	0.02	7.87	0.00	0.13	0.22
Consciousnesses	0.11	0.03	4.08	0.00	0.06	0.16
Extraversion	0.15	0.02	7.55	0.00	0.11	0.19
Agreeableness	0.21	0.02	8.84	0.00	0.17	0.26
Neuroticism	-0.10	0.02	-5.44	0.00	-0.14	-0.06
# of persons in household	-0.06	0.02	-3.33	0.00	-0.10	-0.03
Gender	0.20	0.04	4.67	0.00	0.12	0.29
Birth Cohort	-0.11	0.02	-5.28	0.00	-0.15	-0.07
Style	0.55	0.13	4.26	0.00	0.30	0.81
Makes empty threats						
Fluid Intelligence	-0.12	0.02	-5.16	0.00	-0.16	-0.07
Openness	-0.17	0.05	-3.63	0.00	-0.25	-0.08
Consciousnesses	-0.24	0.06	-4.41	0.00	-0.35	-0.14
Extraversion	0.01	0.04	0.29	0.77	-0.07	0.09
Agreeableness	-0.26	0.05	-5.03	0.00	-0.36	-0.16
Neuroticism	0.49	0.04	10.89	0.00	0.40	0.58
# of persons in household	-0.06	0.04	-1.44	0.15	-0.13	0.02
Gender	-0.07	0.09	-0.78	0.44	-0.25	0.11
Birth Cohort	-0.21	0.05	-4.69	0.00	-0.30	-0.12
Style	-14.23	2.40	-5.94	0.00	-18.93	-9.53
Difficulties with consistent parenting						
Fluid Intelligence	-0.06	0.01	-4.08	0.00	-0.08	-0.03
Openness	-0.12	0.03	-4.39	0.00	-0.18	-0.07
Consciousnesses	-0.29	0.03	-8.52	0.00	-0.36	-0.23
Extraversion	-0.07	0.03	-2.60	0.01	-0.12	-0.02
Agreeableness	-0.05	0.03	-1.57	0.12	-0.11	0.01
Neuroticism	0.40	0.02	16.33	0.00	0.36	0.45
# of persons in household	-0.04	0.02	-1.43	0.15	-0.08	0.01
Gender	0.07	0.06	1.14	0.25	-0.05	0.18
Birth Cohort	0.07	0.03	2.51	0.01	0.02	0.12
Style	-6.53	0.89	-7.34	0.00	-8.27	-4.78
var(Style)	0.05	0.01			0.03	0.08

Table A.11 Father's Parenting Style, Confirmatory Factor Analysis

	Coef.	Std. Error.	z	P>|z|	[95% Conf. Interval]	
Shows twin affection						
Fluid Intelligence	0.01	0.01	0.36	0.72	-0.02	0.03
Openness	0.24	0.03	7.38	0.00	0.17	0.30
Consciousnesses	0.13	0.04	3.74	0.00	0.06	0.20
Extraversion	0.25	0.03	9.01	0.00	0.20	0.31
Agreeableness	0.27	0.03	8.21	0.00	0.20	0.33
Neuroticism	0.06	0.03	2.21	0.03	0.01	0.11
# of persons in household	-0.17	0.03	-6.33	0.00	-0.22	-0.12
Gender	0.29	0.06	4.95	0.00	0.18	0.41
Birth Cohort	-0.59	0.03	-19.64	0.00	-0.65	-0.53
Style	1.00					
Supports twin						
Fluid Intelligence	0.00	0.01	-0.18	0.86	-0.03	0.03
Openness	0.21	0.03	6.48	0.00	0.14	0.27
Consciousnesses	0.13	0.04	3.53	0.00	0.06	0.19
Extraversion	0.16	0.03	5.63	0.00	0.10	0.21
Agreeableness	0.32	0.03	9.66	0.00	0.25	0.38
Neuroticism	0.08	0.03	3.18	0.00	0.03	0.13
# of persons in household	-0.10	0.03	-3.61	0.00	-0.15	-0.04
Gender	0.18	0.06	3.04	0.00	0.06	0.30
Birth Cohort	-0.33	0.03	-11.26	0.00	-0.38	-0.27
Style	0.92	0.10	9.33	0.00	0.73	1.12
Punishes twin						
Fluid Intelligence	0.06	0.02	3.59	0.00	0.03	0.09
Openness	-0.14	0.04	-3.77	0.00	-0.21	-0.06
Consciousnesses	-0.05	0.04	-1.23	0.22	-0.13	0.03
Extraversion	0.09	0.03	2.91	0.00	0.03	0.15
Agreeableness	-0.14	0.04	-3.80	0.00	-0.21	-0.07
Neuroticism	0.13	0.03	4.55	0.00	0.08	0.19
# of persons in household	-0.06	0.03	-1.95	0.05	-0.12	0.00
Gender	-0.42	0.07	-6.25	0.00	-0.55	-0.29
Birth Cohort	-0.56	0.03	-16.36	0.00	-0.63	-0.49
Style	-2.40	0.27	-9.05	0.00	-2.92	-1.88
Yells at twin						
Fluid Intelligence	-0.02	0.02	-0.83	0.41	-0.05	0.02
Openness	-0.18	0.04	-4.22	0.00	-0.26	-0.10
Consciousnesses	-0.11	0.05	-2.30	0.02	-0.20	-0.02
Extraversion	0.14	0.04	3.87	0.00	0.07	0.22
Agreeableness	-0.37	0.04	-8.29	0.00	-0.46	-0.28
Neuroticism	0.32	0.04	8.73	0.00	0.24	0.39
# of persons in household	-0.02	0.04	-0.64	0.52	-0.09	0.05
Gender	-0.62	0.08	-7.69	0.00	-0.78	-0.47
Birth Cohort	-0.40	0.04	-9.96	0.00	-0.48	-0.32
Style	-3.54	0.41	-8.59	0.00	-4.35	-2.73
Gets to know new friends						
Fluid Intelligence	0.01	0.01	0.76	0.45	-0.02	0.04
Openness	0.23	0.03	7.80	0.00	0.17	0.29
Consciousnesses	0.08	0.03	2.52	0.01	0.02	0.15
Extraversion	0.17	0.03	6.57	0.00	0.12	0.22
Agreeableness	0.11	0.03	3.66	0.00	0.05	0.17

	Coef.	Std. Error.	z	P>|z|	[95% Conf. Interval]	
Neuroticism	-0.04	0.02	-1.44	0.15	-0.08	0.01
# of persons in household	-0.09	0.02	-3.62	0.00	-0.14	-0.04
Gender	0.05	0.05	0.87	0.38	-0.06	0.16
Birth Cohort	0.02	0.03	0.70	0.49	-0.03	0.07
Style	0.69	0.09	7.82	0.00	0.52	0.87
Makes empty threats						
Fluid Intelligence	-0.02	0.02	-1.00	0.32	-0.05	0.01
Openness	-0.15	0.04	-4.35	0.00	-0.22	-0.08
Consciousnesses	-0.16	0.04	-4.13	0.00	-0.24	-0.08
Extraversion	0.02	0.03	0.62	0.54	-0.04	0.08
Agreeableness	-0.06	0.04	-1.56	0.12	-0.13	0.01
Neuroticism	0.27	0.03	9.20	0.00	0.21	0.32
# of persons in household	-0.04	0.03	-1.33	0.18	-0.10	0.02
Gender	-0.20	0.06	-3.06	0.00	-0.33	-0.07
Birth Cohort	-0.29	0.03	-9.08	0.00	-0.35	-0.23
Style	-2.40	0.27	-9.04	0.00	-2.92	-1.88
Difficulties with consistent parenting						
Fluid Intelligence	-0.06	0.01	-4.00	0.00	-0.09	-0.03
Openness	-0.09	0.03	-2.84	0.00	-0.16	-0.03
Consciousnesses	-0.37	0.04	-10.09	0.00	-0.44	-0.29
Extraversion	-0.08	0.03	-2.93	0.00	-0.14	-0.03
Agreeableness	-0.05	0.03	-1.65	0.10	-0.12	0.01
Neuroticism	0.26	0.03	9.74	0.00	0.21	0.31
# of persons in household	-0.01	0.03	-0.19	0.85	-0.06	0.05
Gender	-0.13	0.06	-2.12	0.03	-0.24	-0.01
Birth Cohort	0.01	0.03	0.22	0.83	-0.05	0.06
Style	-1.66	0.19	-8.73	0.00	-2.03	-1.29
var(Style)	0.23	0.04			0.16	0.32

Table A.12 Parental Time with Children

	Mean		Standard Deviation		Median		
	Low SES	High SES	Low SES	High SES	Low SES	High SES	Difference in mean (p-value)
singing / playing music	1.750	2.093	1.222	1.349	1	1	0.000
reading/talking about books	2.169	2.689	1.365	1.467	2	3	0.000
sports	2.784	2.966	1.394	1.314	3	3	0.031
walks, day trips	2.785	2.633	1.090	0.990	3	3	0.018
theatre, museum, etc.	1.581	1.718	0.748	0.766	1	2	0.004

Table A.12 shows differences in the frequency of cultural and recreational activities between low and high SES families. On average, high SES parents are more likely to engage in activities like singing or playing music with children (mean: 2.093 vs. 1.750) and reading or discussing books (mean: 2.689 vs. 2.169), with both differences statistically significant (p = 0.000). Participation in sports with their children is also slightly higher among the high SES group (mean: 2.966 vs. 2.784, p = 0.031). However, low SES families have higher reported involvement in walks and day trips with their children, which, though small, is statistically significant (mean: 2.785 vs. 2.633, p = 0.018). The high SES parents engage more frequently in cultural activities such as attending the theatre or visiting museums with their children (mean: 1.718 vs. 1.581, p = 0.004). These differences suggest that higher SES parents tend to participate more in activities with educational or cultural components with their children, while some recreational activities, like day trips, are more common among lower SES parents.

Table A.13 SES Gaps in Offspring Fluid Intelligence and Personality Scores, MZ Twins

	FI	O	C	E	A	ES
Baseline (Low SES)						
High SES	.221***	.122**	-.001	.040	-.256	-.010
	(.060)	(.057)	(.059)	(.060)	(.058)	(.056)
N	392	392	392	392	392	392

*Notes: FI – Fluid Intelligence, O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, E – Emotional Stability. Each coefficient indicates difference between baseline category low SES and each high SES group. Standard errors (in parentheses) are bootstrapped using 1,000 bootstrap replications and are clustered by family. Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A.14 SES Gaps in Offspring Fluid Intelligence and Personality Scores, DZ Twins

	FI	O	C	E	A	ES
Baseline (Low SES)						
High SES	.200***	-.003	-.031	.063*	.040	.173***
	(.042)	(.041)	(.041)	(.039)	(.041)	(.039)
N	648	648	648	648	648	648

*Notes: FI – Fluid Intelligence, O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, E – Emotional Stability. Each coefficient indicates difference between baseline category low SES and each high SES group. Standard errors (in parentheses) are bootstrapped using 1,000 bootstrap replications and are clustered by family. Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A.15: Components of Parental SES Gaps in Offspring Fluid Intelligence and Personality Scores, MZ Twins

	FI	O	C	E	A	ES
Base Category (High SES)						
Low Income	-.092	-.099*	-.020	.003	.105***	-.004
	(.060)	(.054)	(.075)	(.054)	(.040)	(.065)
Low Education	-.178***	-.088	.043	-.023	.050	-.009
	(.060)	(.059)	(.057)	(.063)	(.058)	(.061)
Low Income and Education	-.329***	-.095*	-.023	-.061	-.129*	.063
	(.048)	(.049)	(.072)	(.057)	(.077)	(.057)
N	392	392	392	392	392	392

Notes: FI – Fluid Intelligence, O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, E – Emotional Stability. Each coefficient indicates differences between baseline category high SES and each respective low-SES subgroup. Each column is a regression of intelligence or personality on the three low-SES subgroup dummies. Standard errors (in parentheses) are bootstrapped using 1,000 bootstrap replications and are clustered by family.
*Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A.16: Components of Parental SES Gaps in Offspring Fluid Intelligence and Personality Scores, DZ Twins

	FI	O	C	E	A	ES
Base Category (High SES)						
Low Income	-.129***	.025	.036	-.041	-.027	.060
	(.048)	(.040)	(.040)	(.037)	(.040)	(.046)
Low Education	-.156***	-.018	-.038	-.049	-.040	.161***
	(.044)	(.040)	(.040)	(.041)	(.047)	(.043)
Low Income and Education	-.192***	-.009	-.048	-.075	-.021	.169***
	(.047)	(.041)	(.051)	(.051)	(.040)	(.040)
N	392	392	392	392	392	392

Notes: FI – Fluid Intelligence, O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, E – Emotional Stability. Each coefficient indicates differences between baseline category high SES and each respective low-SES subgroup. Each column is a regression of intelligence or personality on the three low-SES subgroup dummies. Standard errors (in parentheses) are bootstrapped using 1,000 bootstrap replications and are clustered by family.
*Significance at * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A.17 Estimates of the CES production function for fluid intelligence and personality traits, without parental satisfaction, MZ Twins

	FI	O	C	E	A	ES
Distribution Parameters						
Parental Traits	.525***	.372***	.416***	.401***	.391***	.387***
	(.0491)	(.0574)	(.0537)	(.0494)	(.0505)	(.0580)
Parenting Style	.349***	.294***	.287***	.344***	.286***	.363***
	(.0414)	(.0525)	(.0542)	(.0502)	(.0604)	(.0600)
Parental Time	.126**	.335***	.297***	.255***	.323***	.250***
	(.0392)	(.0512)	(.0550)	(.0557)	(.0517)	(.0545)
Productivity Parameters						
SES	1.026	1.137	.981	1.038	.897	.915
	(.102)	(.128)	(.129)	(.113)	(.115)	(.117)
Satisfaction	.940	.992	.981	.992	.989	1.038
	(.008)	(.012)	(.012)	(.012)	(.013)	(.015)
Substitution Parameters						
Substitution parameter	-.092	.290	.188	.386	.420*	.190
	(.184)	(.240)	(.226)	(.248)	(.208)	(.307)
Elasticity of substitution	.916	1.409	1.232	1.630	1.724	1.234
	(.154)	(.477)	(.343)	(.658)	(.618)	(.468)
N	392	392	392	392	392	392

*Notes: The reported standard errors (in parentheses) were bootstrapped using 1,000 bootstrap replications clustered at family level. Parental scores were then calculated using principal component analysis, combining the maternal and paternal scores into a single composite measure. Significance at * p < 0.1, ** p < 0.05, *** p < 0.01. † Significantly different from one at the 10% level. SES, Parental Satisfaction, and Elasticity of Substitution parameters are tested for statistical difference from one.*

Table A.18 Estimates of the CES production function for fluid intelligence and personality traits, without parental satisfaction, DZ Twins

	FI	O	C	E	A	ES
Distribution Parameters						
Parental Traits	.597***	.400***	.324***	.426***	.340***	.355***
	(.049)	(.037)	(.043)	(.032)	(.042)	(.041)
Parenting Style	.201***	.180***	.348***	.205***	.312***	.337***
	(.041)	(.040)	(.039)	(.034)	(.041)	(.042)
Parental Time	.202***	.419***	.329***	.369***	.348***	.308***
	(.038)	(.040)	(.038)	(.036)	(.039)	(.043)
Productivity Parameters						
SES	.879†	.837#	1.014	1.047	.946	1.205†
	(.064)	(.069)	(.091)	(.081)	(.084)	(.108)
Satisfaction	.930	1.011	.988	.993	.997	1.021
	(.0075)	(.008)	(.009)	(.008)	(.009)	(.009)
Substitution Parameters						
Substitution parameter	.227	.309	.124	.206	.213	-.037
	(.235)	(.185)	(.158)	(.141)	(.182)	(.141)
Elasticity of substitution	1.294	1.447	1.142	1.259	1.270	.965
	(.393)	(.387)	(.206)	(.224)	(.294)	(.131)
N	648	648	648	648	648	648

*Notes: The reported standard errors (in parentheses) were bootstrapped using 1,000 bootstrap replications clustered at family level. Parental scores were then calculated using principal component analysis, combining the maternal and paternal scores into a single composite measure. Significance at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. # Significantly different from one at the 5% level. † Significantly different from one at the 10% level. SES, Parental Satisfaction, and Elasticity of Substitution parameters are tested for statistical difference from one.*

4. CHAPTER THREE: MIND VS MATTER: ECONOMIC AND PSYCHOLOGIC DETERMINANTS OF TAKE-UP RATES OF SOCIAL BENEFITS IN THE UK

4.1 INTRODUCTION

Not all eligible individuals for social benefits choose to claim them. The available evidence, although limited, indicates that take-up rates – defined as the percentage of eligible individuals who choose to enrol in a programme – are far from perfect. A review of the literature reveals that there exist significant variations in the take-up rates of social benefits across European states (Currie, 2004; Hernanz, Malherbet and Pellizzari, 2004; Matsaganis, Paulus and Sutherland, 2008; Bargain, Immervoll and Viitamäki, 2012; Bruckmeier and Wiemers, 2012, 2017; Dubois and Ludwinek, 2015; Harnish, 2019; Fuchs *et al.*, 2020). A recent study surveying take-up rates in 20 high-income countries found that less than one-fifth of welfare programmes had a take-up of 80% or higher, while nearly one-quarter had take-up rates of 40% or less (Ko and Moffitt, 2024). While the dynamics of take-up decisions remain not well understood, strong state dependence appears to significantly influence the likelihood of benefit receipt in the UK (Roberts and Taylor, 2022). This aligns with the chapter's objective of distinguishing between heterogeneity (i.e., individual characteristics) and state dependence as contributing factors in take-up behaviour.

Previous literature highlights various cognitive and behavioural barriers that influence decision-making. These include limited comprehension of programme rules and incentives (Duflo *et al.*, 2006; Bhargava and Manoli, 2015; Liebman and Luttmer, 2015), low awareness of the programmes themselves (Chetty and Saez, 2013; Chetty, Friedman and Saez, 2013; Barr and Turner, 2018), procrastination (Bertrand, Mullainathan and Shafir, 2006), inattention (Karlan *et al.*, 2016), psychological barriers stemming from programme complexity (Bertrand, Mullainathan and Shafir, 2006), and feelings of stigma associated with programme enrolment (Celhay, Meyer and Mittag, 2022, 2024). By considering both economic and psychological dimensions, this paper provides a comprehensive understanding of the multifaceted determinants influencing take-up rates of social benefits in the UK.

The objectives of this paper are threefold. The first objective is UK-specific and focuses on updating estimates for the UK context, where information on how take-up rates for various benefits changed over time is limited, and the existing literature is quite dated (Blundell, Fry and Walker, 1988; Craig, 1991; Pudney, Hancock and Sutherland, 2006; Hernandez and Pudney, 2007; Zantomio, Pudney and Hancock, 2010; Zantomio, 2015). The paper investigates the dynamics of individual behaviour over time, exploring why eligible individuals claim benefits and whether certain social groups are more predisposed to do so.

The second and third objectives address broader questions, where research findings for one specific country might hold a more general validity. The paper aims to explain the dynamics of take-up decisions by disentangling the effects of individual characteristics from those of state dependence, which holds significant policy implications. By distinguishing the role of heterogeneity and state dependence, policymakers can better target their intervention to increase take-up, for instance, by offering targeted help for first-time applicants.

Finally, the paper investigates the role of social networks in shaping individual take-up behaviour. Although it is difficult to measure the social network effect due to data limitations, the paper attempts to analyse its influence by analysing take-up behaviour at a fine-grained geographical detail, under the assumption that social networks fade away with distance. We cannot, however, determine whether this social network effect arises due to easier access to information, social norms, or emulation.

We construct a model of take-up decisions for two important classes of benefits in the UK. The first one is Child Benefit (CB), an allowance the government pays to help parents or guardians with the costs of raising a child. The second one is a combination of benefits that form the core of social assistance in the UK context. They comprise six different means-tested benefits (collectively referred to as Legacy Benefits, LB), that are being progressively replaced by a single monthly payment, Universal Credit (UC).[22] The two types of benefits are very different: CB has a broad target with little means testing – in effect a middle-class benefit – while LB/UC directly address situations of need, with significantly more means-testing and conditioning. It is, therefore, particularly interesting to analyse to what extent the mechanisms explaining take-up behaviour are the same, and whether any difference can be related to specific design features of the two schemes.

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[22] The LB and UC are analysed together due to practical necessity. It is the only measure of take-up that can be measured consistently using UKMOD. It is difficult to distinguish between eligibility of LB and UC. UC is a social welfare programme in the UK that combines six different means-tested benefits (collectively referred to as LB) into a single payment. It was initially introduced as a pilot programme in 2013 and gradually expanded to replace the existing benefits system. The introduction of UC took place gradually in different phases. LB claimants had the option to migrate by voluntarily submitting a UC claim, which automatically closed their LB claim. As from 2019, the government began gradually replacing the LB system with UC, also known as “managed migration”. As a result, legacy claimants who have not experienced a change in circumstances started to be approached to submit a UC claim. The main managed migration started from 2023 onwards.

