Personality and Wages Over the Life Cycle*

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Abstract

This paper examines how personality traits impact the wages of low-educated adult men throughout their working lives. The empirical findings reveal economically and statistically significant wage gaps associated with personality traits across the life cycle. For example, highly extraverted early-career workers earn, on average, 18 log points more than their highly introverted counterparts, while highly agreeable mid-career workers experience average wages 24 log points lower than highly disagreeable mid-career workers. Motivated by these empirical findings, I estimate a life cycle model that incorporates on-the-job search and bargaining, personality traits, and skill accumulation. The model explores the role of personality trait heterogeneity in generating observed wage gaps throughout the life cycle via the main model mechanisms. Firms differ in skill-match productivity levels, and skills accumulate on the job, whereas personality traits are fixed upon entry into the labour market. Personality traits influence the search and skill channels, impacting job offer probabilities, job separation probabilities, and the law of motion of skill. The results indicate that personality trait heterogeneity within the on-the-job search channel is most important in generating the observed wage gaps. Eliminating personality trait differences in all channels leads to a reduction in wage inequality over the first 15 years of workers' careers.

*This analysis is based on Statistics Canada's *Longitudinal and International Study of Adults*, 2014, 2016, and 2018 (Waves 2–4). All computations were prepared by Tommas Trivieri. The responsibility for the use and the interpretation of this data is entirely that of the author.

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1 Introduction

Wages rapidly increase during the early stages of a worker's career. For example, the wages of workers holding a high school diploma experience an average growth of 50% within the first ten years of their career (Rubinstein and Weiss, 2006). Traditionally, post-schooling wage growth is attributed to skill accumulation and job search.[1] However, the availability of richer data has allowed researchers to uncover evidence suggesting that other types of skills, such as personality traits, may directly and indirectly, influence life cycle wages through these mechanisms.[2] Understanding how differences in personality traits impact life cycle wages through these avenues is essential for determining the effectiveness of different policies aimed at boosting wages over a worker's career, including on-the-job training and job search assistance.

In this paper, I utilize a unique panel dataset of Canadian workers known as the Longitudinal and International Study of Adults (LISA) to investigate the connection between personality traits (i.e., openness to experience, extraversion, and agreeableness) and life cycle wages among low-educated adult men. The personality traits examined are derived from the widely recognized Big Five personality trait questionnaire, which all participants in the second wave of the panel were required to complete.[3] My empirical analysis uncovers several economically and statistically significant wage disparities associated with distinct personality traits across the life cycle. For instance, early-career workers with high extraversion, on average, earn wages that are 18 log points higher than their highly introverted counterparts. Similarly, mid-career workers characterized as highly agreeable experience average wages

[1]For example, see Yamaguchi (2010), Bowlus and Liu (2013), Bagger, Fontaine, Postel-Vinay, and Robin (2014), and Burdett, Carrillo-Tudela, and Coles (2016) for recent studies exploring the importance of human capital and search mechanisms to life cycle wages.

[2]For example, see Flinn et al. (2021) and Lise and Postel-Vinay (2020).

[3]The Big Five personality traits measure a person's openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism. These measurements are the most widely adopted measure of personality in the psychology literature. For example, see Goldberg (1992), Saucier (1994), and Gosling, Rentfrow, and Swann (2003). Conscientiousness and neuroticism do not have a statistically significant relationship with the life cycle wages observed in my sample and are therefore excluded from this study.

that are 24 log points lower than their highly disagreeable counterparts.[4]

Motivated by these empirical patterns, I estimate a structural life cycle model of skill, labour search, and bargaining. I use the model to investigate whether personality heterogeneity within these mechanisms can rationalize the observed wage gaps associated with different personality traits across the life cycle. Furthermore, I utilize the structural model to explore the overall influence of personality trait heterogeneity on life cycle wages.

In the model, finite-lived workers possess two types of skills: (1) general skills, acquired through a learning-by-doing skill accumulation process while employed, and (2) fixed personality traits, which exert influence on key parameters within the search and skill channels.[5] Job search is random and in each period workers are either employed or unemployed. Worker skills stagnate in unemployment. At the end of each period, workers randomly meet risk-neutral firms that differ in their general skill match productivity values. During these encounters, employed workers negotiate with the most productive firm, considering their outside option of extracting full surplus from the least productive firm. Unemployed workers negotiate with firms using unemployment as their outside option. Employment contracts consist of a wage level that is established through a Rubinstein (1982) style bargaining game à la Cahuc, Postel-Vinay, and Robin (2006).[6] Except for the worker's bargaining power, all parameters within the skill and job search channels are contingent on the level of a worker's personality traits, which is how these traits influence life cycle wages.

I estimate the model parameters in two steps. In the initial stage, I employ structural equation modelling techniques to externally estimate the joint distribution of general skill

[4]In this context, highly extraverted and highly introverted workers are defined as those with extraversion levels at least one standard deviation above and below the average, respectively. The same criteria apply to other personality traits examined in this empirical analysis.