The dynamic aspects of take-up are captured by relating claimants' current take-up to their lagged take-up state and by allowing for correlations between observed characteristics and unobserved heterogeneity. More in detail, we employ the 'lagged dependent variable' model, used *inter alia* for the analysis of the dynamics of social assistance recipiency (Cappellari and Jenkins, 2014; Roberts and Taylor, 2022), and in other contexts, such as the dynamics of unionisation (Vella and Verbeek, 1998), the dynamics of low pay (Cai, Mavromaras and Sloane, 2018), and the dynamics of unemployment (Stewart, 2007). To account for initial conditions, we employ the conditional maximum likelihood estimator proposed by Wooldridge (2005).

The data used in this study are drawn from the first nine waves of the UK Household Longitudinal Study (UKHLS), adjusted to be used as input data for the UKMOD tax-benefit microsimulation model (Richiardi, Bronka and Popova, 2023).[23] UKMOD permits the simulation of eligibility for and amount of various social benefits. Using UKHLS as input data allows us to track individuals over multiple years.

The findings reveal that the level of benefits, state dependence, and factors related to demographics and socioeconomics – what we refer to as 'Matter' in the title – are important factors in determining who claims social benefits. As for 'Mind', we find that personality traits have only a weak direct relationship with take-up. Although not uncontroversial, in our narrative, we include neighbourhood effects as pertaining to 'Mind' – social norms, stigma, and emulation are clearly psychological factors that affect how material costs and benefits are evaluated, while the information channel is

[23] The standard version of UKMOD uses input data coming from the Family Resources Survey (FRS), a cross-sectional dataset.

harder to classify. We find that the greater the take-up in the area where an individual resides compared to other areas, the more likely that individual is to claim the benefit. The rest of the paper is organised as follows. Section 2 provides a brief literature review of the main determinants of take-up behaviour and the effects of personality traits, which serve as the conceptual basis for this study. Section 3 describes our empirical strategy, followed by the data used in the empirical analysis. Section 4 presents and discusses the main estimation results concerning the determinants of take-up of CB and LB/UC separately. Section 5 summarises the main conclusions.

4.2 BRIEF LITERATURE REVIEW

Factors affecting take-up behaviour

Non-take-up of social benefits affects intended targeting.[24] This, in turn, distorts the original aims of the policies and their reach. This is particularly true for means-tested benefits designed to provide essential resources to low-income households. If beneficiaries do not claim these benefits, their effectiveness in redistributing income and reducing poverty can be seriously compromised (Matsaganis, Paulus and Sutherland, 2008).

Imperfect take-up of welfare payments also has budgetary implications. While an imperfect take-up may result in lower-than-expected budgeted outlays in the short

[24] Another deviation from designed targeting involves overpayments to individuals who are not eligible but still claim the benefit. While this may be exacerbated by behavioural traits affecting knowledge of and compliance with the rules, it remains mostly an administrative problem in controlling eligibility. This issue is likely to be relatively minor in systems with a more advanced administrative capacity (such as the UK). Non-take-up can also have an administrative component – for instance, when applications are lost or processed with delays or when the administrative hurdle for claiming is too high – but behavioural aspects are more likely to play a major role.

term, it can exacerbate government spending over the long term. This is because non-take-up may lead to poorer nutrition, delayed medical care, and an impoverished environment, to name a few. Hence, policymakers need to ensure that eligible individuals are aware of the benefits and encouraged to claim them so that welfare schemes can provide essential resources to those in need and act as automatic stabilisers during difficult times.

Several factors, including both recipient characteristics and administrative procedures, are known to influence the occurrence of non-take-up, shaped by welfare policy design and the broader social and legal context (van Oorschot, 1996, 2002; Janssens and Van Mechelen, 2022; Bennett, 2024). Economists have traditionally ground their understanding of benefit take-up on the rational choice theory (Moffitt, 1983; Duclos, 1995; Atkinson, 1996; Hernandez and Pudney, 2007), which sees the claiming process as a utility-maximising decision under uncertainty. According to this framework, individuals weigh the trade-off between anticipated benefits and the costs of accessing social benefits, including psychological costs. Indeed, Moffitt (1983) identifies stigma as the main cost of participation in a means-tested programme, though his model has been extended to include other cost types.

There are four main categories of barriers that can impact take-up rates (Craig, 1991; van Oorschot, 1996; Hernanz, Malherbet and Pellizzari, 2004). These include (i) expected level and duration of entitlement to benefit, subject to uncertainty about the outcome of the application (Creedy, 2002; Dahan and Nisan, 2010); (ii) information costs, i.e., the time and effort required for understanding entitlement rules and mastering application procedures (Van Parys and Struyven, 2013); (iii) transaction costs associated with gathering proof of eligibility, administrative delays and errors; and (iv) psychological costs, including stigma associated with applying for benefits. If the stigma associated with claiming the benefit is high, individuals may fear disapproval from others or perceive it as a personal shortcoming for needing assistance rather than being able to support themselves. In the case of the latter, stigma becomes internalised, leading to personal costs such as low self-esteem rather than social costs (Elster, 1989, p. 119).

Indeed, recent work by Celhay et al. (2022) and Celhay et al. (2024) investigating the association between underreporting of welfare participation and true local welfare participation revealed a negative relationship, implying the existence of stigma costs associated with claiming benefits. Also, individuals generally more associated with labour market participation, such as higher educated and younger persons, may suffer from (perceived) stigma effects and work the hardest to avoid transfer dependence (Bruckmeier and Wiemers, 2012, 2017; Bruckmeier, Müller and Riphahn, 2014). All these factors interact with each other and are also influenced by the administrative, institutional, and broader social context, which can create additional barriers to applying for benefits.

There are two additional factors to consider in this basic model. The first factor is the role of social networks in reducing the cost of making a claim (Currie, 2004; Celhay, Meyer and Mittag, 2024). Social networking can affect take-up behaviour through an information channel and through normative preferences. The information channel refers to how the behaviour of others can shape what individuals know, and what they think they know. For example, community-based knowledge-sharing can reduce information-related costs by providing information on how to deal with administrative requirements or maximise expected benefits. Interactions with benefit recipients can also create a perception that benefits are easily accessible – 'the availability heuristic' (Tversky and Kahneman, 1982). Imitating the behaviour of acquaintances can also be partly attributed to the information channel, as when the cost of acquiring and processing information is high, copying others might be a good strategy.

On the other hand, normative preferences explain how individuals might wish to conform to others – and to views held by others – either because they gain utility from adopting a social norm or because they want to avoid disutility from not adopting it (stigma). This effect might help explain why take-up rates vary between different social networks: where a culture of independence and self-reliance prevails, people might decide not to claim welfare benefits they are entitled to, despite their needs; on the other hand, a lower stigma from welfare participation might push up take-up rates where a culture of dependency prevails (Bertrand, Luttmer and Mullainathan, 2000; Stuber and Schlesinger, 2006; Baumberg *et al.*, 2012; Holford, 2015).[25]

Recent research by Celhay et al. (2022) indicates that stigma decreases with local participation, suggesting that peer evaluation shapes concerns about social image and may give rise to what economists term "positional externalities" (Bursztyn *et al.*, 2018). In a similar vein, Baumberg et al. (2012) also report that individuals in social housing perceive that society at large might not judge them as harshly for claiming benefits,

[25] For normative preferences, it is not only the number of people in the social network who are claiming the benefits that matter, but also the importance of those other claimants to the individual. For example, the reference group theory suggests that a person is more likely to follow other claimants and claim the benefit themselves, the more important those who receive the benefit are as reference persons for the individual (Merton, 1968).

however, they feel similar self-stigma for claiming benefits. This suggests that while the perceived negative consequences of engaging in socially undesirable behaviour decrease as more peers engage in the same behaviour, personal feelings (self-stigma) persist even when the take-up of benefits is not observed or exposed to society at large.

The second factor identified by Currie (2004) takes the form of time-inconsistent preferences. This happens because the costs of claiming are borne immediately, while the benefits are uncertain and will be received at a later time. As a result, some individuals may choose not to claim the benefits, even though they would have benefited from doing so in the future.

Personality, information costs and stigmatisation

Personality traits are “relatively enduring patterns of thoughts, feelings, and behaviours that differentiate individuals from one another” (Roberts, 2009, p. 2). They, therefore, represent general cognitive, affective, and behavioural patterns, i.e., what the individual is likely to do averaged over situations. The Big Five model comprises five broad domains of personality traits, including openness to experience (creativity, curiosity, honesty/humility, and inquisitiveness), conscientiousness (self-discipline, punctuality, competence, and organisation), extraversion (talkativeness, friendliness, energy, and outgoingness), agreeableness (kindness, generosity, warmth, and charity), and neuroticism (fear, worry, stress, and paranoia).[26] Each trait is not the sole

[26] The five factors are believed to be broad and capture the fundamental and general aspects of thought, feeling, and behaviour that people typically do differently (McCrae & John, 1992) (John, et al., 2010). The five-factor model has also taken a prominent place in economic research and is considered a standard module in most longitudinal data sets (Vella, 2024). Although the five-factor model is not without criticism (Block, 2010; Eysenck, 1992), it has been extensively linked to life outcomes, such as

determinant of behaviour but a contributing factor in a given context. Therefore, the Big Five model helps us understand fundamental mechanisms driving human behaviour.

Research linking the Big Five traits to welfare recipients has been scarce to date. However, a recent study using vignette-based experiments sheds some light on how welfare recipients are perceived. Schofield et al. (2019) found that individuals receiving unemployment benefits were perceived as less conscientious, more extroverted, and less agreeable compared to those not receiving benefits. No notable differences in openness to experience and emotional stability were found.

Personality traits can help explain why some people do not claim social benefits. Studies have shown that individuals who are open to new experiences and exhibit agreeable traits tend to face less public stigma and prejudice (Ekehammar and Akrami, 2003, 2007; Yuan *et al.*, 2018; Solmi *et al.*, 2020; Weinberg and Soffer, 2023). Conversely, people who have low levels of openness often conform to societal norms and may hold specific prejudices, such as anti-immigrant or racist attitudes (Sibley & Duckitt, 2008). Additionally, research has shown that those with high openness scores are more inquisitive and driven to enhance their abilities and knowledge (Komarraju and Karau, 2005; Komarraju, Karau and Schmeck, 2009; Clark and Schroth, 2010). This implies that those with higher openness may be more inclined to participate in welfare programmes due to the lower transaction costs associated with acquiring and processing information.

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wages, health, and longevity (Heckman, et al., 2021). The five-factor model has long been recognised as internally consistent, stable, and enjoys cross-cultural support (John, 2011).

Turning to conscientiousness, research has consistently shown that individuals with this trait tend to be motivated, self-sufficient, and organised (Egan *et al.*, 2017). As a result, they are more likely to set and achieve ambitious goals and to approach tasks diligently. When it comes to benefits take-up, conscientious individuals may be more inclined to utilise contributory benefits due to a lower perceived stigma of laziness (Brown-Iannuzzi *et al.*, 2021). However, it is also essential to consider the negative "stigma effect", as individuals with high levels of conscientiousness attach more stigma to claiming benefits (Schofield, Haslam and Butterworth, 2019). The stigma may stem from perceptions of welfare recipients as less conscientious or lazy (McKay, 2014; Schofield and Butterworth, 2015; Schofield, Haslam and Butterworth, 2019), undeserving (Jensen and Petersen, 2017; Buss, 2019), or ill-intentioned and incompetent (Fiske, 2018).

Regarding neuroticism, extant literature indicates that individuals with high levels of this trait tend to exhibit increased rates of absenteeism and decreased productivity (Egan, Daly and Delaney, 2015; Cubel *et al.*, 2016), potentially resulting in self-stigmatisation and reduced take-up.

The influence of extraversion on take-up behaviour is *a priori* less clear, as it can have both positive and negative effects. On the one hand, extroverts may benefit from lower information and processing costs because of their extensive social networks. On the other hand, extraverts may feel stigmatised if their benefit usage is seen as excessive or inappropriate. The literature about extraversion presents a blend of results. While some studies, such as Ekehammar and Akrami (2007), find a negative link to general prejudice, others, like Solmi et al. (2020) and Yuan et al. (2018), suggest a positive association with stigma. However, it is important to note that these correlations, albeit present, tend to be modest.

The role of policy and institutions

While much attention has been devoted to factors at the individual level, policy design plays a role in determining take-up behaviour. It has been argued that targeted welfare programmes aimed at specific groups often exhibit higher rates of non-take-up compared to universal programmes (Mood, 2006; Bruckmeier and Wiemers, 2012). Eligible individuals may opt not to claim targeted benefits because doing so can intensify stigma by directly confirming their need for support. This effect is more pronounced in communities that value self-dependence and personal responsibility, where individuals may fear social stigmatisation for seeking social benefits. Moreover, fragmented targeted benefits can increase information and processing costs for potential claimants. An excess of social programmes may not only increase information costs but also give rise to choice overload (Beshears *et al.*, 2013; Briere, Poterba and Szafarz, 2021).

Some contend that offering a single universal benefit (such as UC in the UK) instead of multiple targeted welfare programmes could reduce stigmatisation. A single benefit might be more visible, potentially leading to greater identification as welfare-dependent (Kildal and Kuhnle, 2005; Larsen, 2006; Baumberg *et al.*, 2012). However, there is generally a lack of evidence to support this claim, and in the UK it has even been suggested that UC could help reduce the stigma attached to welfare payments among non-workers (Rotik and Perry, 2011).

Social stigma may persist even with universal welfare benefits (Jones, 1980; Wong, 1998). This suggests that simply reducing selective social benefits may not address the root causes of stigma. Universal benefits might also lead to a higher non-take-up rate among those who perceive it as an undeserved and unreciprocated gift rather than an entitled benefit. Entitlements are generally considered less stigmatising than non-contributory benefits. Recipients of non-contributory benefits often feel judged or looked down upon, contributing to the stigma associated with these benefits.[27]

The effect size of stigmatisation can differ depending on whether the social benefit is designed to be contributory or non-contributory. Benefits can be based on the principle of equity, where recipients are identified through contribution records, typically involving social security contributions, and the principle of support, where recipients can claim the benefit not based on insurance (non-contributory benefits). Recipients of non-contributory benefits often feel more subjected to judgment or condescension, contributing to the stigma associated with these benefits (Baumberg *et al.*, 2012).[28]

Government administrations also play a role in affecting take-up rates. To enhance take-up, administrations have adopted strategies from large-scale digitalisation efforts

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[27] Rotik and Perry (2011) argue that some working people opposed the idea of UC because they feel they are being treated the same way as those who are out of work.

[28] A telephone survey conducted by HM Revenue and Customs in the UK in 2011 found that people who received tax credits and CB expressed more discomfort when claiming social security benefits (Breese, 2011). This was because they attributed a higher degree of stigma to the latter. According to the survey results, 25% of the respondents considered tax credits as stigmatised, while 66% associated stigma with social security benefits. Tax credits were perceived as recognition of past work contributions, so they had a reduced stigma. CB, on the other hand, had the lowest stigma likely due to its broader eligibility criteria. When respondents were asked about the household income limits for CB eligibility, a notable distinction emerged at higher income levels, where there was greater support for providing CB as compared to Tax Credits. This distinction could be attributed to the universal nature of CB during the survey period.

to establishing one-stop shops. This approach allows individuals applying for one benefit to receive automatic information about other programmes they may be eligible for. Moreover, administrators can proactively identify eligible claimants or implement an automated registration process, such as accessing the registry of registered unemployed individuals. Clear and effective communication campaigns have also been shown to boost the uptake of benefits (Bhargava and Manoli, 2015; Gestel *et al.*, 2023).

4.3 ANALYTICAL STRATEGY

Measuring take-up

One of the main challenges in studying the take-up of social benefits through empirical analysis lies in accurately measuring it. A precise measure of take-up rates necessitates valid information on both programme eligibility and recipients. However, this can prove to be a difficult task, primarily because the eligible population is not directly observable in survey data (nor it is generally known in administrative sources). Moreover, household eligibility may change between the time the household sought entry to the welfare programme and when it was surveyed. Duclos (1995) further elaborates on this using econometric methods to show that analyst error can lead to substantial misestimates of take-up rates.

Given that eligibility is generally not observable, one has to resort to simulating benefit entitlements, where policy rules, including eligibility criteria and means-testing thresholds, are implemented on an observed population of interest.

Take-up rate is then measured as

$$\text{take-up} = \frac{\text{observed recipiency}}{\text{simulated eligibility}} \tag{4.1}$$

If using administrative data on recipients, we can assume that measurement error on the numerator is not an issue, while approximations in the simulation of eligibility criteria and measurement errors in the characteristics of the population used for simulating eligibility potentially bias the denominator. Administrative data on actual recipients is not publicly available, at least in the UK. Instead, we recur to survey data, exploiting available information on detailed income sources. Several factors, however, can contribute to the mismeasurement of benefit receipt in survey data. For example, some respondents may have forgotten about past benefit receipt (recall bias) or may have reported past benefit receipt as more recent than it occurred (Celhay, Meyer and Mittag, 2024). Additionally, respondents who claim multiple benefits may misreport by inadvertently omitting received benefits and reporting unreceived ones (Hancock and Barker, 2005; Call *et al.*, 2013; Krafft, Davis and Tout, 2015), a phenomenon referred to as benefit confusion. Another contributing factor to misreporting is the "social desirability bias" (Bound, Brown and Mathiowetz, 2001; Celhay, Meyer and Mittag, 2024), which occurs when the receipt of means-tested social welfare benefits is perceived as stigmatising, leading respondents to underreport their receipt of these benefits. For instance, individuals who are close to the labour market, without children, and with relatively high household incomes and savings are likely to under-report their welfare receipt (Bruckmeier, Müller and Riphahn, 2014).

Some studies discussed the relevance of misreporting for the reliability of survey data. Meyer et al. (2022) found that between 23% and 50% of actual food stamp recipient households in the USA do not report benefit receipts, and a substantial number of actual nonrecipients are also recorded as recipients. The study also found that error rates vary with household characteristics. Similarly, Bruckmeier et al. (2021) investigated the take-up for the German minimum income support programme Unemployment Benefit II (UB II) and found instances of both under- and overreporting of benefit programme participation in survey data when compared to linked administrative records. Their analysis of corrected versus uncorrected data showed statistically significant and substantial differences in estimated marginal effects, suggesting that correcting for misreporting not only alters the magnitude of non-take-up but also modifies the influence of factors associated with the decision to avail benefits. Additionally, Krafft et al. (2015), utilising pooled data across two states in the USA, explored factors influencing subsidy using both survey and administrative datasets. The study found that the frequency and systematic nature of misreporting bias estimates of the predictors of programme receipt.

Measuring take-up is subject to various sources of measurement errors, both at the numerator and at the denominator of eq. (4.1) (see Table 4.1). To start with the numerator (observed behaviour), individuals might not report receiving the benefit, for instance, for recall errors or to avoid feeling stigmatised (false negatives). If eligibility is correctly simulated, they would be wrongly classified as non-take-uppers.[29] Conversely, false positives can occur if individuals incorrectly report receiving the benefit, for instance, because they confuse the month when they claimed it. If they are simulated as eligible, this would result in an upward bias in the take-up rates.[30]

[29] If, on the other hand, they are (incorrectly) simulated as non-eligible, they would be dropped from the analysis, still resulting in a downward bias in the estimated take-up rate, although less severe.
[30] From the data, we observe that the false positive error rate is 6.8% for CB and 10.4% for LB/UC. The false negative is unmeasurable.

Table 4.1 Measurement errors

Affecting the numerator		
	Observed recipiency	
True recipiency		
Yes	Yes	No
No	Take-up biased upwards	Take-up biased downwards

Affecting the denominator		
	Simulated eligibility	
True eligibility		
Yes	Yes	No
No	Take-up biased downwards	Take-up biased upwards

False positives and false negatives can also occur at the denominator, determining (simulated) eligibility. Over- (under-) estimation of eligibility would then result in a downward (upward) bias in the take-up rates.

Measurement errors in a binary dependent variable can lead to biased coefficient estimates, even if the measurement error is independent of covariates, as opposed to a continuous variable (Hausman, Abrevaya and Scott-Morton, 1998; Bound, Brown and Mathiowetz, 2001). If take-up is measured with random error, the coefficient estimates for predictors of take-up will be biased towards zero.[31] If, on the other hand, the measurement error is systematically related to the covariates, the estimated coefficients in a model with take-up as the dependent variable can be biased in either direction.

[31] When a continuous variable is mismeasured, it is possible to use instrumental variable techniques to correct for random measurement errors. However, when it comes to binary variables, instrumental variable techniques cannot be used because measurement errors in binary variables are mean-reverting and are correlated with the true value (Bound, Brown and Mathiowetz, 2001).

However, we do not expect measurement error in take-up rates to be unduly high, because of the high-quality of both the survey data (Fisher and Hussein, 2023), and the tax-benefit model (van de Ven and Popova, 2024), which has undergone extensive validation. Furthermore, given that the focus of the study is on analysing *changes* in take-up rates over time, the problem would be, to a considerable extent, differenced out. Nevertheless, we subject results to a robustness test where we extend the pool of eligible individuals to include cases who are not simulated to be eligible, but are observed to receive the benefits. If selective measurement error were an issue, including these individuals in the analysis would lead to significant changes in the results.

Microsimulation and data

To simulate benefit entitlements, we use UKMOD, which is based on the UK component of EUROMOD (Sutherland and Figari, 2012). UKMOD is a static microsimulation model comprising a detailed implementation of the UK tax and transfer system (Richiardi, Collado and Popova, 2021). The model is mainly used for the ex-ante evaluation of social policy reforms directed at households in the UK. The model has been validated and tested at the micro and macro levels (van de Ven and Popova, 2023).

The standard version of UKMOD is based on FRS data. The cross-sectional nature of the data, however, precludes analysis of persistence in take-up behaviour. Therefore, this study uses a version of UKMOD that utilises longitudinal data from UKHLS, recently made available for research (Richiardi, Bronka and Popova, 2023).

UKHLS is an ongoing panel survey of over 40,000 households that started in 2009 (Univeristy of Essex, 2019). Study design involves oversampling of certain segments of the UK population, including regions such as Northern Ireland, as well as areas within England, Scotland, and Wales with significant migrant and ethnic minority populations. Further details regarding the sampling frame and data collection procedures can be found in (Burton, Laurie and Lynn, 2011).

For this research, we have used the first nine waves of UKHLS, which allow us to measure how individual eligibility and benefit recipiency change over time for a large sample of benefit units. Another advantage of using UKHLS data comes from the fact that the survey includes information on various life course domains. This permits a comprehensive understanding of the factors that influence the take-up rates of social benefits in the UK.

While the UKHLS data used in this study is not specifically meant to measure income, it nevertheless provides high-quality income data (Fisher and Hussein, 2023). The survey aims to collect data on household incomes after taxes and National Insurance contributions. To do this, each individual in the household is asked about each income source they have. A comprehensive set of income sources is collected, up to 46 in total, including earnings from jobs, social security benefits, pensions, and investment income. Total household income is then computed by summing over individual income sources, for all household members.

There are several other aspects of the survey that increase the reliability of income data and reduce measurement error in take-up rates. Respondents are asked about their "current income" or income during the survey interview, which allows validation with official UK (cross-sectional) income statistics. For specific income sources, respondents are allowed to choose the reporting period, and the reported amounts are standardised post-data collection. Deriving final household net income involves data cleaning to identify reporting errors where they are clear, imputation for missing data, and simulation for tax calculations. If a household reports the same income source more than once (for example, if both members of a couple report receiving the same state benefit), this is identified to avoid double-counting. Additionally, deductions for household taxes are made using external information on council tax. This implies that the potential measurement error in reported incomes is likely to be low.[32] Nevertheless, as a robustness test, we include individuals in the eligible population who are simulated not to be eligible but still receive benefits. The presence of non-random measurement error will potentially lead to significant changes in the reported results.

Finally, by linking the UKMOD-UKHLS input data with the special license version of UKHLS, we can attempt a geographical characterisation of take-up rates across the UK. This linkage allows us to calculate the take-up in each local authority district. To address the potential problem of endogeneity between take-up rate and the proportion of recipients in each local area district, we recalibrate the ratio by excluding the eligibility unit from the count of eligible units of the benefit and those claiming the benefit if the unit is already claiming the benefit.

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[32] See Fisher (2019) for further details.

Measuring personality traits and cognitive skills

The third wave of the UKHLS includes a module designed to construct a psychological profile of the respondent. Questions asked pertain to the Five Factor Model, which includes the fundamental psychological dimensions: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Given the impracticality of conducting extensive psychological assessments in large-scale surveys, the UKHLS offers a set of fifteen items, with three items dedicated to each personality dimension.[33] Respondents provide their answers using a Likert-type scale with seven points, ranging from 1 – “does not apply” to 7 – “applies perfectly” (refer to Appendix A for the list of items used). The analysis in this study utilises measures derived by standardising the scores obtained from the factor analysis. Three items were used to assess each of the five dimensions. The Cronbach's alpha was 0.57 for Agreeableness, 0.55 for Conscientiousness, 0.60 for Extraversion, 0.71 for Neuroticism, and 0.66 for Openness to Experience.[34]

In the third wave, a battery of four tests was administered to survey participants to assess cognitive ability (McFall, Stephen, 2013). These tests comprise: Immediate Word Recall (quantified by the number of correct items); Subtract (assessed by the number of correct answers); Verbal fluency (evaluated by the count of correct answers) and Numeric Ability (determined by the count of correctly answered items). This approach has been widely used elsewhere (Huppert *et al.*, 1995; Lang *et al.*,

[33] The full inventory, the NEO PI-R, comprises 240 questions (Costa Jr. and McCrae, 2008).
[34] The alpha value provides a measure of internal consistency, that is, how closely related a set of items are as a group. Cronbach (1951) alpha values of 0.7 or higher indicate acceptable internal consistency. Values of alpha less than 0.7 are common for one-dimensional scales with less than ten items (Cortina, 1993; Sijtsma, 2009). Although a high value of Cronbach’s alpha is desirable, there is no general rule where alpha becomes acceptable (Schmitt, 1996).

2007; Banks, O'Dea and Oldfield, 2010; Börsch-Supan *et al.*, 2013; Hurst *et al.*, 2013). For this study, we obtain one standardised score from these measures, by means of a principal component analysis.[35]

4.4 DESCRIPTIVE STATISTICS

This paper studies take-up rates for several benefit schemes, the first being Child Benefit (CB). CB is a universal flat-rate non-contributory benefit paid to the carer of each dependent child (under 16 or under 19 and in full-time education or training). There is a higher rate for the eldest or only dependent child; otherwise, the rate does not vary. CB is not generally taxable, and has been subject to a means-test since 2013. This involves a High Income Child Benefit Charge (HICBC), payable if the carer or their partner has an income over £50,000 in a given tax year. The amount of the tax is 1% of the benefit for every £100 of income additional to £50,000, effectively resulting in a taper rate that brings the benefit to 0 if the income of one of the two partners surpasses £60,000. These income thresholds and the HICBC have remained unchanged between 2013 and 2023.[36]

Next, we turn to Legacy Benefits (LB), a group of six different means-tested benefits in the process of being phased out: Income-based job seekers allowance, Income-Related Employment and Support Allowance, Income Support, Housing Benefit, Child

[35] The inclusion of the personality traits and cognitive ability limits the analysis to focus upon respondents present in the third wave. As shown in the Appendix B excluding personality traits and cognitive ability does not substantially the results.

[36] The HICBC was introduced in 2013 following initial proposals announced in 2010 for withdrawing CB from families with a higher rate taxpayer, which was then modified in the 2012 Budget. Thresholds and rates were changed in the 2024 Spring budget announcement, with effects from April 6, 2024, which is beyond our period of observation.

Tax Credit, and Working Tax Credit. All LBs are subject to a means test and non-contributory benefits.

In 2013, the UK government introduced a new social welfare programme called Universal Credit (UC), consisting in a benefit for working-age people on a low income who are in or out of work. The scheme represents a major restructuring of the UK social assistance system and has been rolled out progressively with the aim to completely replace LBs by 2028/9. It was initially introduced as a pilot programme in certain areas and later expanded across the UK. To be eligible for UC, a claimant must meet two sets of conditions: 'basic conditions' and 'financial conditions'. The basic conditions require the claimant to be over 18, under State Pension age, and not in education. The financial conditions require the benefit unit to have sufficiently low income and capital. Only one claim for UC can be made per benefit unit. Unfortunately, within the current UKMOD modelling, take-up rates cannot be analysed separately for LB and UC. Therefore, the two benefits are analysed together.

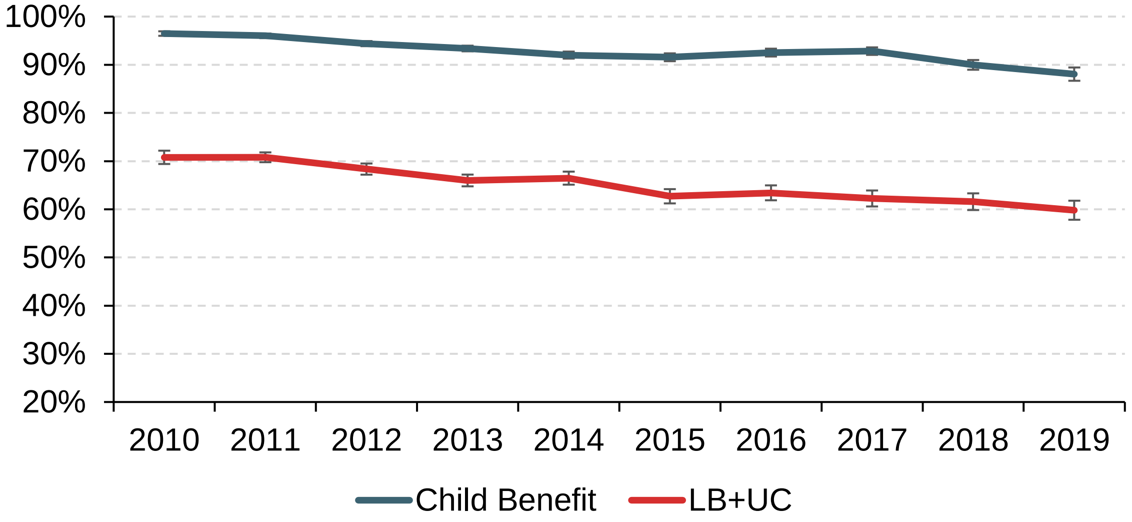
Official statistics on take-up for CB are provided by HM Revenue and Customs. Estimates reveal that the take-up rate has declined steadily over time, from 97% in 2012 to 89% in 2022. This is attributed to the introduction of HICBC in 2013, dissuading some families from claiming (HM Revenue & Customs, 2023). Additionally, the Covid-19 pandemic has likely exacerbated this decline in more recent years. The CB take-up rate is calculated using three separate data sources: (i) administrative data which is used to calculate the caseload and (ii) population data produced by the Office for National Statistics (ONS). Take-up rates are estimated by dividing administrative data totals by population figures. The Labour Force Survey (LFS) data is used to adjust rates for participation in education for 17 to 19-year-olds.

Official take-up estimates for LB and UC are not currently provided. In 2010 the take-up rate for Child Tax Credit was 83%, while the take-up rate for Working Tax Credit was 64%. From 2010 to 2012 there was a noticeable increase in the take-up rates for both credits. In 2012, the take-up rate for the Child Tax Credit peaked at 88%, while the Working Tax Credit reached a take-up rate of 66%. Subsequently, from 2013 to 2017, there were slight fluctuations in the take-up rates for both credits, with some years showing small increases or decreases (HM Revenue & Customs, 2019). The estimates published by the Department for Work and Pensions (DWP) indicate that the Housing Benefit take-up rate varied from 78% in 2016 to 83% in 2018, while the take-up rate for Income Support/ESA (Income-related) ranged from 82% in 2010 to 90% in 2019 (DWP, 2020). However, year-on-year comparisons need to be carried out with caution due to the rollout of UC and methodological refinements.

Our estimates show a marked decline for both CB and LB/UC over the years (Figure 4.1). Starting with CB we note that prior to the implementation of HICBC, the CB take-up remained consistently high, averaging at 96%. However, following the introduction of HICBC in 2013, there was a notable decline in overall take-up, which stood at 92% by 2015. Subsequently, the take-up rate remained relatively stable until a further decline to 88% by 2019.

One of the primary factors implicated in this decline is the introduction of the HICBC. The introduction of the HICBC has raised concerns regarding the number of taxpayers

Figure 4.1: Take-up rates (%)



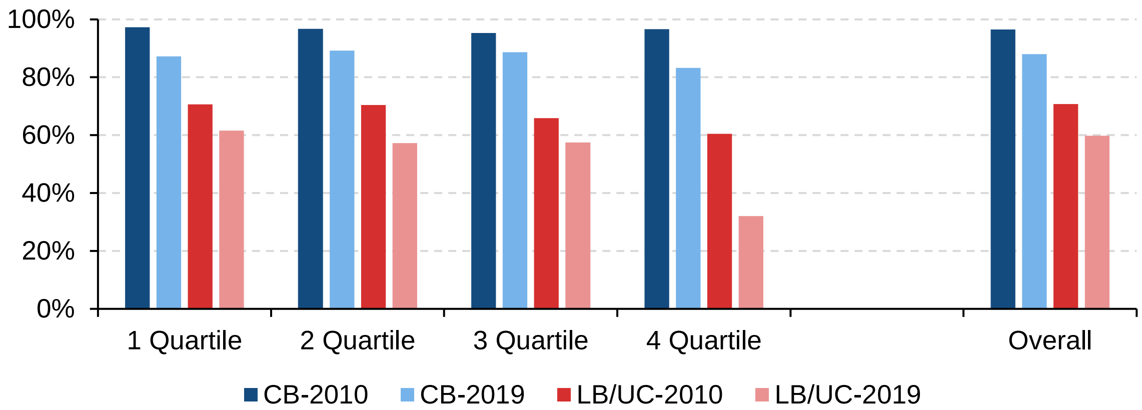
Note: The error bars represent the 95% confidence interval bars
Source: our computation on UKMOD-UKHLS output data, 2010-2019

facing penalties for failing to register their HICBC liability and pay the charge through their tax return. Additionally, the lack of adjustments to the £50,000 threshold since its inception has led to more taxpayers being liable to pay the charge. Therefore, some individuals eligible for CB may opt not to claim the benefit to avoid paying the HICBC (Seely and Kennedy, 2023).

Indeed, when examining the take-up rates separately among parents with taxable income less than £50,000 per year and those with taxable income exceeding £50,000 per year, we observe a significant impact of the HICBC. While the overall decline in CB take-up rates mirrored the general trend, parents affected by the HICBC policy experienced a more pronounced decline. Specifically, their take-up declined from 92% to 63% by 2013, further dropping to 50% in 2015, before partially recovering to 59% thereafter. However, this increase needs to be interpreted with caution due to the wide confidence intervals. The study will only focus on parents below the HICBC threshold.

Likewise, LB/UC have experienced a parallel decline in its take-up rate over time, despite the gradual introduction of UC in 2013. Estimations indicate a slight recovery in 2014, but take-up has steadily declined in subsequent years. A recent report by Ipsos, commissioned by DWP, identifies various reasons for this lower take-up (NAO, 2024). These include individuals mistakenly believing that the migration notice does not pertain to them, assuming they are ineligible due to recent changes in circumstances, or having misconceptions about automatic transfer to UC. Furthermore, digital literacy, access issues, and ongoing maintenance requirements for claims posed additional difficulties, causing some claimants to abandon the process or delay their applications (Bennett, 2024). Another factor that could explain the downward trend is that UC combined both in-work support and out-of-work benefits (like Jobseeker's Allowance), which the latter carrying significant stigma. The consolidation of social benefits may have dissuaded some eligible individuals from claiming. Indeed, during the COVID-19 pandemic, (Baumberg Geiger *et al.*, 2021) found that a significant proportion of eligible individuals did not claim UC, with stigma being a notable factor.

Figure 4.2: Take-up rates (%), by (gross) income quartile



Source: our computation on UKMOD-UKHLS output data, 2010-2019

Between 2010 and 2019, take-up rates changed across different gross income levels, as shown in Figure 4.2, categorised by income quartiles.[37] In 2010, take-up rates for CB were consistently high, ranging from 95% to 97% across all quartiles, reflecting widespread claiming prior to HICBC. However, by 2019 there was a notable decrease in take-up, particularly evident amongst the high-income group, where the rate dropped to 83%. While the first and second quartiles experienced relatively smaller declines, they also saw decreases, indicating a general trend of reduced take-up rates over the decade. On the other hand, LB/UC in 2010 had lower take-up rates compared to CB, ranging across all income quartiles. In 2019, all income groups saw a decrease in take-up, with the fourth quartile experiencing the most significant drop to 32%. These statistics indicate that the transition to UC did not help to reverse or reduce the declining trend in take-up.

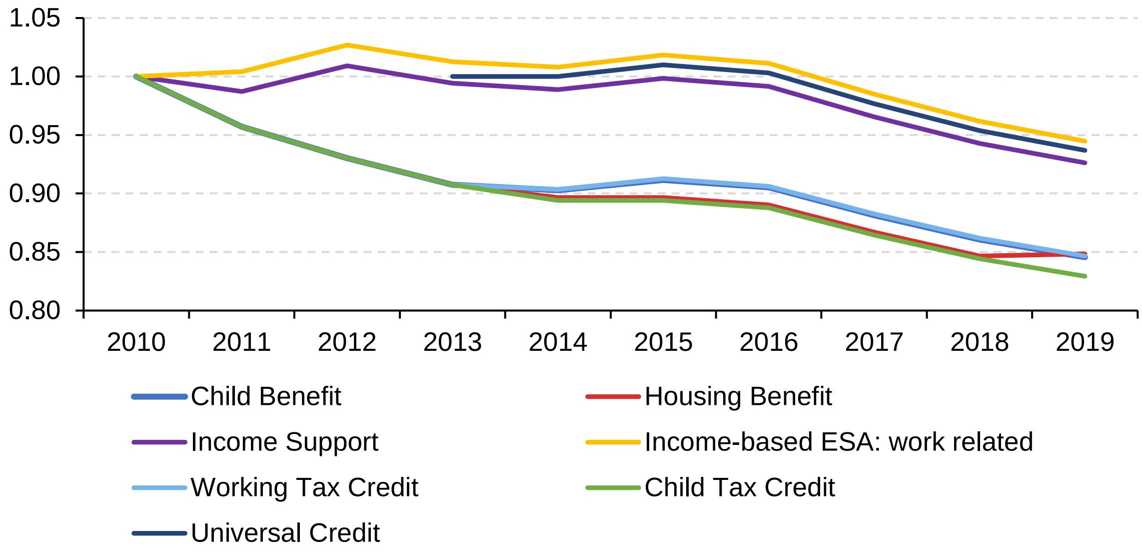
Table 4.2: Take-up transition matrix

	t+1		
	Child Benefit		
t	Not take-up	Take-up	Total
Non take-up	70.0%	30.0%	100%
Take-up	2.7%	97.3%	100%
Total	6.0%	93.9%	100%
	Legacy Benefits/Universal Credit		
	Not take-up	Take-up	Total
Non take-up	81.0%	19.1%	100%
Take-up	7.2%	92.8%	100%
Total	22.6%	77.4%	100%

Sample: Individuals eligible in both t and t+1.
Source: our computation on UKMOD-UKHLS output data, 2010-2019

[37] Gross (original) income is the sum of employment income, investment income, income of children under 16, property income, private pension, private transfers received, income from self-employment, minus maintenance payments paid.

Figure 4.3: Index of benefit rates, 2010 = 1.00



Source: our computation on UKMOD-UKHLS output data, 2010-2019

A likely explanation of the declining trends illustrated above points to the relevance of economic factors. Figure 4.3 illustrates the benefit rates in real terms from 2010 to 2019, presenting each benefit rate relative to its 2010 (base year) value. By 2019, the indices had decreased, indicating a reduction in each benefit's relative level of support. In real terms, all benefits were approximately 15% lower in 2019 than in 2010, except for Income Support and Income-based Employment and Support Allowance which have experienced a 6% decrease since 2010. Moreover, UC rates are also 6% lower in real terms relative to 2013. This reduction in benefit value stems from inadequate indexing of benefit amounts and may have deterred eligible individuals from taking social benefits.

Table 4.2 describes transitions between take-up status over the period under analysis. The data shows that there is a high level of stability, with 97% of eligible units continuing to be observed to claim the benefit the following year, while the remaining

3% is observed to stop claiming. 70% of eligible units classified as non-take-up in any year remain so in the next year, but 30% switch to (observed) take-up. A similar pattern is observed for LB/UC. Approximately 93% of eligible units who claimed the benefit in a particular year continued to claim the next year, while 80% of those who did not claim persisted in not claiming it. Moreover, there was a 30% chance that those who did not claim the benefit in a year would start claiming it the following year.

4.5 MODEL SPECIFICATION

To investigate the dynamics of take-up behaviour, accounting for past behaviour and unobserved heterogeneity, we employ a dynamic random effects probit framework (Wooldridge, 2005). The inclusion of the lagged dependent variable introduces the issue of initial conditions, implicitly assuming that the initial observations are independent of unobserved variables. Simply put, this assumption implies that the behavioural process begins at the same time as the observation period for each individual. However, this assumption is too restrictive for this study, which uses data from 2010 to 2019 since, for some individuals, 2010 does not mark the start of their behavioural process. The adopted framework accounts for correlated random effects and endogenous initial conditions, allowing us to separate the contribution of genuine state dependence from various forms of (observed and unobserved) heterogeneity on take-up behaviour. The latent variable equation for the dynamic random effects panel probit model can be written as:

$$y_{it}^* = \mathbf{z}_i\alpha + \mathbf{x}_{it}\beta + \gamma y_{it-1} + u_i + \varepsilon_{it} \tag{4.2}$$

where the subscript $i = 1, 2, \dots, N$ indexes eligible units, the subscript $t = 2, \dots, T$ indexes time periods, T_{it}^{*} is the latent dependent variable for taking up the benefit, $\mathbf{z}_i$ is a vector of time-invariant characteristics, $\mathbf{x}_{it}$ is a vector of time-varying characteristics, u_i are unobserved time-invariant individual-specific random effects, and the ε_{it} are the idiosyncratic error term, and they are assumed to be normally distributed $N(0, \sigma_{\varepsilon}^{2})$.