[5]Research by Cobb-Clark and Schurer (2012) examines the stability of Big Five personality traits over time using HILDA, an Australian representative survey, finding minimal mean- and median-level changes in these traits for working-age adults over four years. Similarly, Elkins, Kassenboehmer, and Schurer (2017) leverage HILDA to further study the stability of these traits and show that mean-level changes in the Big Five personality traits are negligible over eight-year time periods and tend towards zero after the age of 20. Thus, reinforcing the idea that these traits remain stable for working-age adults.

[6]It is worth noting that the wage outcomes in this framework are observationally equivalent to the ones in Dey and Flinn (2005).

and personality traits. This approach allows me to fully utilize all the rich data available in LISA. For each worker in my simulation, I draw samples from this distribution, obtaining a vector of initial conditions necessary for forward-simulating life cycle labor market outcomes. The remaining structural model parameters are estimated using indirect inference.[7]

To examine how the wage gaps linked to personality traits evolve across the life cycle and are influenced by personality trait heterogeneity within the skill and search channels, I systematically eliminate such heterogeneity in these channels and observe how the gaps change in each scenario. In assessing the overall impact of personality trait heterogeneity on life cycle wages, I compare the percentage differences between average wages in various simulation scenarios relative to the baseline scenario at different ages.

The counterfactual outcomes highlight that personality trait heterogeneity within the on-the-job search channel plays a predominant role in generating observed wage gaps associated with personality traits throughout the life cycle. This effect is particularly pronounced in the case of early-career extraversion and openness to experience wage gaps, with the elimination of heterogeneity within the search channel resulting in a notable reduction in the wage gaps of 50.26% and 36.34%, respectively, relative to the baseline scenario. Fully eliminating heterogeneity within both channels leads to an additional 6 pp and 4 pp reduction in the early-career extraversion and openness to experience wage gaps, respectively, on top of only eliminating heterogeneity in the search channel. Heterogeneity within the skill channel has a modest impact on shaping the late-career openness to experience wage gap, causing a decrease of approximately 18% when personality differences within this channel are eliminated. Nevertheless, substantial portions of the wage gaps persist even after fully removing personality trait differences within the skill and search channels. These stem from differences in workers' initial skill levels that are correlated with their personality traits.

Additionally, I investigate the broader impact of personality traits by examining the evolution of average wages and the standard deviation of wages over the life cycle in each

[7] See Gourieroux, Monfort, and Renault (1993).

of the different simulation scenarios used in the initial counterfactual exercise. When I fully remove differences in personality traits within the search and skill channels, I observe a reduction in average wages and wage inequality during the initial 15 years of workers' careers compared to the baseline simulation. However, as before, these impacts are primarily driven by personality trait differences in the on-the-job search channel.

Specifically, workers at the lower end of the wage distribution, who previously faced significant disadvantages in finding jobs while employed due to their personality traits, no longer experience these disadvantages in the final simulation scenario. This enables them to reach out to employers more frequently, leading to faster wage growth during the initial fifteen years of their careers compared to the baseline scenario. Conversely, those at the higher end of the wage distribution, who previously had advantages in on-the-job search due to their personality traits, now find themselves at a disadvantage in the final scenario. As a result, they contact fewer firms and progress up the job ladder more slowly than they would in the baseline scenario. The negative impacts on the high-wage workers outweigh the positive impacts on the low-wage workers, which explains the reduction in average wage levels and the reduction in wage inequality during the first fifteen years of workers' careers.

Overall, these counterfactual exercises underscore that personality traits wield a non-trivial influence on life cycle wages, especially in the early phase of workers' careers. They also demonstrate policies aimed at minimizing search frictions may be more effective than policies like on-the-job training. Especially for workers with high levels of introversion or openness to experience.

This paper extends the existing literature on human capital and job search. Prior studies in this literature typically build and estimate unified frameworks of human capital and job search, aiming to quantify the respective contributions of these mechanisms to life cycle wage growth and wage inequality.[8] In these frameworks, human capital is often specified as unidimensional and general across firms, while the search process is frequently assumed

[8]Examples of such studies include Barlevy (2008), Yamaguchi (2010), Michelacci and Pijoan-Mas (2012), Bowlus and Liu (2013), Bagger et al. (2014), and Burdett et al. (2016).

to be constant across workers.[9] The collective findings of this literature suggest that both human capital and job search are vital contributors to life cycle wage growth, with human capital generally playing a more important role.

This paper contributes by introducing additional dimensions of skill heterogeneity within the traditional model setups employed in this literature. Specifically, the model incorporates individual-level personality trait heterogeneity, that influences the rate of skill accumulation, the likelihood of contacting firms in employment or unemployment, and the probability of job separation. The results of the counterfactual exercises reveal a significant impact of these traits in the search channel, suggesting that job search may be a more influential source of life cycle earnings growth for low-educated men than indicated by previous evidence in this literature.