The observed binary outcome is:

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^{*} \geq 0 \\ 0 & \text{if } y_{it}^{*} < 0 \end{cases}$$

When unobserved individual heterogeneity influences take-up behaviour, the assumption that u_i is independent of $\mathbf{x}_{it}$ becomes invalid. To address this, we can approximate the individual effect as a function of the individual means of time-varying characteristics, following the approach proposed by Mundlak (1978):

$$u_i = \mu + \bar{\mathbf{x}}_i \boldsymbol{\delta} + \eta_i \tag{4.3}$$

where $\eta_i | \bar{\mathbf{x}}_i \sim N\left(0, \sigma_{\eta}^{2}\right)$ and is independent of $\mathbf{x}_{it}$ and ε_{it}. η_i represents the residual and is assumed to be normally distributed with zero mean and variance σ_{η}^{2}, indicating the degree of dispersion due to unobserved heterogeneity.

The latent regression becomes:

$$y_{it}^{*} = \mu + \mathbf{z}_i \alpha + \mathbf{x}_{it} \beta + \gamma y_{it-1} + \bar{\mathbf{x}}_i \boldsymbol{\delta} + \eta_i + \varepsilon_{it} \tag{4.4}$$

A test of $\mathrm{cov}(\eta_i, \mathbf{x}_{it}) = 0$ is a test of $H_0: \boldsymbol{\delta} = 0$. If the test rejects H_0, then the random effects model is biased. The resulting parameter estimates are also not consistent if the initial observation of the dependent variable y_{it-1} and the unobserved individual effect η_i are correlated. This is the initial conditions problem, because y_{i0} is probably not the true starting point of the "process", just the start of our sample. In any case, y_{i0} is probably not randomly allocated but related to u_i as are the other y_{it}. If take-up behaviour in the initial year is indeed correlated with the time-invariant unobserved heterogeneity, as expected, failing to account for this unobserved individual heterogeneity will lead to an estimate of state dependency that is biased upwards. To address this issue, we follow Wooldridge's method of controlling for initial conditions by including in the specification the value of the dependent variable in the first wave – that is by conditioning on y_{i0} – and model the density of u_i conditional on $y_{i0}, \mathbf{x}_i$. This implies that u_i could be specified as:

$$u_i = \mu + \bar{\mathbf{x}}_i\boldsymbol{\delta} + \gamma_0 y_{i0} + \eta_i \tag{4.5}$$

where $\eta_i | \bar{\mathbf{x}}_i, y_{i0} \sim N(0, \sigma_\eta^2)$ and the latent regression can be expressed as follows:

$$y_{it}^* = \mu + \mathbf{z}_i\alpha + \mathbf{x}_{it}\beta + \gamma y_{it-1} + \bar{\mathbf{x}}_i\boldsymbol{\delta} + \gamma_0 y_{i0} + \eta_i + \varepsilon_{it} \tag{4.6}$$

Our dataset in the panel analysis comprises 16,491 unique eligible units for CB and 7,723 unique eligible units for LB/CB for the years 2011-2019. Due to changes in eligibility or attrition, some units drop out of the sample or join at a later wave during the period of analysis, making the dataset unbalanced. Restricting the analysis to a 9-wave balanced panel reduces sample size substantially to 6,817 and 3,297 respectively for CB and LB/UC, thereby reducing the precision of parameter estimates. Additionally, a balanced sample may not necessarily be a random sub-sample of all respondents because unobserved characteristics associated with attrition may also be associated with unobserved heterogeneity. We, therefore, opt for using the unbalanced panel for the regression analysis but perform robustness checks on the balanced panel.[38]

UKHLS contains detailed income data as well as a broad range of demographic and labour market information. To better understand the factors influencing take-up, we include four types of explanatory variables in our analysis. The first group consists of individual-level variables that capture key characteristics of each respondent, such as age, gender, education, and original income. This group also includes personality traits, which are considered stable over time in which we use the measurements from the third wave, assuming they remain consistent thereafter. This method is akin to establishing an average personality trait for all years based on the data from the third wave.

The second group of variables includes those at the eligible benefit-unit level, which takes the same value for each adult in the same benefit unit. Examples are the presence of dependent children in the benefit unit, household composition, housing

[38] While we acknowledge that the Wooldridge estimators were developed assuming a balanced panel, it may be applied to unbalanced panels assuming that sample dropout is ignorable, i.e., if the unobservable determinants of attrition are not correlated with the unobservables determining take-up. We also note that even where researchers have found that sample dropout is nonignorable when modelling of labour market dynamics, the impact of attrition is small (see e.g. Cappellari and Jenkins (2014) and the references cited therein). To check the robustness of our results, we report estimates derived using the Wooldridge estimators, and using both balanced and unbalanced panels. Overall, the results suggest that accounting for item non-response in this manner makes little difference to the estimated effect of regressors. This conclusion may not be applicable to situations where the prevalence of item non-response on the dependent variable is much greater.

tenure, as well as neighbourhood characteristics. Importantly, the eligible amount itself is included here, as it is determined by government policy and not influenced by an individual's decision to take up benefits, which allows us to consider it exogenous. In contrast, income could potentially be endogenous because, although original income excludes benefit amounts, it may be influenced by unobserved factors like financial planning, which might also affect benefit take-up decisions. This could lead to income being correlated with the error term in the take-up equation. We do not consider this endogeneity to be substantial after accounting for the time-averaged variables. Additionally, the universal nature of CB makes it highly unlikely that income is affected by the take-up of CB, and the more demanding work-related requirements of UC make it harder for individuals to plan their income to become eligible for these benefits.

The third set of variables are longitudinal means derived from the first two groups, used to implement the Mundlak-Chamberlain approach. This method accounts for unobserved heterogeneity by averaging time-varying variables over time, helping to control for time-invariant unobserved factors and reduce potential bias, thereby mitigating endogeneity concerns. We also control for time-fixed effects to take into account time trends.

Additionally, we considered the recipiency of other LB/UC benefits to capture factors influencing take-up behaviour that are not explicitly included in the model. However, this could introduce endogeneity if decisions on different benefits are jointly determined or share common underlying causes.

The sign of the estimated parameters indicates the direction of the effect of the associated variables on the probability of taking up the benefit. However, due to the non-linearity of the model, determining the magnitude of the effects directly from the parameters is not straightforward. To address this issue, we follow the common practice of presenting marginal effects for benchmark individuals (such as “average” individuals with average characteristics). The marginal effect of an explanatory variable on the probability of take-up is, therefore, the change in the probability of take-up resulting from a one-unit change in the explanatory variable (if continuous) or a change from 0 to 1 (if it is a dummy variable), for an average individual.

For cross-sectional statistics and descriptive probit analysis, we use the UKMOD-UKHLS cross-sectional household weights. However, for longitudinal regressions, we use unweighted data. This is because it is not clear what the appropriate weight would be when multiple waves are pooled together - longitudinal weights are available for UKHLS data only for the original sample respondents who were interviewed at the first wave and at every wave up to and including the wave of interest. This means that using longitudinal weights would cause losing any individual who at some point dropped out of from the UKHLS, restricting the focus on the balanced sample. As a sensitivity test, we estimate weighted regressions to evaluate sensitivity to weighting, which may arise, for instance, if there are heterogeneous effects.[39] For this, we correct the UKHLS longitudinal weights by the inverse of the probability of being included in

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[39] When the effect varies across subgroups within a population, the weighted regression accounts for this heterogeneity. However, when the variance in the characteristics that influence the effect is different across subgroups, the weighted regression may not yield an accurate estimate of the effect. See Solon et al., (2015) for a discussion of weighting.

the estimation sample, estimated by a simple probit model. The estimates in the weighted models remained largely consistent.

4.6 ESTIMATION RESULTS

Take-up decisions

The dynamic model is estimated separately for CB and LB/UC. As mentioned earlier, the parameters are opaque to interpret due to the non-linearity of the model; we, therefore, pre sent results as marginal effects for selected variables. (The original and

Table 4.3. Marginal effects on the probability of taking-up benefit, dynamic random effects probit model

	CB		LB/UC	
Lagged value of take-up	.154***	(.034)	.244***	(.033)
Initial take-up	.177***	(.035)	.384***	(.042)
Log Simulated Eligible Amount	.002***	(.001)	.029***	(.005)
Age	.000	(.000)	.000	(.000)
Gender (Base: Female)				
Male	-.001	(.001)	.023**	(.010)
Marital Status (Base: Married/Cohabitating)				
Single	-.001	(.004)	.052***	(.019)
Separated, Divorced, Widowed	-.010	(.012)	.029	(.026)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean Black African Asian	.001	(.003)	.013	.018
Asian or Asian British Chinese	.001	(.002)	.012	.011
Black or Black British	-.001	(.003)	-.019	.017
Arab and any other	-.011	(.016)	.009	.047
Disability (Base: Not Disabled)				
Disabled	-.002	(.004)	.011	(.013)
Children in Household (Base: One)				
Two	.000	(.002)	.045**	(.023)
Three or more	.000	(.004)	.076***	(.025)
Minimum age of child in household	-.006**	(.003)	-.035**	(.012)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	-.001	(.002)	.01	(.015)
Education (Base: Non-Tertiary)				
Tertiary	-.001	(.001)	.001	(.007)

	CB		LB/UC	
Number of rooms in the house	-.002***	(.001)	.002	(.006)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.001	(.001)	.011	(.016)
Rented	-.002	(.002)	.039***	(.010)
Reduced Rented	-.006	(.01)	.020	(.023)
Social Rented	.000	(.002)	.056***	(.009)
Free	-.003	(.007)	.058***	(.015)
Other	-.006	(.013)	-.0114	(.110)
Labour Market Status (Base: Inactive)				
Professional and Managerial Roles	-.004	(.003)	-.018	(.026)
Technical and Skilled Roles	-.005	(.003)	-.004	(.019)
Service Manual and Support Roles	-.001	(.003)	.000	(.023)
Log of Original Income	.004*	(.002)	-.027**	(.011)
Neighbourhood effect	.015*	(.009)	-.001	.005
Receipt of other benefits	.010***	(.002)	.049***	(.011)
Personality Traits				
Openness to Experience	.000	(.001)	-.003	(.004)
Conscientiousness	-.001	(.001)	-.004	(.004)
Extraversion	.000	(.001)	.004	(.003)
Agreeableness	.000	(.001)	-.001	(.004)
Neuroticism	.000	(.001)	.006	(.003)
Cognitive Ability	.000	(.001)	.004	(.004)
Time-average of log original income	-.010**	(.004)	-.014	(.013)
Time-average of neighbourhood effect	.000	(.011)	.009*	(.005)
Receipt of other benefits	.010***	(.002)	.049***	(.011)
N	16,009		7,723	

Note: The table shows selected reported marginal effects of the results. The complete results can be found in Appendix B. Personality traits are only measured in the third wave and are assumed to remain constant, representing an average personality trait for all years.

full parameter estimates are available in Appendix B for reference.) The results comparing CB and LB/UC take-up decisions highlight several notable differences.[40]

An important finding is the strong state dependence and persistence in take-up choices, in that current take-up behaviour is significantly affected by previous take-up

[40] For comparison, we also estimated a simple pooled probit model, without controlling for individual effects. The estimated coefficients from the pooled probit regressions are discernibly different to those from the RE probit regressions, stressing the importance of unobserved heterogeneity (results are reported in Appendix B). When applying the correction suggested by Arulampalam (1999), the RE probit coefficients would differ by about 15%-25% on average (in absolute terms).

decisions. The marginal effects of the lagged take-up choice suggest that past behaviour strongly influences present decisions (Table 4.3). Indeed, if an individual with an average set of characteristics and circumstances claimed CB in a given year, he or she would be 15.4 percentage points more likely to claim it in the following year (from 84.1% to 99.6%), if still eligible, with respect to a similar individual who did not claim. For LB/UC, the same figure is 24.4 percentage points more likely (from 71.7% to 97.1%). From a robustness test, the results for CB take-up also reveal a significant drop in state dependency when a child turns 16. This is because parents must reapply to maintain eligibility.[41] Specifically, when the child is over 16, the take-up rate decreases by almost 20 percentage points, dropping from a near-perfect 99.6% to 80.8%.

The state dependency result is expected, and this dynamic is partly a consequence of the fact that, if circumstances remain unchanged, individuals typically remain enrolled without the need to re-apply. In such cases, transitions from take-up to non-take-up are few and likely to reflect measurement errors either in reported recipiency, simulated eligibility, or the observed circumstances themselves. Analysis of dynamic take-up is, however, still meaningful even when continued enrolment is automatic, given the possibility of transitions from non-take-up to take-up.

The estimated coefficients for the initial take-up demonstrate a significant positive effect for both benefits, indicating that eligible units are more likely to continue claiming

[41] For CB, parents must reapply to maintain eligibility when a child turns 16, if the child has left full-time non-advanced education or approved training and has registered for further education, work, or training with a careers service. Unsurprisingly, this is associated to a lower take-up (HM Revenue & Customs, 2023).

the benefit if they initially claimed it. The significance also rejects the null hypothesis that initial conditional conditions are exogenous. The initial value of LB/UC take-up also implies that there is a substantial correlation between unobserved heterogeneity and the initial conditions. In fact, the coefficient on the initial value of take-up is positive and larger than the coefficient on the lagged value of take-up, suggesting that without controlling for unobserved heterogeneity, the effect of state dependency would be significantly overestimated.

At first glance, results suggest that income-related factors have distinctive patterns for CB and LB/UC take-up decisions. For CB, income has a positive effect on take-up: a one-standard-deviation increase in the log of original income leads to a 0.2 percentage points increase in the probability of CB take-up. In contrast, LB/UC exhibits a negative coefficient: a one-standard-deviation increase in the log of original income results in a 2.9 percentage point decrease in the probability of LB/UC take-up.

However, for CB the effect of the time average of income, to control for unobserved heterogeneity, is negative. This implies that individuals with higher average income over time are less likely to apply for CB, with the marginal effect being a decrease of 1.0 percentage points. Consequently, the overall marginal effect of income on CB take-up is also negative. In contrast, average income is not significant for LB/UC. It is noteworthy that when also including all eligible units impacted by the HICBC, the negative effect of time-average income on CB take-up becomes notably pronounced, closer to 2 percentage points, aligning with *a priori* expectations, and the yearly income becomes insignificantly different from zero.

These findings suggest that CB appears more responsive to long-term “permanent” income. This may be because eligible units tend to have more stable income over time, given the broader eligibility nature of the benefit. Conversely, take-up for LB/UC demonstrates greater sensitivity to short-term income fluctuations.

Other income-related factors also play a role. For example, the number of rooms in the dwelling where individuals live, a proxy for financial wealth, shows a negative effect, indicating that households in larger dwellings are less likely to claim CB, everything else remaining constant. Additionally, the findings reveal distinct patterns for housing tenure categories. For CB, no clear effect emerges. However, for LB/UC, renters and individuals living in a subsidised accommodation exhibit a higher propensity for LB/UC participation than those who own their house on a mortgage. This suggests that rental accommodation (as well as social housing) might be associated with greater financial need that aligns with the purpose of LB/UC. Furthermore, we observe no differences between occupations.

Demographic factors such as gender and marital status exhibit distinct effects on take-up behaviour for the two benefits. For example, men are no more likely than women to claim CB, but significantly more likely to claim LB/UC. Being single does not affect the uptake of CB, but it increases the likelihood of claiming LB/UC. Having more children does not significantly affect CB take-up, but it increases the likelihood of claiming LB/UC. The minimum age of the youngest child in the household demonstrates consistent negative coefficients for both benefits, indicating that households with older children are less inclined to take up these benefits. Lack of significance of some possible determinants is also of interest. For instance, we do not find evidence of ethnic variability, as well as education. This might seem surprising at first, but can be rationalised by considering that the effect of these variables is at least partly mediated by income. Overall, these findings show that the mechanisms underlying take-up for the two benefits are very different, with financial needs – and related socio-demographic characteristics – playing a stronger role for LB/UC. This goes beyond the stricter means testing for LB/UC (results are conditional on eligibility), indicating that the design of the benefit has been to some extent over-internalised by the target population.

These findings seem to be true irrespective of psychological and intellectual characteristics: personality traits and cognitive skills do not have a direct effect on the take-up of benefits. The absence of a direct influence from these characteristics reinforces the idea that structural determinants, such as financial, play a more dominant role in shaping take-up behaviour.[42]

Neighbourhood effects are captured in our analysis by the average take-up rate in the local area district. From Table 4.3, we can observe that individual take-up is relatively higher in areas where more individuals are claiming the benefit. As already discussed, recent studies suggest that stigma decreases with local participation, indicating that peer evaluation influences individuals' concerns about their social image, leading to "positional externalities". As a result, the perceived disutility reduces as the number of peers who engage in the same behaviour increases. At the same time, social norms and imitative behaviour (which we can also consider as factors pertaining to the

[42] Tables B.7 and B.8 in Appendix B present the full regression results excluding personality traits. The findings remain largely consistent with those from the main model, indicating that the exclusion of personality traits does not significantly alter the results.

"mind"), as well as better information targeting on the part of the Government and knowledge sharing among communities (factors which we can better classify as pertaining to "matter", or material conditions), also play a role in lowering the barriers to claiming the benefits.

Considering the overall contribution of time-average variables (reported in the Appendix B), we observe that not all variables are individually statistically significant at conventional levels. However, a Wald test of the joint hypothesis that all the coefficients for time-averaged variables are equal to zero is rejected at 90% confidence interval for CB. The significance of time-averaged variables for LB/UC is stronger (hypothesis rejected at 95% confidence interval). In the context of the Mundlak (1978) approach, the significance of a time-averaged variable implies that the unobserved heterogeneity it captures has a systematic impact on the outcome variable. This shows the importance of incorporating time-averaged variables to account for individual-specific characteristics that may not be directly observable but still influence the take-up decision. Thus, the significance of the time-averaged variables implies that not accounting for unobserved heterogeneity in the random-effect model would result in biased estimates.[43]

The parameter ρ measures the proportion of the total variance in take-up rates due to variability between sampling units of individuals with different observed characteristics. Our estimate for ρ, close to 0.4 for both benefits, suggest that a substantial proportion of the total variance in the take-up process is within individuals sharing the same

[43] The results produced in the Appendix B confirm that the exclusion of time-averaged variables would result in an upward bias of the estimates.

observed characteristics, indicating that the contribution of unobserved heterogeneity is substantial.

State dependency in benefit recipiency

To further characterise the role of state dependency, we generate a set of predicted patterns for the dependent variable over time, using the model's estimates. This describes the asymptotic inflows and outflows into benefit recipiency in a hypothetical scenario where individual characteristics remained unchanged.

As indicated in Table 4.4, the positive state dependency implies a high persistence probability and a low exit probability. The entry rate for CB is 0.80, while for LB/UC, it is slightly lower at 0.68. Both benefit groups exhibit nearly perfect persistence and a high long-term steady-state probability.

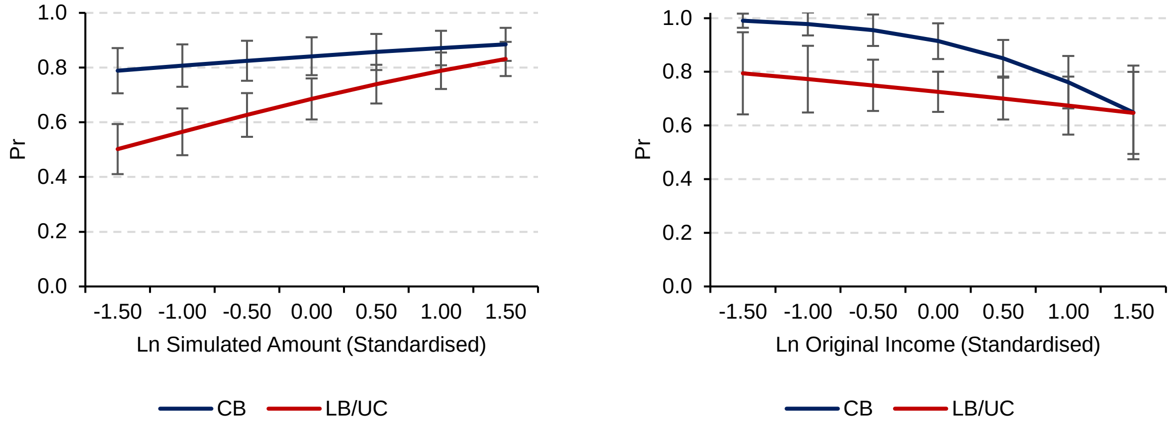
We assess the role of state dependence on an individual's take-up and its effect across the different amounts of eligibility and original income (in real terms). The margins plots in Figure 4.4 reveal a clear trend for an individual with an average set of characteristics. As the benefit amount increases, the likelihood of individuals claiming the benefits also increases. This positive relationship shows that higher benefit

Table 4.4. Asymptotic inflows and outflows into benefit recipiency

	CB		LB/UC	
Entry Probability (1|0)	.802***	(.029)	.678***	(.024)
Persistence Probability (1|1)	.981***	(.002)	.896***	(.005)
Exit Probability (0|1)	.018***	(.002)	.104***	(.005)

*Notes: Standard errors are shown in parentheses. * p < .10, ** p < .05, *** p < .01. The numbers reported are the average predicted probabilities.*

Figure 4.4: Entry probability by eligibility amount and original income



Notes: The figures present the take-up probability, conditional on non-take-up in the previous period. The numbers reported are the predicted probabilities evaluated at the mean of the covariates. The predicted values are the fitted values at the mean of the covariates. The error bars represent the 95% confidence interval bars. Income is standardised at the average level of real income across all waves.

amounts serve as incentives, encouraging more people to participate and increasing the opportunity cost of not claiming the benefits.

The role of material factors is also demonstrated through the original income. The entry probability for CB is notably higher than LB/UC. As income levels increase, we observe a decrease in the entry probabilities for both CB and LB/UC. However, the change in entry probability for LB/UC appears less sensitive to income in comparison to CB. This indicates that the entry probability for CB gradually approaches that of LB/UC at relatively higher income levels.

Robustness check for measurement error

We further test how sensitive our results are with respect to different assumptions concerning measurement errors. As explained earlier, in the baseline analysis we adopt a broad definition of eligibility, which include individuals who are not simulated to be eligible but still receive benefits. If measurement errors are present and non-random, including these individuals in the analysis could potentially lead to significant changes in the reported results. As a robustness, we replicate the analysis excluding such individuals. Results exhibit only minimal deviations with respect to the baseline (see Appendix B).

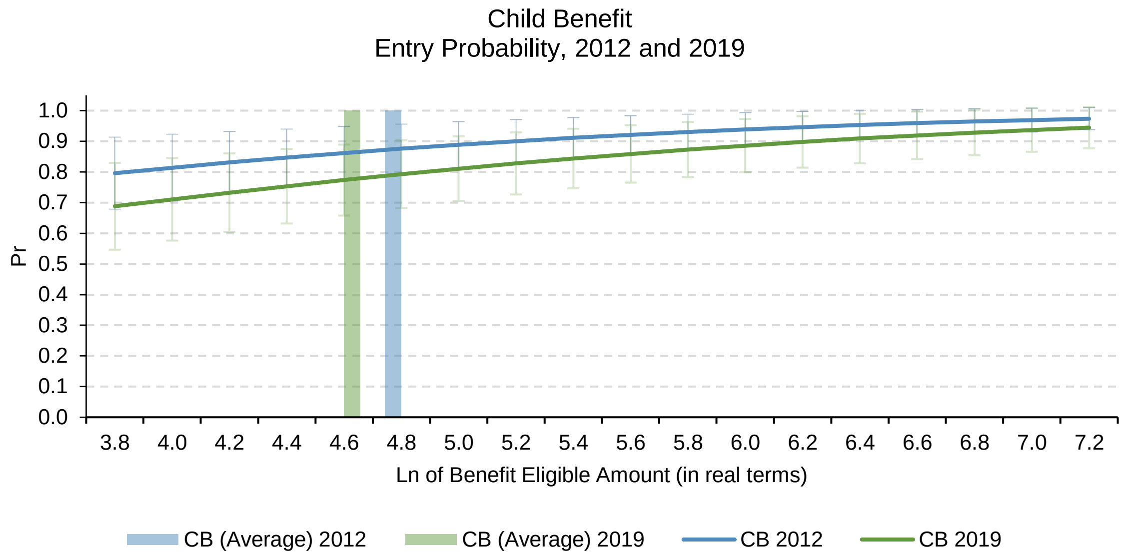
The break-even point of claiming benefit

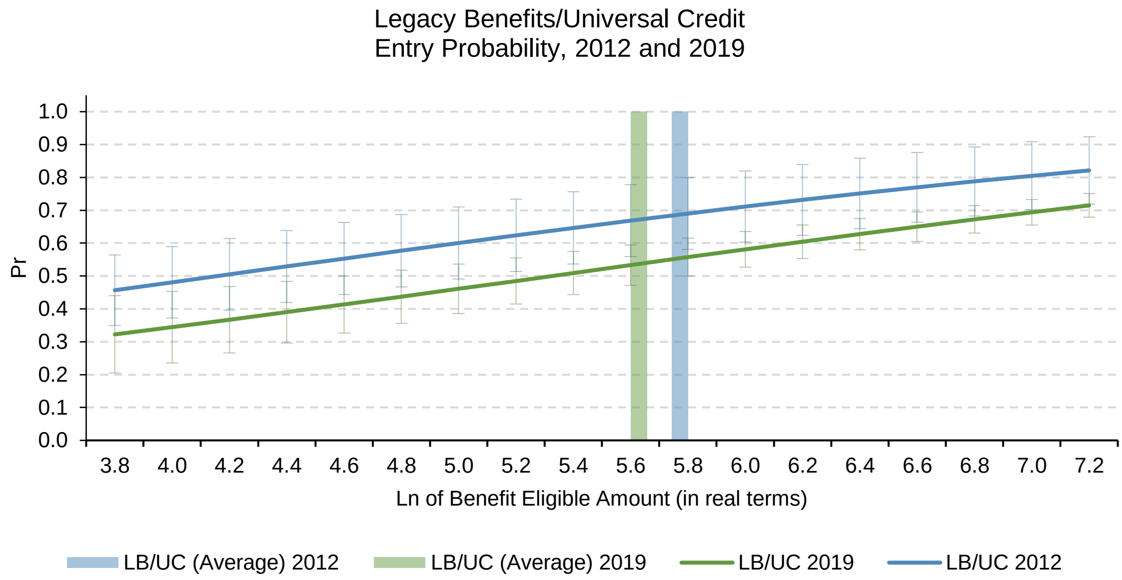
The economic interpretation of non-take-up points to the implicit or explicit take-up costs – material costs, information costs, psychological costs – being higher than the benefits – the extra income generated by the benefit. Along these lines, based on our estimates we can compute, for each eligible individual, the probability of take-up associated to different levels of the benefit. The amount associated to a probability of 50% can then be interpreted as the break-even point of claiming the benefit: at that amount, an individual is indifferent between claiming and non-claiming. Said differently, the break-even point represents the expected benefit amount required to offset implicit costs associated with claiming the benefit.

The margins plot depicting the probability of individuals opting for both types of benefits as a function of the eligible amount (in real terms) reveals a clear trend, when fixing all other variables at their means (cf. Figure 4.5). As the entitlement amount increases, there is a corresponding rise in the likelihood of individuals choosing to claim the benefits. This positive relationship signifies that higher benefit amounts serve as incentives, encouraging more individuals to participate and increasing the opportunity cost of not claiming the benefits.

In both 2012 and 2019, the likelihood of claiming the CB was notably higher than LB/UC across all entitlement levels. However, the probabilities of claiming the CB were lower in 2019 compared to 2012. This decrease is statistically significant at the 95%

Figure 4.5. Predicted probabilities of take-up





Notes: The numbers reported are the predicted probabilities evaluated at the mean of the covariates. The error bars represent the 95% confidence interval bars. Base year for prices is 2010. In 2012, the average Legacy Benefits/Universal Credit (LB/UC) rate received was £321 per month, which decreased to £287 per month in real terms by 2019. Similarly, the average Child Benefit (CB) rate was £117 per month in 2012, dropping to £98 per month in real terms by 2019. The figures present the take-up probability, conditional on non-take-up in the previous period.

confidence level and coincides with a reduction in the average eligible benefits CB amount during this period.

Shifting to LB/UC, in 2012, it took £800 per year (in real terms) to push the probability of take-up just above 50%. Given that the average eligible amount was £3,846 per year, this indicates that the “average” individual obtained a net utility gain from claiming the benefit. In 2019, the entitlement amount to attain a 50% probability of claiming the benefits rose to £2,657 per year (in real terms). To contextualise, the 2019 average eligible payments were £3,446 per year, implying that the average payment deteriorated at 2010 prices. The higher threshold associated with LB/UC compared to CB suggests the possibility of greater implicit costs in claiming these benefits compared to CB. Furthermore, we observe that in 2019, the probability of claiming LB/UC was significantly lower at each level of entitlement than in 2012.

The increasing implicit cost suggests that the decline in take-up rates is not solely due to the decrease in the real value of the benefits. Starting with CB, the introduction of the HICBC has contributed to the rise in the implicit cost of claiming CB, particularly for higher-income parents. The static threshold for HICBC implies that as wages increase with inflation, more parents become subject to the charge, leading to a higher administrative burden. The increase in implicit costs is more evident in the case of LB/UC, indicating that take-up rates are influenced not only by the real value of the benefits but also by increasing administrative complexities. Confusion about eligibility, fear of penalties, misunderstanding of migration notices, and assumptions about automatic transfers (from LB to UC) have also contributed to increased costs and barriers associated with claiming benefits. The higher implicit costs of claiming LB/UC could also reflect social barriers, including a sense of stigma, that can stop citizens from applying.

4.7 DISCUSSION AND CONCLUSION

This paper has studied the take-up rate and the economic and psychological factors influencing take-up rates for Child Benefit and Legacy Benefits / Universal Credit, two of the main welfare programs in the UK. Using a dynamic model estimated on panel data, we reveal that unobserved characteristics of eligible individuals influence the probability of taking up benefits. We also show evidence of strong state dependency, where past claiming behaviour affects current take-up.

Our analysis suggests that whether or not to take up a particular benefit is primarily influenced by economic factors, namely the amount of benefit an individual is entitled to and their original income. This indicates that the financial implications of the decision are the most crucial determinants of take-up. Interestingly, we have found no significant effect of personality traits or cognitive skills on the take-up decision, which suggests a subordination of “mind” versus “matter” in explaining claiming behaviour. This is an important finding as it emphasises the role of economic incentives in shaping the behaviour of individuals when it comes to accessing social benefits. It also corroborates the common approach in the (economic) literature of disregarding psychological factors, often grounded in data availability.

The results also reveal that individual take-up is affected by the average take-up in the local area. This factor may reflect a combination of matter and mind factors that work in the same direction: decreased stigma, accommodating social norms, emulating behaviour, and improved access to information within communities.

The findings may not come as a surprise, but they may have important implications for related policies. In particular, the strong persistence in take-up behaviour, as well as spillovers within local communities, suggest focussing efforts towards facilitating first-time claims in more deprived areas. This could be done with a combination of financial measures (e.g. a “first claim bonus”) to increase perceived gains, administrative/communication actions (e.g. “claim workshops”) and collaboration among key stakeholders (e.g. working with non-governmental organisations like trade unions and employers) to lower associated costs. Additionally, automatic enrolment, eliminating the need for applications, could enhance claim rates, particularly for benefits with minimal administrative complexities.

REFERENCES

Arulampalam, W. (1999) ‘A Note on Estimated Coefficients in Random Effects Probit Models’, *Oxford Bulletin of Economics and Statistics*, 61(4), pp. 597–602. Available at: https://doi.org/10.1111/1468-0084.00146.

Atkinson, A.B. (ed.) (1996) ‘On targeting and family benefits’, in *Incomes and the Welfare State: Essays on Britain and Europe*. Cambridge: Cambridge University Press, pp. 223–261. Available at: https://doi.org/10.1017/CBO9780511559396.014.

Bargain, O., Immervoll, H. and Viitamäki, H. (2012) ‘No claim, no pain. Measuring the non-take-up of social assistance using register data’, *The Journal of Economic Inequality*, 10(3), pp. 375–395. Available at: https://doi.org/10.1007/s10888-010-9158-8.

Barr, A. and Turner, S. (2018) ‘A Letter and Encouragement: Does Information Increase Postsecondary Enrollment of UI Recipients?’, *American Economic Journal: Economic Policy*, 10(3), pp. 42–68. Available at: https://doi.org/10.1257/pol.20160570.

Banks, J., O’Dea, C. and Oldfield, Z. (2010) ‘Cognitive Function, Numeracy and Retirement Saving Trajectories’, *The Economic Journal*, 120(548), pp. F381–F410. Available at: https://doi.org/10.1111/j.1468-0297.2010.02395.x.

Baumberg, B. *et al.* (2012) *Benefits stigma in Britain*. London: Elizabeth Finn Care/Turn2us.

Baumberg Geiger, B. *et al.* (2021) *Non-take-up of Benefits at the Start of the COVID-19 Pandemic*. Welfare at a (Social) Distance and The Health Foundation. Available at: https://62608d89-fc73-4896-861c-0e03416f9922.usrfiles.com/ugd/62608d_602f7840f4114361a4dbf6d007d3825b.pdf.

Bennett, F. (2024) ‘Take-up of social security benefits: past, present – and future?’, *Journal of Poverty and Social Justice*, 32(1), pp. 2–25. Available at: https://doi.org/10.1332/17598273Y2023D000000005.

Bertrand, M., Luttmer, E.F.P. and Mullainathan, S. (2000) ‘Network Effects and Welfare Cultures’, *The Quarterly Journal of Economics*, 115(3), pp. 1019–1055. Available at: https://doi.org/10.1162/003355300554971.

Bertrand, M., Mullainathan, S. and Shafir, E. (2006) ‘Behavioral Economics and Marketing in Aid of Decision Making among the Poor’, *Journal of Public Policy & Marketing*, 25(1), pp. 8–23.

Beshears, J. *et al.* (2013) ‘Simplification and saving’, *Journal of Economic Behavior & Organization*, 95, pp. 130–145. Available at: https://doi.org/10.1016/j.jebo.2012.03.007.

Bhargava, S. and Manoli, D. (2015) ‘Psychological Frictions and the Incomplete Take-Up of Social Benefits: Evidence from an IRS Field Experiment’, *American*

Economic Review, 105(11), pp. 3489–3529. Available at: https://doi.org/10.1257/aer.20121493.

Blundell, R., Fry, V. and Walker, I. (1988) 'Modelling the Take-up of Means-Tested Benefits: The Case of Housing Benefits in the United Kingdom', *The Economic Journal*, 98(390), pp. 58–74. Available at: https://doi.org/10.2307/2233304.

Bound, J., Brown, C. and Mathiowetz, N. (2001) 'Measurement Error in Survey Data', in *Handbook of Econometrics*. Elsevier, pp. 3705–3843. Available at: https://doi.org/10.1016/S1573-4412(01)05012-7.

Börsch-Supan, A. *et al.* (2013) 'Data Resource Profile: The Survey of Health, Ageing and Retirement in Europe (SHARE)', *International Journal of Epidemiology*, 42(4), pp. 992–1001. Available at: https://doi.org/10.1093/ije/dyt088.

Breese, H. (2011) *Views on eligibility for tax credits and Child Benefit and any stigma associated with claiming these*. 150. United Kingdom: HM Revenue and Customs.

Briere, M., Poterba, J. and Szafarz, A. (2021) *Choice Overload? Participation and Asset Allocation in French Employer-Sponsored Saving Plans*. w29601. Cambridge, MA: National Bureau of Economic Research, p. w29601. Available at: https://doi.org/10.3386/w29601.

Brown-Iannuzzi, J.L. *et al.* (2021) 'Investigating the Interplay Between Race, Work Ethic Stereotypes, and Attitudes Toward Welfare Recipients and Policies', *Social Psychological and Personality Science*, 12(7), pp. 1155–1164. Available at: https://doi.org/10.1177/1948550620983051.

Bruckmeier, K., Müller, G. and Riphahn, R.T. (2014) 'Who misreports welfare receipt in surveys?', *Applied Economics Letters*, 21(12), pp. 812–816. Available at: https://doi.org/10.1080/13504851.2013.877566.

Bruckmeier, K., Riphahn, R.T. and Wiemers, J. (2021) 'Misreporting of program take-up in survey data and its consequences for measuring non-take-up: new evidence from linked administrative and survey data', *Empirical Economics*, 61(3), pp. 1567–1616. Available at: https://doi.org/10.1007/s00181-020-01921-4.

Bruckmeier, K. and Wiemers, J. (2012) 'A new targeting: a new take-up?: Non-take-up of social assistance in Germany after social policy reforms', *Empirical Economics*, 43(2), pp. 565–580. Available at: https://doi.org/10.1007/s00181-011-0505-9.

Bruckmeier, K. and Wiemers, J. (2017) 'Differences in welfare take-up between immigrants and natives – a microsimulation study', *International Journal of Manpower*, 38(2), pp. 226–241. Available at: https://doi.org/10.1108/IJM-03-2015-0053.

Bursztyn, L. *et al.* (2018) 'Status Goods: Experimental Evidence from Platinum Credit Cards', *The Quarterly Journal of Economics*, 133(3), pp. 1561–1595. Available at: https://doi.org/10.1093/qje/qjx048.

Burton, J., Laurie, H. and Lynn, P. (2011) *Appendix: Understanding Society design overview*. Colchester: University of Essex. Available at:

https://www.understandingsociety.ac.uk/research/publications/publication-519664/ (Accessed: 7 May 2024).

Buss, C. (2019) ‘Public opinion towards targeted labour market policies: A vignette study on the perceived deservingness of the unemployed’, *Journal of European Social Policy*, 29(2), pp. 228–240. Available at: https://doi.org/10.1177/0958928718757684.

Cai, L., Mavromaras, K. and Sloane, P. (2018) ‘Low Paid Employment in Britain: Estimating State-Dependence and Stepping Stone Effects’, *Oxford Bulletin of Economics and Statistics*, 80(2), pp. 283–326. Available at: https://doi.org/10.1111/obes.12197.

Call, K.T. *et al.* (2013) ‘Comparing Errors in Medicaid Reporting across Surveys: Evidence to Date’, *Health Services Research*, 48(2pt1), pp. 652–664. Available at: https://doi.org/10.1111/j.1475-6773.2012.01446.x.

Cappellari, L. and Jenkins, S.P. (2014) ‘The Dynamics of Social Assistance Benefit Receipt in Britain’, *Safety Nets and Benefit Dependence*, 39, pp. 41–79. Available at: https://doi.org/10.1108/S0147-912120140000039000.

Celhay, P., Meyer, B. and Mittag, N. (2022) *Stigma in Welfare Programs*. w30307. Cambridge, MA: National Bureau of Economic Research, p. w30307. Available at: https://doi.org/10.3386/w30307.

Celhay, P., Meyer, B.D. and Mittag, N. (2024) ‘What leads to measurement errors? Evidence from reports of program participation in three surveys’, *Journal of Econometrics*, 238(2), p. 105581. Available at: https://doi.org/10.1016/j.jeconom.2023.105581.

Chetty, R., Friedman, J.N. and Saez, E. (2013) ‘Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings’, *American Economic Review*, 103(7), pp. 2683–2721. Available at: https://doi.org/10.1257/aer.103.7.2683.

Chetty, R. and Saez, E. (2013) ‘Teaching the Tax Code: Earnings Responses to an Experiment with EITC Recipients’, *American Economic Journal: Applied Economics*, 5(1), pp. 1–31. Available at: https://doi.org/10.1257/app.5.1.1.

Clark, M.H. and Schroth, C.A. (2010) ‘Examining relationships between academic motivation and personality among college students’, *Learning and Individual Differences*, 20(1), pp. 19–24. Available at: https://doi.org/10.1016/j.lindif.2009.10.002.

Cortina, J.M. (1993) ‘What is coefficient alpha? An examination of theory and applications.’, *Journal of Applied Psychology*, 78(1), pp. 98–104. Available at: https://doi.org/10.1037/0021-9010.78.1.98.

Costa Jr., P.T. and McCrae, R.R. (2008) ‘The Revised NEO Personality Inventory (NEO-PI-R)’, in *The SAGE handbook of personality theory and assessment, Vol 2: Personality measurement and testing*. Thousand Oaks, CA, US: Sage Publications, Inc, pp. 179–198. Available at: https://doi.org/10.4135/9781849200479.n9.

Craig, P. (1991) 'Costs and Benefits: A Review of Research on Take-up of Income-Related Benefits', *Journal of Social Policy*, 20(4), pp. 537–565. Available at: https://doi.org/10.1017/S0047279400019796.

Creedy, J. (2002) 'Take–up of Means–tested Benefits and Labour Supply', *Scottish Journal of Political Economy*, 49(2), pp. 150–161. Available at: https://doi.org/10.1111/1467-9485.00226.

Cronbach, L.J. (1951) 'Coefficient alpha and the internal structure of tests', *Psychometrika*, 16(3), pp. 297–334. Available at: https://doi.org/10.1007/BF02310555.

Cubel, M. *et al.* (2016) 'Do Personality Traits Affect Productivity? Evidence from the Laboratory', *The Economic Journal*, 126(592), pp. 654–681. Available at: https://doi.org/10.1111/ecoj.12373.

Currie, J. (2004) *The Take Up of Social Benefits*. w10488. Cambridge, MA: National Bureau of Economic Research, p. w10488. Available at: https://doi.org/10.3386/w10488.

Dahan, M. and Nisan, U. (2010) 'The effect of benefits level on take-up rates: evidence from a natural experiment', *International Tax and Public Finance*, 17(2), pp. 151–173. Available at: https://doi.org/10.1007/s10797-009-9109-0.

Dubois, H. and Ludwinek, A. (2015) *Access to social benefits: Reducing non-take-up*. Dublin: Eurofound. Available at: https://www.eurofound.europa.eu/en/publications/2015/access-social-benefits-reducing-non-take (Accessed: 7 May 2024).

Duclos, J.-Y. (1995) 'Modelling the take-up of state support', *Journal of Public Economics*, 58(3), pp. 391–415. Available at: https://doi.org/10.1016/0047-2727(94)01484-6.

Duflo, E. *et al.* (2006) 'Saving Incentives for Low- and Middle-Income Families: Evidence from a Field Experiment with H&R Block', *The Quarterly Journal of Economics*, 121(4), pp. 1311–1346. Available at: https://doi.org/10.1093/qje/121.4.1311.

DWP (2020) *Income-related benefits: estimates of take-up: financial year 2018 to 2019*, *Department for Work and Pensions: Benefits entitlement*. Available at: https://www.gov.uk/government/statistics/income-related-benefits-estimates-of-take-up-financial-year-2018-to-2019 (Accessed: 26 March 2024).

Egan, M. *et al.* (2017) 'Adolescent conscientiousness predicts lower lifetime unemployment.', *Journal of Applied Psychology*, 102(4), pp. 700–709. Available at: https://doi.org/10.1037/apl0000167.

Egan, M., Daly, M. and Delaney, L. (2015) 'Childhood psychological distress and youth unemployment: Evidence from two British cohort studies', *Social Science & Medicine*, 124, pp. 11–17. Available at: https://doi.org/10.1016/j.socscimed.2014.11.023.

Ekehammar, B. and Akrami, N. (2003) 'The relation between personality and prejudice: a variable- and a person-centred approach', *European Journal of Personality*, 17(6), pp. 449–464. Available at: https://doi.org/10.1002/per.494.

Ekehammar, B. and Akrami, N. (2007) 'Personality and Prejudice: From Big Five Personality Factors to Facets', *Journal of Personality*, 75(5), pp. 899–926. Available at: https://doi.org/10.1111/j.1467-6494.2007.00460.x.

Elster, J. (ed.) (1989) 'Social Norms', in *Nuts and Bolts for the Social Sciences*. Cambridge: Cambridge University Press, pp. 113–123. Available at: https://doi.org/10.1017/CBO9780511812255.013.

Fisher, P. (2019) 'Does Repeated Measurement Improve Income Data Quality?', *Oxford Bulletin of Economics and Statistics*, 81(5), pp. 989–1011. Available at: https://doi.org/10.1111/obes.12296.

Fisher, P. and Hussein, O. (2023) 'Understanding Society: the income data', *Fiscal Studies*, 44(4), pp. 377–397. Available at: https://doi.org/10.1111/1475-5890.12353.

Fiske, S.T. (2018) 'Stereotype Content: Warmth and Competence Endure', *Current Directions in Psychological Science*, 27(2), pp. 67–73. Available at: https://doi.org/10.1177/0963721417738825.

Fuchs, M. *et al.* (2020) 'Falling through the social safety net? Analysing non-take-up of minimum income benefit and monetary social assistance in Austria', *Social Policy & Administration*, 54(5), pp. 827–843. Available at: https://doi.org/10.1111/spol.12581.

Gestel, R.V. *et al.* (2023) 'Improving Take-Up by Reaching Out to Potential Beneficiaries. Insights from a Large-Scale Field Experiment in Belgium', *Journal of Social Policy*, 52(4), pp. 740–760. Available at: https://doi.org/10.1017/S004727942100088X.

Hancock, R. and Barker, G. (2005) 'The Quality of Social Security Benefit Data in the British Family Resources Survey: Implications for Investigating Income Support Take-up by Pensioners', *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 168(1), pp. 63–82.

Harnish, M. (2019) *Non-Take-Up of Means-Tested Social Benefits in Germany*. Berlin: DIW. Available at: https://www.diw.de/de/diw_01.c.616590.de/publikationen/diskussionspapiere/2019_1793/non_take_up_of_means_tested_social_benefits_in_germany.html (Accessed: 7 May 2024).

Hausman, J.A., Abrevaya, J. and Scott-Morton, F.M. (1998) 'Misclassification of the dependent variable in a discrete-response setting', *Journal of Econometrics*, 87(2), pp. 239–269. Available at: https://doi.org/10.1016/S0304-4076(98)00015-3.

Hernandez, M. and Pudney, S. (2007) 'Measurement error in models of welfare participation', *Journal of Public Economics*, 91(1), pp. 327–341. Available at: https://doi.org/10.1016/j.jpubeco.2006.06.006.

Hernanz, V., Malherbet, F. and Pellizzari, M. (2004) *Take-Up of Welfare Benefits in OECD Countries: A Review of the Evidence*. OECD Social, Employment and Migration Working Papers 17. Available at: https://doi.org/10.1787/525815265414.

HM Revenue & Customs (2023) *Child Benefit Statistics: annual release, data at August 2022*, *GOV.UK*. Available at: https://www.gov.uk/government/statistics/child-benefit-statistics-annual-release-august-2022/child-benefit-statistics-annual-release-data-at-august-2022 (Accessed: 24 March 2024).

Holford, A. (2015) 'Take-up of Free School Meals: Price Effects and Peer Effects', *Economica*, 82(328), pp. 976–993. Available at: https://doi.org/10.1111/ecca.12147.

Huppert, F.A. *et al.* (1995) 'CAMCOG—A concise neuropsychological test to assist dementia diagnosis: Socio-demographic determinants in an elderly population sample', *British Journal of Clinical Psychology*, 34(4), pp. 529–541. Available at: https://doi.org/10.1111/j.2044-8260.1995.tb01487.x.

Hurst, L. *et al.* (2013) 'Lifetime Socioeconomic Inequalities in Physical and Cognitive Aging', *American Journal of Public Health*, 103(9), pp. 1641–1648. Available at: https://doi.org/10.2105/AJPH.2013.301240.

Janssens, J. and Van Mechelen, N. (2022) 'To take or not to take? An overview of the factors contributing to the non-take-up of public provisions', *European Journal of Social Security*, 24(2), pp. 95–116. Available at: https://doi.org/10.1177/13882627221106800.

Jensen, C. and Petersen, M.B. (2017) 'The Deservingness Heuristic and the Politics of Health Care', *American Journal of Political Science*, 61(1), pp. 68–83. Available at: https://doi.org/10.1111/ajps.12251.

Jones, P. (1980) 'Rights, Welfare and Stigma', in N.W. Timms (ed.) *Social Welfare: Why and How?* 1st edn. Routledge, pp. 123–144. Available at: https://www.routledge.com/Social-Welfare-Why-and-How/Timms/p/book/9781138604988 (Accessed: 24 March 2024).

Karlan, D. *et al.* (2016) 'Getting to the Top of Mind: How Reminders Increase Saving', *Management Science*, 62(12), pp. 3393–3411. Available at: https://doi.org/10.1287/mnsc.2015.2296.

Kildal, N. and Kuhnle, S. (2005) *Normative Foundations of the Welfare State: The Nordic Experience*. Routledge.

Ko, W. and Moffitt, R. (2024) 'Take-up of Social Benefits', in K.F. Zimmermann (ed.) *Human Resources and Population Economics*. Cham: Springer International Publishing, pp. 1–42. Available at: https://doi.org/10.3386/w30148.

Komarraju, M. and Karau, S.J. (2005) 'The relationship between the big five personality traits and academic motivation', *Personality and Individual Differences*, 39(3), pp. 557–567. Available at: https://doi.org/10.1016/j.paid.2005.02.013.

Komarraju, M., Karau, S.J. and Schmeck, R.R. (2009) 'Role of the Big Five personality traits in predicting college students' academic motivation and achievement', *Learning and Individual Differences*, 19(1), pp. 47–52. Available at: https://doi.org/10.1016/j.lindif.2008.07.001.

Krafft, C., Davis, E.E. and Tout, K. (2015) 'The Problem of Measurement Error in Self-Reported Receipt of Child-Care Subsidies: Evidence from Two States', *Social Service Review*, 89(4), pp. 686–726. Available at: https://doi.org/10.1086/684967.

Lang, F.R. *et al.* (2007) 'Assessing Cognitive Capacities in Computer-Assisted Survey Research: Two Ultra-Short Tests of Intellectual Ability in the German Socio-Economic Panel (SOEP)', *Journal of Contextual Economics – Schmollers Jahrbuch*, 127(1), pp. 183–191. Available at: https://doi.org/10.3790/schm.127.1.183.

Larsen, C.A. (2006) 'Selectivism and Stigmatisation', in *The Institutional Logic of Welfare Attitudes*. Routledge.

Liebman, J.B. and Luttmer, E.F.P. (2015) 'Would People Behave Differently If They Better Understood Social Security? Evidence from a Field Experiment', *American Economic Journal: Economic Policy*, 7(1), pp. 275–299. Available at: https://doi.org/10.1257/pol.20120081.

Matsaganis, M., Paulus, A. and Sutherland, H. (2008) *The take up of social benefits*. European Commission Directorate-General 'Employment, Social Affairs and Equal Opportunities'.

McKay, S. (2014) 'Benefits, poverty and social justice', *Journal of Poverty and Social Justice*, 22(1), pp. 3–10. Available at: https://doi.org/10.1332/175982714X13910760153802.

Merton, R.K. (1968) *Social theory and social structure*. 1968th edn. New York: Free Press.

Meyer, B.D., Mittag, N. and Goerge, R.M. (2022) 'Errors in Survey Reporting and Imputation and Their Effects on Estimates of Food Stamp Program Participation', *Journal of Human Resources*, 57(5), pp. 1605–1644. Available at: https://doi.org/10.3368/jhr.58.1.0818-9704R2.

Moffitt, R. (1983) 'An Economic Model of Welfare Stigma', *The American Economic Review*, 73(5), pp. 1023–1035.

Mood, C. (2006) 'Take-up down under: Hits and Misses of Means-Tested Benefits in Australia', *European Sociological Review*, 22(4), pp. 443–458.

Mundlak, Y. (1978) 'On the Pooling of Time Series and Cross Section Data', *Econometrica*, 46(1), pp. 69–85. Available at: https://doi.org/10.2307/1913646.

NAO (2024) *Progress in implementing Universal Credit*. United Kingdom: National Audit Office.

van Oorschot, W.J.H. (1996) 'New perspectives on the non-take-up of social security benefits', in W.J.H. van Oorschot (ed.) *New Perspectives on the non-Take-up of Social Security Benefits*. Tilburg: Tilburg University Press, pp. 7–59.

van Oorschot, W.J.H. (2002) ‘Targeting welfare: On the functions and dysfunctions of means-testing in social policy’, in P. Townsend and D. Gorden (eds) *World poverty: new policies to defeat an old enemy*. Bristol: Bristol University Press, Policy Press, pp. 171–193. Available at: https://econpapers.repec.org/paper/tiutiuwor/bd80ff6a-2b5b-4c74-b3d8-a83cc8c8c842.htm (Accessed: 7 May 2024).

Pudney, S., Hancock, R. and Sutherland, H. (2006) ‘Simulating the Reform of Means-tested Benefits with Endogenous Take-up and Claim Costs’, *Oxford Bulletin of Economics and Statistics*, 68(2), pp. 135–166. Available at: https://doi.org/10.1111/j.1468-0084.2006.00156.x.

Richiardi, M., Bronka, P. and Popova, D. (2023) ‘UKHLS input data for UKMOD (2010-2019)’, *Centre for Microsimulation and Policy Analysis Working Paper Series* [Preprint]. Available at: https://ideas.repec.org//p/ese/cempwp/cempa7-23.html (Accessed: 7 May 2024).

Richiardi, M., Collado, D. and Popova, D. (2021) ‘UKMOD – A new tax-benefit model for the four nations of the UK’, *International Journal of Microsimulation*, 14(1), pp. 92–101. Available at: https://doi.org/10.34196/IJM.00231.

Roberts, B.W. (2009) ‘Back to the future: Personality and Assessment and personality development’, *Journal of Research in Personality*, 43(2), pp. 137–145. Available at: https://doi.org/10.1016/j.jrp.2008.12.015.

Roberts, J. and Taylor, K. (2022) ‘New Evidence on Disability Benefit Claims in Britain: The Role of Health and the Local Labour Market’, *Economica*, 89(353), pp. 131–160. Available at: https://doi.org/10.1111/ecca.12382.

Rotik, M. and Perry, L. (2011) *Perceptions of welfare reform and Universal Credit*. Department for Work and Pensions Research Report No 778. United Kingdom: Department for Work and Pensions.

Schmitt, N. (1996) ‘Uses and abuses of coefficient alpha.’, *Psychological Assessment*, 8(4), pp. 350–353. Available at: https://doi.org/10.1037/1040-3590.8.4.350.

Schofield, T.P. and Butterworth, P. (2015) ‘Patterns of Welfare Attitudes in the Australian Population’, *PLOS ONE*, 10(11), p. e0142792. Available at: https://doi.org/10.1371/journal.pone.0142792.

Schofield, T.P., Haslam, N. and Butterworth, P. (2019) ‘The persistence of welfare stigma: Does the passing of time and subsequent employment moderate the negative perceptions associated with unemployment benefit receipt?’, *Journal of Applied Social Psychology*, 49(9), pp. 563–574. Available at: https://doi.org/10.1111/jasp.12616.

Sijtsma, K. (2009) ‘On the Use, the Misuse, and the Very Limited Usefulness of Cronbach’s Alpha’, *Psychometrika*, 74(1), pp. 107–120. Available at: https://doi.org/10.1007/s11336-008-9101-0.

Solmi, M. *et al.* (2020) ‘Predictors of stigma in a sample of mental health professionals: Network and moderator analysis on gender, years of experience, personality traits, and levels of burnout', *European Psychiatry*, 63(1), p. e4. Available at: https://doi.org/10.1192/j.eurpsy.2019.14.

Solon, G., Haider, S.J. and Wooldridge, J.M. (2015) 'What Are We Weighting For?', *Journal of Human Resources*, 50(2), pp. 301–316. Available at: https://doi.org/10.3368/jhr.50.2.301.

Stewart, M.B. (2007) 'The Interrelated Dynamics of Unemployment and Low-Wage Employment', *Journal of Applied Econometrics*, 22(3), pp. 511–531.

Stuber, J. and Schlesinger, M. (2006) 'Sources of stigma for means-tested government programs', *Social Science & Medicine*, 63(4), pp. 933–945. Available at: https://doi.org/10.1016/j.socscimed.2006.01.012.

Sutherland, H. and Figari, F. (2012) 'EUROMOD: the European Union tax-benefit microsimulation model', *International Journal of Microsimulation*, 6(1), pp. 4–26. Available at: https://doi.org/10.34196/ijm.00075.

Tversky, A. and Kahneman, D. (1982) *Judgment under uncertainty: Heuristics and biases*. New York: Cambridge University Press.

Univeristy of Essex (2019) *Understanding Society: Waves 1-9, 2009-2018 and Harmonised BHPS: Waves 1-18, 1991-2009*. Colchester: UK Data Service.

Van Parys, L. and Struyven, L. (2013) 'Withdrawal from the public employment service by young unemployed: a matter of non-take-up or of non-compliance? How non-profit social work initiatives may inspire public services', *European Journal of Social Work*, 16(4), pp. 451–469. Available at: https://doi.org/10.1080/13691457.2012.724387.

Vella, F. and Verbeek, M. (1998) 'Whose Wages do Unions Raise? A Dynamic Model of Unionism and Wage Rate Determination for Young Men', *Journal of Applied Econometrics*, 13(2), pp. 163–183.

Vella, M. (2024) 'The relationship between the Big Five personality traits and earnings: Evidence from a meta-analysis', *Bulletin of Economic Research*, n/a(n/a). Available at: https://doi.org/10.1111/boer.12437.

van de Ven, J. and Popova, D. (2023) *UKMOD – United Kingdom (UK) country report 2020-2026 – Institute for Social and Economic Research*. CeMPA5/23. Colchester: Centre for Mirosimulation and Policy Analysis. Available at: https://www.iser.essex.ac.uk/research/publications/working-papers/cempa/cempa5-23 (Accessed: 7 May 2024).

Weinberg, M. and Soffer, M. (2023) 'The Relationships Between Personality Traits and Public Stigma Attached to Families Bereaved Due To Suicide', *OMEGA - Journal of Death and Dying*, 87(3), pp. 872–883. Available at: https://doi.org/10.1177/00302228211029147.

Wong, C. (1998) 'Rethinking Selectivism and Selectivity by Means Test', *The Journal of Sociology & Social Welfare*, 25(2). Available at: https://doi.org/10.15453/0191-5096.2491.

Wooldridge, J.M. (2005) ‘Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity’, *Journal of Applied Econometrics*, 20(1), pp. 39–54. Available at: https://doi.org/10.1002/jae.770.

Yuan, Q. *et al.* (2018) ‘Direct and moderating effects of personality on stigma towards mental illness’, *BMC Psychiatry*, 18(1), p. 358. Available at: https://doi.org/10.1186/s12888-018-1932-3.

Zantomio, F. (2015) ‘The Route to Take-up: Evidence from the UK Pension Credit Reform’, *Oxford Bulletin of Economics and Statistics*, 77(5), pp. 719–739. Available at: https://doi.org/10.1111/obes.12080.

Zantomio, F., Pudney, S. and Hancock, R. (2010) ‘Estimating the Impact of a Policy Reform on Benefit Take-up: The 2001 extension to the Minimum Income Guarantee for UK Pensioners’, *Economica*, 77(306), pp. 234–254.

APPENDIX A

Measures of Personality Traits

In Wave 3, the UKHLS dataset contains a battery of items to measure personality traits using the 15-item version of the Big Five Inventory (John et al., 1991), employing a Likert scale ranging from 1 (“disagree strongly”) to 5 (“agree strongly”). The precise set of questions asked to participants is detailed in Table A.1. “R” is used to indicate reversed values. The short version of the Big Five is considered to be as a valid measure of the Big Five personality traits, with good reliability (Hahn et al., 2012; Soto & John, 2017).

Table A.1: BFI-S Items, pre-selected set of items

Openness to Experience	scptrt5o1	I see myself as someone who is original, comes up with new ideas.	
	scptrt5o2	I see myself as someone who values artistic, aesthetic experiences.	
	scptrt5o3	I see myself as someone who has an active imagination.	
Conscientiousness	scptrt5c1	I see myself as someone who does a thorough job.	
	scptrt5c2	I see myself as someone who tends to be lazy.	R
	scptrt5c3	I see myself as someone who does things efficiently.	
Extraversion	scptrt5e1	I see myself as someone who is talkative.	
	scptrt5e2	I see myself as someone who is outgoing, sociable.	
	scptrt5e3	I see myself as someone who is reserved.	R
Agreeableness	scptrt5a1	I see myself as someone who is sometimes rude to others.	R
	scptrt5a2	I see myself as someone who has a forgiving nature.	
	scptrt5a3	I see myself as someone who is considerate and kind to almost everyone.	
Neuroticism	scptrt5n1	I see myself as someone who worries a lot.	
	scptrt5n2	I see myself as someone who gets nervous easily.	
	scptrt5n3	I see myself as someone who is relaxed, handles stress well.	R

An Exploratory Factor Analysis (EFA) was applied to reduce multiple items to a common factor. EFA was carried out using principal factor components and Bartlett scores. The results are presented in Tables A.2-A.7.

Table A.2: The factor loadings for Openness to Experience

	Openness to Experience		
Variable	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j
scptrt5o1	.79	.63	.37
scptrt5o2	.73	.53	.47
scptrt5o3	.81	.66	.34
Variance accounted for	1.815	1.815	
Proportion of total variance	.605		
Cumulative proportion	.605		

Table A.3: The factor loadings for Conscientiousness

	Conscientiousness		
Variable	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j
scptrt5c1	.79	.63	.37
scptrt5c2	-.51	.27	.73
scptrt5c3	.82	.68	.32
Variance accounted for	1.569	1.569	
Proportion of total variance	.523	.523	
Cumulative proportion	.523		

Table A.4: The factor loadings for Extraversion

	Extraversion		
Variable	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j
scptrt5e1	.83	.68	.32
scptrt5e2	.82	.66	.34
scptrt5e3	-.56	.31	.69
Variance accounted for	1.656	1.656	
Proportion of total variance	.552	.552	
Cumulative proportion	.552		

Table A.5: The factor loadings for Agreeableness

	Agreeableness		
Variable	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j
scptrt5a1	-.58	.32	.68
scptrt5a2	.78	.60	.40
scptrt5a3	.82	.67	.33
Variance accounted for	1.600	1.600	
Proportion of total variance	.533	.533	
Cumulative proportion	.533		

Table A.6: The factor loadings for Neuroticism

	Neuroticism		
Variable	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j
scptrt5n1	.84	.70	.30
scptrt5n2	.80	.64	.36
scptrt5n3	-.71	.51	.49
Variance accounted for	1.858	1.858	
Proportion of total variance	.619	.619	
Cumulative proportion	.619		

Table A.7: The factor loadings for Cognitive Ability

	Cognitive Ability		
Variable	Loadings λ_j	Communalities h_j^2	Specific Variance ψ_j
cgvfc	.48	.79	.21
cgna	.52	.91	.09
cgs7ca	.50	.85	.15
cgwri	.49	.82	.18
Variance accounted for	3.372	3.372	
Proportion of total variance	.843	.843	
Cumulative proportion	.843		

APPENDIX B

Association with individual characteristics

In order to better understand how characteristics of eligible units are associated with take-up behaviour, we present results from a probit model of take-up for CB and LB/UC, estimated on pooled data for all years of analysis, except 2010 (Table 2).[44] The most prominent economic features that predict take-up are the eligible amount and the gross income of the eligible unit. As expected, the higher the eligible amount and the lower the original income, the greater the take-up rate. When it comes to psychological factors, the personality traits do not have a significant relationship with take-up. When examining the interaction effects by gender, we observe that personality traits do not show a significant correlation with CB take-up. We also find that conscientiousness is negatively associated with LB/UC take-up for females, whereas for males, conscientiousness is positively correlated with LB/UC take-up.

Turning to demographics, we observe an inverse U-shaped relationship between age and CB take-up. On average, men tend to display higher take-up for LB/UC and a slightly lower take-up for CB as compared to women, but the difference for the latter is not significant. For CB, being separated, divorced, or widowed is associated with a significantly lower take-up as compared to being married or cohabitating. However, the reverse is true for LB/UC, probably because of the higher rates for couples. In addition, certain ethnic groups, such as Chinese, Black, and Arab, have a lower

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[44] Except 2010 because personality traits and cognitive ability are not recorded for that year. Since personality traits are largely stable, we utilise the recordings from the third wave and assume they remain the same thereafter.

tendency to claim benefits than White. A higher take-up of benefits is associated with households having more children. Those who claim CB benefits usually have younger children as compared to those who claim LB/UC. Living in certain regions, such as London, is associated with significantly lower take-up rates.

Socio-economic status is an important factor that can demonstrate both economic and psychological aspects. Individuals with tertiary education are less likely to take up benefits. People in service, manual, and support roles are more likely to seek benefits compared to those in higher-status occupations. However, the take-up rate for CB is more evenly distributed across occupations, as eligibility is not heavily reliant on the means test aspect. All this is of course *ceteris paribus*, and in particular conditional on income.

Table B.1. Estimates from a probit model of take-up, all years

	CB		LB/UC	
Log Simulated Eligible Amount	.173***	(.020)	.281***	(.017)
Age	.040*	(.023)	.012	(.013)
Age2	-.001**	(.000)	-.000	(.000)
Gender (Base: Female)				
Male	-.042	(.053)	.293***	(.046)
Marital Status (Base: Married/Cohabitating)				
Single	-.034	(.063)	.098**	(.039)
Separated, Divorced, Widowed	-.304***	(.079)	.370***	(.047)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean	-.136	(.154)	-.143	(.101)
Asian or Asian British Chinese	-.447***	(.074)	.048	(.054)
Black or Black British	-.466***	(.122)	-.255***	(.068)
Arab and any other	-.515***	(.193)	.435*	(.231)
Health (Base: Not Disabled)				
Disabled	-.007	(.155)	.402***	(.105)
Children in Household (Base: One)				
Two	.097**	(.048)	.226***	(.034)
Three or more	.151*	(.080)	.616***	(.050)
Minimum age of the child in the household	-.011**	(.005)	.019***	(.004)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	-.051	(.041)	.041	(.034)

	CB		LB/UC	
Education (Non-Tertiary)				
Tertiary	-.120**	(.050)	-.176***	(.033)
Number of rooms in the dwelling	-.184***	(.039)	-.144***	(.031)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.084	(.074)	.090*	(.051)
Rented	-.215***	(.070)	.325***	(.041)
Reduced Rented	-.524***	(.153)	.163	(.159)
Social Rented	-.054	(.082)	.666***	(.046)
Free	-.016	(.230)	.797***	(.173)
Other	-.586	(.433)	.268	(.366)
Labour Market Status (Base: Inactive)				
Professional and Managerial Roles	.464***	(.152)	-.073	(.082)
Technical and Skilled Roles	.519***	(.146)	.202***	(.075)
Service Manual and Support Roles	.732***	(.155)	.376***	(.079)
Log of Original Income (standardised)	-.150**	(.066)	-.306***	(.053)
Neighbourhood effect (standardised)	.064***	(.021)	.811***	(.184)
Personality Traits				
Openness to Experience	.003	(.027)	-.016	(.017)
Conscientiousness	-.035	(.027)	-.015	(.017)
Extraversion	-.018	(.026)	.013	(.016)
Agreeableness	.006	(.026)	.028*	(.016)
Neuroticism	.016	(.025)	.079***	(.016)
Cognitive Ability	-.026	(.026)	-.007	(.018)
Receipt of LB/UC (Base: Not in receipt)				
Receipt	.985***	(.077)	.491***	(.041)
Time Effects (Base: 2011)				
2012	.047	(.051)	-.255***	(.051)
2013	-.112**	(.052)	-.341***	(.052)
2014	-.157***	(.057)	-.383***	(.055)
2015	-.184***	(.057)	-.495***	(.056)
2016	-.200***	(.058)	-.557***	(.058)
2017	-.184***	(.062)	-.598***	(.060)
2018	-.336***	(.062)	-.657***	(.065)
2019	-.410***	(.067)	-.877***	(.069)
Constant	.749	(.471)	-.329	(.285)
Observations	22,395		12,607	
Wald chil2(50)	622.07		2,191.79	
Prob > chi2	.000		.000	

*Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Standard errors are in the brackets.*

As for neighbourhood effects, the descriptive analysis presented in Table 2 indicates that eligible units residing in neighbourhoods with higher take-up rates are more likely to claim social benefits.

Additionally, the correlations indicate that individuals who claim other benefits are more likely to claim the benefits under study. Furthermore, the probit analysis confirms the gradual decline in take-up rates over the years.

Dynamic Model Results

Table B.2. Probability of Claiming CB and LB/UC, dynamic random-effects probit model

	CB		LB/UC	
Lagged value of take-up	1.629***	(.091)	1.328***	(.084)
Initial Value	1.709***	(.176)	1.699***	(.152)
Log Simulated Eligible Amount	.133***	(.028)	.318***	(.038)
Age	-.073*	(.038)	-.017	(.029)
Age2	.001**	(.000)	.000	(.000)
Gender (Base: Female)				
Male	-.047	(.080)	.248**	(.109)
Marital Status (Base: Married/Cohabitating)				
Single	-.068	(.254)	.539***	(.177)
Separated, Divorced, Widowed	-.451	(.354)	.255	(.231)
Ethnicity (Base: White)				
Mixed: White and Black	.069	(.251)	.150	(.241)
Asian or Asian British Chinese	.039	(.136)	.146	(.142)
Black or Black British	-.049	(.175)	-.170	(.135)
Arab and any other	-.411	(.419)	.099	(.590)
Disability (Base: Not Disabled)				
Disabled	-.101	(.226)	.160	(.178)
Children in Household (Base: One)				
Two	-.012	(.163)	.354**	(.162)
Three or more	-.009	(.263)	.825***	(.271)
Minimum age of the child in the household (standardised)	-.395***	(.151)	-.368***	(.136)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	-.042	(.155)	.105	(.151)
Education (Non-Tertiary)				
Tertiary	-.052	(.070)	.010	(.080)
Number of rooms in the dwelling	-.156***	(.046)	.043	(.065)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.039	(.108)	.081	(.126)
Rented	-.095	(.105)	.351***	(.097)
Reduced Rented	-.270	(.346)	.160	(.220)
Social Rented	.031	(.124)	.624***	(.105)
Free	-.170	(.305)	.643**	(.306)
Other	-.264	(.464)	-.075	(.678)
Labour Market Status (Base: Inactive)				

	CB		LB/UC	
Professional and Managerial Roles	-.332	(.336)	-.238	(.276)
Technical and Skilled Roles	-.391	(.329)	-.097	(.231)
Service Manual and Support Roles	-.158	(.413)	.043	(.288)
Log of Original Income (standardised)	.251*	(.131)	-.287**	(.122)
Neighbourhood effect (standardised)	.081*	(.045)	-.009	(.053)
Personality Traits				
Openness to Experience	-.005	(.040)	-.031	(.039)
Conscientiousness	-.047	(.041)	-.042	(.041)
Extraversion	-.010	(.036)	.042	(.038)
Agreeableness	.017	(.036)	.004	(.040)
Neuroticism	-.006	(.038)	.060	(.038)
Cognitive Ability	-.020	(.038)	.046	(.042)
Receipt of other benefits	.818***	(.124)	.475***	(.092)
Time Effects (Base: 2011)				
2012	.396**	(.159)	.353**	(.149)
2013	.093	(.144)	.508***	(.145)
2014	.256*	(.140)	.512***	(.140)
2015	.187	(.131)	.394***	(.139)
2016	.210*	(.120)	.410***	(.137)
2017	.281**	(.118)	.318**	(.136)
2018	.063	(.124)	.158	(.131)
Time-averaged characteristics				
Responsible for housing costs	-.003	(.167)	-.171	(.172)
Married, Cohabitating	.058	(.267)	.655***	(.198)
Separated, Divorced, Widowed	.375	(.409)	.515**	(.238)
Two children in household	-.113	(.185)	-.291	(.184)
Three or more children in household	-.073	(.292)	-.320	(.286)
Minimum age of child in household	.245	(.170)	.434***	(.152)
Professional and Managerial Roles	.866*	(.454)	.102	(.343)
Technical and Skilled Roles	1.091**	(.444)	.254	(.301)
Service Manual and Support Roles	1.074**	(.520)	.169	(.351)
Log of Original Income (standardised)	-.658***	(.238)	-.148	(.144)
Neighbourhood effect (standardised)	.000	(.049)	.093*	(.056)
Constant	.222	(.912)	-2.473***	(.653)
/				
variance	.583***	(.117)	.671***	(.135)
rho	.368		.401	
Observations	16,009		7,723	

*Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Standard errors are in the brackets.*

Table B.3. Probability of Claiming CB, dynamic probit model

	(1)	(2)	(3)	(4)
	Pooled Probit	RE- Probit	RE-Probit	Wooldridge
Log Simulated Eligible Amount	.101***	.109***	.199***	.133***
	(.023)	(.025)	(.025)	(.028)
Age	-.038	-.040	-.062	-.073*
	(.027)	(.030)	(.038)	(.038)
Age2	.000	.000	.001	.001**
	(.000)	(.000)	(.000)	(.000)
Gender (Base: Female)				
Male	-.027	-.030	-.095	-.047
	(.060)	(.065)	(.077)	(.080)
Marital Status (Base: Married/Cohabitating)				
Single	-.040	-.036	-.068	-.068
	(.208)	(.219)	(.086)	(.254)
Separated, Divorced, Widowed	-.304	-.314	-.194*	-.451
	(.280)	(.299)	(.115)	(.354)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean Black African Asian	.045	.024	-.102	.069
	(.169)	(.184)	(.234)	(.251)
Asian or Asian British Chinese	-.104	-.135	.080	.039
	(.090)	(.097)	(.130)	(.136)
Black or Black British	-.114	-.140	-.046	-.049
	(.128)	(.140)	(.162)	(.175)
Arab and any other	-.427	-.475*	-.312	-.411
	(.262)	(.282)	(.418)	(.419)
Health (Base: Not Disabled)				
Disabled	-.027	-.012	-.104	-.101
	(.175)	(.189)	(.228)	(.226)
Children in Household (Base: One)				
Two	.011	.025	-.115*	-.012
	(.128)	(.136)	(.070)	(.163)
Three or more	-.016	.020	-.134	-.009
	(.211)	(.227)	(.097)	(.263)
Minimum age of child in household	-.156	-.174	-.127***	-.395***
	(.120)	(.129)	(.046)	(.151)
Housing Cost (Base: Not responsible)	.000	.000	.000	.000
Responsible for housing costs	-.023	-.019	-.046	-.042
	(.116)	(.125)	(.059)	(.155)
Education (Non-Tertiary)				
Tertiary	-.042	-.058	-.152**	-.052
	(.052)	(.057)	(.066)	(.070)
Number of rooms in a house	-.129***	-.139***	-.211***	-.156***

	(1)	(2)	(3)	(4)
	(.035)	(.038)	(.047)	(.046)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.054	.067	.129	.039
	(.079)	(.087)	(.105)	(.108)
Rented	-.102	-.112	-.113	-.095
	(.078)	(.083)	(.101)	(.105)
Reduced Rented	-.338	-.388*	-.296	-.270
	(.206)	(.225)	(.322)	(.346)
Social Rented	.012	.011	-.028	.031
	(.087)	(.094)	(.125)	(.124)
Free	-.117	-.144	.122	-.170
	(.216)	(.234)	(.329)	(.305)
Other	-.039	.008	-.282	-.264
	(.368)	(.383)	(.453)	(.464)
Labour Market Status (Base: Inactive, Unemployed, Sick, Disabled, Student)				
Professional and Managerial Roles	-.252	-.270	.368**	-.332
	(.261)	(.279)	(.176)	(.336)
Technical and Skilled Roles	-.234	-.251	.549***	-.391
	(.252)	(.268)	(.172)	(.329)
Service Manual and Support Roles	-.070	-.078	.842***	-.158
	(.313)	(.338)	(.193)	(.413)
Log of Original Income	.204*	.227**	-.467***	.251*
	(.105)	(.111)	(.131)	(.131)
Neighbourhood effect	.072*	.074*	.096***	.081*
	(.037)	(.040)	(.030)	(.045)
Personality Traits				
Openness to Experience	-.013	-.012	.004	-.005
	(.030)	(.032)	(.037)	(.040)
Conscientiousness	-.031	-.039	-.030	-.047
	(.030)	(.032)	(.038)	(.041)
Extraversion	-.008	-.005	-.004	-.010
	(.027)	(.029)	(.034)	(.036)
Agreeableness	.009	.011	.033	.017
	(.026)	(.028)	(.034)	(.036)
Neuroticism	-.001	-.000	.009	-.006
	(.027)	(.029)	(.036)	(.038)
Cognitive Ability	-.025	-.025	-.011	-.020
	(.029)	(.031)	(.037)	(.038)
Receipt of LB/UC (Base: Not in receipt)				
Receipt	.703***	.771***	.862***	.818***
	(.094)	(.108)	(.125)	(.124)
Time Effects (Base: 2011)				
2012	.311**	.327**	.283**	.396**
	(.124)	(.133)	(.114)	(.159)

	(1)	(2)	(3)	(4)
2013	.054	.068	.041	.093
	(.113)	(.122)	(.108)	(.144)
2014	.217*	.246**	.229**	.256*
	(.111)	(.121)	(.113)	(.140)
2015	.202*	.209*	.146	.187
	(.106)	(.115)	(.112)	(.131)
2016	.157	.174*	.285**	.210*
	(.097)	(.105)	(.115)	(.120)
2017	.217**	.240**	.328***	.281**
	(.095)	(.103)	(.120)	(.118)
2018	.039	.040	.116	.063
	(.102)	(.111)	(.126)	(.124)
Time-average variables				
Responsible for housing costs	-.009	-.017		-.003
	(.124)	(.134)		(.167)
Single	.021	.034		.058
	(.216)	(.228)		(.267)
Separated, Divorced, Widowed	.190	.196		.375
	(.339)	(.356)		(.409)
Two	-.031	-.033		-.113
	(.143)	(.153)		(.185)
Three or more	.043	.022		-.073
	(.230)	(.247)		(.292)
Minimum age of child in household	.049	.056		.245
	(.136)	(.145)		(.170)
Professional and Managerial Roles	.675**	.758**		.866*
	(.332)	(.355)		(.454)
Technical and Skilled Roles	.760**	.851**		1.091**
	(.322)	(.344)		(.444)
Service Manual and Support Roles	.762**	.868**		1.074**
	(.378)	(.408)		(.520)
Log of Original Income	-.421**	-.466**		-.658***
	(.181)	(.194)		(.238)
Neighbourhood effect	-.005	.002		.000
	(.039)	(.042)		(.049)
Lagged value of take-up	2.263***	2.236***	1.621***	1.629***
	(.066)	(.074)	(.087)	(.091)
Initial Value			1.647***	1.709***
			(.168)	(.176)
Constant	.044	.179	.344	.222
	(.658)	(.708)	(.845)	(.912)
/				
var(_cons[idperson])		.167**	.606***	.583***
		(.066)	(.112)	(.117)
Observations	16009	16009	16009	16009

	(1)	(2)	(3)	(4)
ll	-1979.393	-1973.419	-2152.927	-1867.031
Wald test	1785	1438	1050	985
p	.000	.000	.000	.000
rho		.143	.378	.368

*Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Standard errors are in the brackets.*

Table B.4. Probability of Claiming LB/UC, dynamic probit model

	(1)	(2)	(3)	(4)
	Pooled Probit	RE- Probit	RE-Probit	Wooldridge
Log Simulated Eligible Amount	.258***	.280***	.321***	.318***
	(.027)	(.030)	(.038)	(.038)
Age	.003	.001	-.006	-.017
	(.021)	(.022)	(.029)	(.029)
Age2	-.000	-.000	.000	.000
	(.000)	(.000)	(.000)	(.000)
Gender (Base: Female)	.000	.000	.000	.000
Male	.218***	.242***	.209**	.248**
	(.077)	(.084)	(.104)	(.109)
Marital Status (Base: Married/Cohabitating)				
Single	.343**	.389**	.010	.539***
	(.151)	(.160)	(.087)	(.177)
Separated, Divorced, Widowed	.208	.224	.144	.255
	(.188)	(.201)	(.104)	(.231)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean Black African Asian	.185	.188	.176	.150
	(.173)	(.189)	(.246)	(.241)
Asian or Asian British Chinese	.035	.039	.184	.146
	(.093)	(.101)	(.140)	(.142)
Black or Black British	-.214**	-.236**	-.189	-.170
	(.095)	(.104)	(.132)	(.135)
Arab and any other	.183	.214	.110	.099
	(.395)	(.456)	(.566)	(.590)
Health (Base: Not Disabled)				
Disabled	.145	.159	.176	.160
	(.155)	(.163)	(.176)	(.178)
Children in Household (Base: One)	.000	.000	.000	.000
Two	.224*	.259*	.157**	.354**
	(.126)	(.135)	(.080)	(.162)
Three or more	.439**	.513**	.594***	.825***
	(.209)	(.224)	(.120)	(.271)
Minimum age of child in household	-.214**	-.225**	-.028	-.368***
	(.096)	(.103)	(.050)	(.136)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	.016	.019	-.033	.105
	(.115)	(.123)	(.074)	(.151)
Education (Non-Tertiary)	.000	.000	.000	.000
Tertiary	.005	-.002	-.002	.010
	(.055)	(.060)	(.079)	(.080)
Number of rooms in dwelling	-.017	-.027	.043	.043

	(1)	(2)	(3)	(4)
	(.040)	(.043)	(.067)	(.065)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.068	.080	.099	.081
	(.088)	(.096)	(.125)	(.126)
Rented	.269***	.306***	.352***	.351***
	(.066)	(.075)	(.096)	(.097)
Reduced Rented	.016	.039	.130	.160
	(.190)	(.205)	(.226)	(.220)
Social Rented	.448***	.513***	.635***	.624***
	(.071)	(.084)	(.104)	(.105)
Free	.416*	.438*	.625**	.643**
	(.238)	(.257)	(.300)	(.306)
Other	-.085	-.061	-.268	-.075
	(.493)	(.540)	(.664)	(.678)
Labour Market Status (Base: Inactive, Unemployed, Sick, Disabled, Student)				
Professional and Managerial Roles	.023	.007	-.222	-.238
	(.211)	(.224)	(.190)	(.276)
Technical and Skilled Roles	.105	.091	.053	-.097
	(.179)	(.191)	(.177)	(.231)
Service Manual and Support Roles	.278	.259	.125	.043
	(.220)	(.236)	(.182)	(.288)
Log of Original Income	-.207**	-.213**	-.392***	-.287**
	(.098)	(.104)	(.104)	(.122)
Neighbourhood effect	-.005	-.010	.056	-.009
	(.041)	(.045)	(.035)	(.053)
Personality Traits				
Openness to Experience	-.013	-.014	-.029	-.031
	(.027)	(.030)	(.038)	(.039)
Conscientiousness	-.034	-.036	-.041	-.042
	(.029)	(.031)	(.041)	(.041)
Extraversion	.025	.030	.040	.042
	(.027)	(.030)	(.038)	(.038)
Agreeableness	.025	.027	.010	.004
	(.027)	(.029)	(.040)	(.040)
Neuroticism	.048*	.056**	.063*	.060
	(.026)	(.028)	(.037)	(.038)
Cognitive Ability	.027	.027	.040	.046
	(.029)	(.032)	(.042)	(.042)
Receipt of CB (Base: Not in receipt)				
Receipt	.371***	.403***	.453***	.475***
	(.067)	(.075)	(.089)	(.092)
Time-Effects				
2012	.172	.219*	.579***	.353**
	(.107)	(.116)	(.128)	(.149)

	(1)	(2)	(3)	(4)
2013	.361***	.415***	.696***	.508***
	(.108)	(.117)	(.129)	(.145)
2014	.372***	.420***	.686***	.512***
	(.106)	(.114)	(.129)	(.140)
2015	.283***	.318***	.525***	.394***
	(.105)	(.114)	(.132)	(.139)
2016	.271**	.308***	.521***	.410***
	(.106)	(.115)	(.132)	(.137)
2017	.193*	.220*	.398***	.318**
	(.105)	(.114)	(.136)	(.136)
2018	.054	.075	.208	.158
	(.106)	(.113)	(.130)	(.131)
Time-average variables				
Responsible for housing costs	-.044	-.049		-.171
	(.130)	(.139)		(.172)
Single	.426**	.460***		.655***
	(.166)	(.175)		(.198)
Separated, Divorced, Widowed	.329*	.387*		.515**
	(.193)	(.208)		(.238)
Two	-.154	-.168		-.291
	(.140)	(.150)		(.184)
Three or more	-.037	-.052		-.320
	(.220)	(.235)		(.286)
Minimum age of child in household	.287***	.302***		.434***
	(.108)	(.116)		(.152)
Professional and Managerial Roles	-.191	-.221		.102
	(.267)	(.283)		(.343)
Technical and Skilled Roles	-.036	-.032		.254
	(.237)	(.251)		(.301)
Service Manual and Support Roles	-.130	-.099		.169
	(.271)	(.290)		(.351)
Log of Original Income	-.086	-.091		-.148
	(.104)	(.112)		(.144)
Neighbourhood effect	.075*	.090*		.093*
	.000	(.046)		.000
Lagged value of take-up	1.978***	1.990***	1.338***	1.328***
	(.058)	(.064)	(.083)	(.084)
Initial Value		.403***	1.652***	1.699***
		(.075)	(.149)	(.152)
	-1.734***	-1.793***	-2.322***	-2.473***
	(.487)	(.525)	(.624)	(.653)
/				
var(_cons[idperson])		.161**	.653***	.671***
		(.071)	(.131)	(.135)
Observations	7723	7723	7723	7723

	(1)	(2)	(3)	(4)
ll	-1957.594	-1952.935	-1813.524	-1798.137
Wald test	2245	1605	899	926
p	.000	.000	.000	.000
rho		.139	.395	.401

*Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Standard errors are in the brackets.*

Table B.5. Probability of Claiming CB, alternative take-up measure dynamic probit model

	CB		CB – Alternative Measure	
Log Simulated Eligible Amount	.133***	(.028)	.140***	(.028)
Age	-.073*	(.038)	-.066*	(.037)
Age2	.001**	(.000)	.001*	(.000)
Gender (Base: Female)				
Male	-.047	(.080)	-.095	(.079)
Marital Status (Base: Married/Cohabitating)	-.068	(.254)	-.150	(.247)
Single				
Separated, Divorced, Widowed	-.451	(.354)	-.606*	(.338)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean Black African Asian	.069	(.251)	.097	(.254)
Asian or Asian British Chinese	.039	(.136)	.013	(.130)
Black or Black British	-.049	(.175)	-.077	(.172)
Arab and any other	-.411	(.419)	-.398	(.438)
Health (Base: Not Disabled)				
Disabled	-.101	(.226)	-.121	(.214)
Children in Household (Base: One)				
Two	-.012	(.163)	-.035	(.154)
Three or more	-.009	(.263)	-.143	(.254)
Minimum age of child in household	-.395***	(.151)	-.465***	(.146)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	-.042	(.155)	-.101	(.156)
Education (Non-Tertiary)				
Tertiary	-.052	(.070)	-.038	(.069)
Number of rooms in house	-.156***	(.046)	-.161***	(.045)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.039	(.108)	-.007	(.100)
Rented	-.095	(.105)	-.083	(.104)
Reduced Rented	-.270	(.346)	-.458	(.343)
Social Rented	.031	(.124)	.041	(.123)
Free	-.170	(.305)	-.148	(.302)
Other	-.264	(.464)	-.189	(.494)
Labour Market Status (Base: Inactive, Unemployed, Sick, Disabled, Student)				
Professional and Managerial Roles	-.332	(.336)	-.387	(.335)
Technical and Skilled Roles	-.391	(.329)	-.381	(.329)
Service Manual and Support Roles	-.158	(.413)	-.227	(.414)
Log of Original Income	.251*	(.131)	.254*	(.134)
Neighbourhood effect	.081*	(.045)	.076*	(.044)
Personality Traits				
Openness to Experience	-.005	(.040)	.018	(.039)
Conscientiousness	-.047	(.041)	-.045	(.040)
Extraversion	-.010	(.036)	-.025	(.035)
Agreeableness	.017	(.036)	.030	(.035)
Neuroticism	-.006	(.038)	-.006	(.037)
Cognitive Ability	-.020	(.038)	-.016	(.037)
Receipt of Other Benefits (Base: Not in receipt)				

	CB		CB – Alternative Measure	
Receipt of Other Benefits	.818***	(.124)	.846***	(.122)
Lagged Take-up	1.629***	(.091)	1.574***	(.090)
Initial Value	1.709***	(.176)	1.814***	(.175)
Time-average variables				
Responsible for housing costs	-.003	(.167)	.058	(.168)
Single	.058	(.267)	-.007	(.260)
Separated, Divorced, Widowed	.375	(.409)	.464	(.398)
Two	-.113	(.185)	-.041	(.176)
Three or more	-.073	(.292)	.100	(.281)
Minimum age of child in household	.245	(.170)	.286*	(.165)
Professional and Managerial Roles	.866*	(.454)	.849*	(.452)
Technical and Skilled Roles	1.091**	(.444)	1.011**	(.442)
Service Manual and Support Roles	1.074**	(.520)	1.130**	(.518)
Log of Original Income	-.658***	(.238)	-.643***	(.234)
Neighbourhood effect	.000	(.049)	.004	(.047)
Time Effects (Base: 2011)				
2012	.396**	(.159)	.386**	(.156)
2013	.093	(.144)	.083	(.141)
2014	.256*	(.140)	.201	(.137)
2015	.187	(.131)	.190	(.127)
2016	.210*	(.120)	.213*	(.117)
2017	.281**	(.118)	.283**	(.115)
2018	.063	(.124)	.062	(.121)
Constant	.222	(.912)	.100	(.883)
Observations	16,009		16,567	

Table B.6. Probability of Claiming LB/UC, alternative take-up measure dynamic probit model

	LB/UC		LB/UC – Alternative Measurement	
Log Simulated Eligible Amount	.318***	(.038)	.314***	(.036)
Age	-.017	(.029)	-.014	(.029)
Age2	.000	(.000)	.000	(.000)
Gender (Base: Female)				
Male	.248**	(.109)	.229**	(.107)
Marital Status (Base: Married/Cohabitating)	.539***	(.177)	.540***	(.176)
Single				
Separated, Divorced, Widowed	.255	(.231)	.311	(.235)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean Black African	.150	(.241)	.170	(.244)
Asian				
Asian or Asian British Chinese	.146	(.142)	.180	(.142)
Black or Black British	-.170	(.135)	-.156	(.133)
Arab and any other	.099	(.590)	.120	(.594)
Health (Base: Not Disabled)				
Disabled	.160	(.178)	.182	(.174)
Children in Household (Base: One)				
Two	.354**	(.162)	.373**	(.160)
Three or more	.825***	(.271)	.779***	(.266)
Minimum age of child in household	-.368***	(.136)	-.377***	(.134)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	.105	(.151)	.141	(.153)
Education (Non-Tertiary)				
Tertiary	.010	(.080)	-.030	(.078)
Number of rooms in house	.043	(.065)	.024	(.062)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.081	(.126)	.047	(.124)
Rented	.351***	(.097)	.372***	(.096)
Reduced Rented	.160	(.220)	.131	(.212)
Social Rented	.624***	(.105)	.635***	(.103)
Free	.643**	(.306)	.736**	(.313)
Other	-.075	(.678)	-.010	(.692)
Labour Market Status (Base: Inactive, Unemployed, Sick, Disabled, Student)				
Professional and Managerial Roles	-.238	(.276)	-.152	(.270)
Technical and Skilled Roles	-.097	(.231)	-.096	(.227)
Service Manual and Support Roles	.043	(.288)	.024	(.282)
Log of Original Income	-.287**	(.122)	-.267**	(.118)
Neighbourhood effect	-.009	(.053)	.012	(.053)
Personality Traits				
Openness to Experience	-.031	(.039)	-.024	(.038)
Conscientiousness	-.042	(.041)	-.033	(.041)
Extraversion	.042	(.038)	.027	(.037)
Agreeableness	.004	(.040)	-.006	(.040)
Neuroticism	.060	(.038)	.058	(.037)

	LB/UC		LB/UC – Alternative Measurement	
Cognitive Ability	.046	(.042)	.050	(.042)
Receipt of LB/UC (Base: Not in receipt)				
Receipt	.475***	(.092)	.461***	(.088)
Lagged Take-up	1.328***	(.084)	1.196***	(.081)
Initial Value	1.699***	(.152)	1.910***	(.145)
Time-average variables				
Responsible for housing costs	-.171	(.172)	-.224	(.174)
Single	.655***	(.198)	.624***	(.197)
Separated, Divorced, Widowed	.515**	(.238)	.484**	(.238)
Two	-.291	(.184)	-.265	(.182)
Three or more	-.320	(.286)	-.247	(.281)
Minimum age of child in household	.434***	(.152)	.428***	(.150)
Professional and Managerial Roles	.102	(.343)	.046	(.335)
Technical and Skilled Roles	.254	(.301)	.314	(.294)
Service Manual and Support Roles	.169	(.351)	.281	(.344)
Log of Original Income	-.148	(.144)	-.162	(.144)
Neighbourhood effect	.093*	(.056)	.078	(.055)
Time Effects (Base: 2011)				
2012	.353**	(.149)	.359**	(.147)
2013	.508***	(.145)	.516***	(.143)
2014	.512***	(.140)	.489***	(.138)
2015	.394***	(.139)	.345**	(.138)
2016	.410***	(.137)	.429***	(.135)
2017	.318**	(.136)	.318**	(.133)
2018	.158	(.131)	.186	(.130)
Constant	-2.473***	(.653)	-2.642***	(.650)
Observations	7,723		8,002	

Table B.7. Probability of Claiming CB, dynamic probit model without personality traits

	CB		CB – excluding personality traits	
Log Simulated Eligible Amount	.133***	(.028)	.121***	(.026)
Age	-.073*	(.038)	-.079**	(.032)
Age2	.001**	(.000)	.001**	.000
Gender (Base: Female)				
Male	-.047	(.080)	.014	(.067)
Marital Status (Base: Married/Cohabitating)	-.068	(.254)	-.166	(.221)
Separated, Divorced, Widowed	-.451	(.354)	-.464	(.292)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean Black African	.069	(.251)	-.024	(.214)
Asian				
Asian or Asian British Chinese	.039	(.136)	-.006	(.100)
Black or Black British	-.049	(.175)	-.036	(.146)
Arab and any other	-.411	(.419)	-.381	(.369)
Health (Base: Not Disabled)				
Disabled	-.101	(.226)	-.010	(.199)
Children in Household (Base: One)				
Two	-.012	(.163)	.000	(.143)
Three or more	-.009	(.263)	.181	(.228)
Minimum age of child in household	-.395***	(.151)	-.420***	(.129)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	-.042	(.155)	.093	(.146)
Education (Non-Tertiary)				
Tertiary	-.052	(.070)	-.080	(.061)
Number of rooms in dwelling	-.156***	(.046)	-.167***	(.039)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.039	(.108)	-.01	(.091)
Rented	-.095	(.105)	-.095	(.094)
Reduced Rented	-.27	(.346)	-.202	(.307)
Social Rented	.031	(.124)	-.012	(.106)
Free	-.17	(.305)	-.325	(.248)
Other	-.264	(.464)	-.607	(.751)
Labour Market Status (Base: Inactive, Unemployed, Sick, Disabled, Student)				
Professional and Managerial Roles	-.332	(.336)	-.364	(.290)
Technical and Skilled Roles	-.391	(.329)	-.409	(.289)
Service Manual and Support Roles	-.158	(.413)	-.142	(.349)
Log of Original Income	.251*	(.131)	.293***	(.106)
Neighbourhood effect	.081*	(.045)	.057	(.039)
Personality Traits				
Openness to Experience	-.005	(.040)		
Conscientiousness	-.047	(.040)		
Extraversion	-.010	(.041)		
Agreeableness	.017	(.036)		
Neuroticism	-.006	(.036)		
Cognitive Ability	-.020	(.038)		

Time Effects (Base: 2011)				
2012	.396**	(.159)	.326**	(.133)
2013	.093	(.124)	.084	(.120)
2014	.256*	(.091)	.232**	(.118)
2015	.187	(.176)	.179	(.111)
2016	.210*	(.120)	.159	(.102)
2017	.281**	(.167)	.209**	(.099)
2018	.063	(.267)	.077	(.104)
Time-average variables				
Responsible for housing costs	-.003	(.167)	-.132	(.157)
Single	.058	(.267)	-.177	(.234)
Separated, Divorced, Widowed	.375	(.409)	.160	(.336)
Two	-.113	(.185)	-.109	(.163)
Three or more	-.073	(.292)	-.281	(.251)
Minimum age of child in household	.245	(.170)	.242*	(.145)
Professional and Managerial Roles	.866*	(.454)	.879**	(.375)
Technical and Skilled Roles	1.091**	(.444)	1.100***	(.370)
Service Manual and Support Roles	1.074**	(.520)	.995**	(.428)
Log of Original Income	-.658***	(.238)	-.611***	(.183)
Neighbourhood effect	.000	(.049)	-.006	(.042)
Receipt of LB/UC (Base: Not in receipt)				
Receipt	.818***	(.131)	.982***	(.116)
Lagged Take-up	1.629***	(.118)	1.582***	(.079)
Initial take-up	1.709***	(.176)	1.744***	(.150)
Constant	.222	(.912)	.580	(.762)
Observations	16,009		20,444	

Table B.8. Probability of Claiming LB/UC, dynamic probit model without personality traits

	LB/UC		LB/UC – excluding personality traits	
Log Simulated Eligible Amount	.318***	(.038)	.313***	(.032)
Age	-.017	(.029)	-.058**	(.024)
Age2	.000	.000	.001**	.000
Gender (Base: Female)				
Male	.248**	(.109)	.236***	(.088)
Marital Status (Base: Married/Cohabitating)	.539***	(.177)	.292*	(.157)
Separated, Divorced, Widowed	.255	(.231)	.234	(.208)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean Black African Asian	.150	(.241)	.207	(.212)
Asian or Asian British Chinese	.146	(.142)	.198*	(.108)
Black or Black British	-.170	(.135)	-.230**	(.113)
Arab and any other	.099	(.590)	.005	(.444)
Health (Base: Not Disabled)				
Disabled	.160	(.178)	.236	(.162)
Children in Household (Base: One)				
Two	.354**	(.162)	.351**	(.138)
Three or more	.825***	(.271)	.796***	(.228)
Minimum age of child in household	-.368***	(.136)	-.400***	(.117)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	.105	(.151)	.196	(.134)
Education (Non-Tertiary)				
Tertiary	.010	(.080)	-.025	(.067)
Number of rooms in dwelling	.043	(.065)	.028	(.053)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.081	(.126)	.015	(.104)
Rented	.351***	(.097)	.254***	(.081)
Reduced Rented	.160	(.220)	.187	(.189)
Social Rented	.624***	(.105)	.558***	(.087)
Free	.643**	(.306)	.494*	(.260)
Other	-.075	(.678)	-.614	(.604)
Labour Market Status (Base: Inactive, Unemployed, Sick, Disabled, Student)				
Professional and Managerial Roles	-.238	(.276)	-.286	(.247)
Technical and Skilled Roles	-.097	(.231)	-.242	(.209)
Service Manual and Support Roles	.043	(.288)	-.205	(.252)
Log of Original Income	-.287**	(.122)	-.313***	(.107)
Neighbourhood effect	-.009	(.053)	.015	(.047)
Personality Traits				
Openness to Experience	-.031	(.039)		
Conscientiousness	-.042	(.041)		
Extraversion	.042	(.038)		
Agreeableness	.004	(.040)		
Neuroticism	.06	(.038)		
Cognitive Ability	.046	(.042)		
Time Effects (Base: 2011)				
2012	.353**	(.149)	.230*	(.122)

2013	.508***	(.145)	.386***	(.119)
2014	.512***	(.140)	.417***	(.115)
2015	.394***	(.139)	.257**	(.115)
2016	.410***	(.137)	.287**	(.112)
2017	.318**	(.136)	.252**	(.110)
2018	.158	(.131)	-.002	(.106)
Time-average variables				
Responsible for housing costs	-.171	(.172)	-.198	(.152)
Single	.655***	(.198)	.418**	(.172)
Separated, Divorced, Widowed	.515**	(.238)	.221	(.214)
Two	-.291	(.184)	-.227	(.157)
Three or more	-.32	(.286)	-.27	(.241)
Minimum age of child in household	.434***	(.152)	.470***	(.129)
Professional and Managerial Roles	.102	(.343)	.143	(.300)
Technical and Skilled Roles	.254	(.301)	.328	(.264)
Service Manual and Support Roles	.169	(.351)	.373	(.302)
Log of Original Income	-.148	(.144)	-.164	(.121)
Neighbourhood effect	.093*	(.056)	.046	(.048)
Receipt of LB/UC (Base: Not in receipt)				
Receipt	.475***	(.092)	.527***	(.078)
Lagged Take-up	1.328***	(.084)	1.312***	(.071)
Initial take-up	1.699***	(.152)	1.662***	(.130)
Constant	-2.473***	(.653)	-1.207**	(.523)
Observations	7,723		10,170	

5. CONCLUSION

This thesis studies the role of personality traits in the human capital model of earnings and economic outcomes, examining three key areas. The studies uncover several important findings. First, the study demonstrates the effect of personality traits on earnings within the human capital model, uncovering heterogenous returns primarily based on socioeconomic status. Second, the thesis delves into the intergenerational transmission of these traits, highlighting the influence of socioeconomic background and parental input during early life. Finally, the research discusses the implications of personality traits in social policy, particularly how they can affect the take-up of social benefits to supplement income.

5.1 EMPIRICAL CUES

Traditional human capital models emphasise education and cognitive skills amongst primary determinants of earnings. This research extends the model to include personality traits, providing new insights. In Chapter One, a meta-analysis shows that openness and conscientiousness are positively correlated with earnings, while extraversion has a weaker positive correlation. Conversely, agreeableness and neuroticism are negatively correlated with earnings. However, accounting for publication bias diminishes the apparent influence of these traits. Chapter One also shows that socioeconomic factors, such as education and occupation, and cognitive skills explain a portion of the variance in the observed effects. This implies that personality traits may be susceptible to omitted variable bias, potentially leading to misleading estimates if these factors are left unaccounted for. Moreover, while personality traits have traditionally been perceived as distinct constructs, this research aligns with the emerging perspective that personality traits are conceptually and empirically intertwined with socioeconomic factors and cognitive skills.

Chapter Two investigates the impact of parental socioeconomic status (SES) on the Big Five personality traits and intelligence using data from the German TwinLife study. The findings show that children from high SES families tend to have higher fluid intelligence and emotional stability. The study finds gaps in personality traits and fluid intelligence between SES groups, indicating that factors beyond genetics play an important role in personality development, which supports the social investment principle. Additionally, Chapter Two shows that lower parental education results in reduced parental time investments, which indirectly affects intelligence and personality traits among children from different socioeconomic backgrounds. Interestingly, the chapter found no evidence of varying investment productivity among parents from different SES groups. This suggests that similar parental investments could result in similar personality traits for children, regardless of their SES. The findings are consistent with the neo-socioanalytic theoretical framework, which considers personality as a system of traits, abilities, motives, and situational factors. This perspective supports the results of Chapter One, linking varying returns to personality traits to socioeconomic factors and cognitive skills.

Chapter Three extends the human capital model to include social benefit take-up in the UK using a combination of microsimulation and longitudinal data (UKMOD-UKHLS). The research finds that economic factors primarily determine benefit take-up, with personality traits playing a direct insignificant role. Additionally, local benefit take-up rates influence individual decisions possibly by reducing stigma and information costs, thereby facilitating greater access to social benefits.

5.2 PERSPECTIVES FOR POLICY

The findings of this thesis have significant policy implications. In terms of earnings, personality traits complement cognitive skills in enhancing earnings potential. Interventions should focus on developing personality traits, or noncognitive skills in general, especially for low-income earners, and could include training programmes that foster traits like conscientiousness and openness to experience.

Regarding socioeconomic status, while personality traits have long been considered stable and persistent over an individual’s life, the systemic relationship between SES and personality traits highlights the need for policy action to address gaps in personality traits, or noncognitive skills in general, for disadvantaged children. These children often receive less parental investment and are in environments that do not support the sound development of such skills. Policymakers should consider implementing early education programmes and parental support initiatives that encourage positive parenting styles and investments in children’s development. These interventions can help nurture personality traits that are valued in the labour market. By fostering attitudes and work ethics from an early age, these policies can improve children’s future success in the labour market and help them exit the low-income trap.

In the context of social benefits, addressing non-take-up requires an understanding of cultural and information barriers. Improved communication strategies, community engagement, targeted nudges and policy framing can enhance benefit take-up, ensuring that social support reaches those in need. This is essential to mitigate the long-term consequences of poor nutrition, delayed healthcare, and an impoverished environment, which can exacerbate public spending over time.

5.3 FUTURE RESEARCH ON PERSONALITY

The research contained in this thesis can benefit from a number of extensions. By incorporating personality traits into the empirical models, we have gained a more comprehensive understanding of the human capital model and how individual outcomes are determined. It is worth noting, however, that the use of personality traits rests on two assumptions: that they remain consistent over time and stable across different circumstances. These assumptions are sometimes misunderstood, leading to the belief that personality traits are independent of the environment. Several studies suggest that personality is shaped by both genetics and environment and while individuals may be born with certain personalities, they can still develop them as they experience life.

Future research should further investigate the dynamic nature of personality traits, considering both genetic and environmental influences. Longitudinal studies are necessary to track changes in personality traits over time and to understand their stability and evolution. Assessing the effect of specific interventions, such as educational programmes and parental training, on personality development is also important. Additionally, cross-cultural comparisons can provide valuable insights into how different cultural and environmental contexts shape personality traits and their economic implications.

By incorporating personality traits into the human capital model, this thesis provides a more comprehensive understanding of the determinants of economic outcomes. The findings emphasise the need for policies that foster both cognitive and noncognitive skills, ultimately aiming to contribute to a more equitable and prosperous society.