This paper also contributes to the ongoing research examining the relationship between personality traits and wages. Numerous studies, such as Nyhus and Pons (2005), Heineck (2011), Mueller and Plug (2006), and Braakmann (2011), have highlighted the link between gender-specific personality traits and wage disparities. Some of these studies, including Mueller and Plug (2006), Braakmann (2011), Nyhus and Pons (2012), Risse et al. (2018), and Collischon (2021), employ the Oaxaca-Blinder decomposition framework to investigate this correlation, emphasizing the role of agreeableness and emotional stability in gender wage gaps. Additionally, there is a burgeoning literature that integrates personality traits into behavioral models to explore gender wage gaps, intra-household bargaining, and occupational choices, as seen in Flinn et al. (2021), Flinn et al. (2018), and Todd and Zhang (2020).

This paper makes two primary contributions to this literature. First, it empirically documents significant wage gaps associated with personality traits throughout the life cycle, providing additional evidence that personality trait heterogeneity can lead to other types of wage gaps. Furthermore, the evidence underscores the importance of non-cognitive skills in understanding the determination of wages.

[9] Bowlus and Liu (2013) stands out as a notable exception to the latter by endogenizing search effort in their framework.

Second, I complement this literature by introducing personality traits into a non-stationary life cycle model with skill accumulation and job search. The results of the counterfactual exercises highlight that these traits have important implications for life cycle wages, and the impacts of these traits vary quite substantially throughout the life cycle. In contrast, the other structural study in this small literature introduces personality traits into canonical job search and bargaining models with fixed skill differences that are set in stationary time.[10]

This paper proceeds as follows. Section 2 delves into a discussion of LISA and outlines the process of sample construction. Section 3 contains an exploration of the relationship between personality traits and wages, along with other labor market outcomes. Section 4 introduces the life cycle model encompassing skill accumulation, job search, and bargaining. The estimation and identification of the model parameters are discussed in Section 5, while Section 6 presents the parameter estimates and evaluates the model fit. In Section 7, the main results from the counterfactual exercises are discussed. Section 8 concludes.

2 Data and Estimation Sample

The Longitudinal and International Study of Adults (LISA) is a novel representative data set of Canadian workers. It is a recent worker-level panel study designed by Statistics Canada in partnership with the Organisation of Economic Co-operation and Development's (OECD) Programme for the International Assessment of Adult Competencies (PIAAC). Its objective is to enhance understanding of people's jobs, labour market behaviour, skill development, health, income, and families through time. In 2012 Statistics Canada interviewed approximately 11,000 representative Canadian households compromising approximately 34,000 individuals 15 years of age or older.[11] So far, the survey spans years 2012–2020 on a biennial

[10]For example, Flinn et al. (2021) introduce personality traits into a canonical job search and bargaining model to investigate the influence of personally traits on the gender wage for through the main model mechanisms for a sample of German workers. The model they estimate is set in stationary time and features both cognitive skills and personality traits that are fixed.

[11]To protect the privacy of respondents, Statistics Canada requires all those who use LISA to round sample sizes and frequency counts to the nearest 100. Further, all proportions must be rounded to the third decimal,

basis.

To my knowledge, LISA is one of the few data sets in existence that collects worker-level questions about the levels of different skills used on the job over time, how a worker's skill has changed over a two-year period, personality traits, and standard human capital and labour market variables found in other data sets such as the NLSY.[12]

2.1 Construction of Key Variables

Wages. The primary wage measure utilized in this study's empirical analysis and model estimation is LISA's weekly wage level. For a worker to have a non-missing wage, LISA imposes the following restrictions: the respondent must have worked during the survey's reference week, been employed by a non-family business, and received remuneration from the company. Moreover, information on wages are collected with each survey. Therefore, I do not observe wages between survey periods.

For each year I observe wages, I set to missing all values below the average provincial full-time weekly minimum wage or above $250,000/50. Average provincial minimum weekly wages are calculated by multiplying the average provincial minimum hourly wage by 30 hours. Additionally, if a worker's usual hours worked are below 30 hours, their wages are set to missing as well to ensure the sample contains full-time workers. Finally, to account for inflation, wages are adjusted to constant 2010 dollars using the consumer-price index.

General skill. To obtain a measure of general skill, I leverage the sequence of skill questions found in the Skills Used at Work section in LISA. In this section, there are worker-level measures of skills along six dimensions over time. The skill dimensions are (1) reading; (2) writing; (3) math; (4) communication; (5) manual dexterity; and (6) physical strength. Along each skill dimension, workers who were employed during the reference week or refer-

while averages, rates, and percentages must be rounded to the first decimal. All results presented throughout this paper satisfy these conditions and should be interpreted as such.

[12] For example, LISA contains education, years of actual experience, years of job tenure, wages, retrospective labour market histories, and the start and stop dates for jobs.

ence period were asked to choose a number between one and seven that best described the level of skill required to perform their job, where the number one represents a low skill-level requirement, while seven represents a very high skill-level requirement. Each question contains descriptions of the skill levels to facilitate a common understanding amongst workers of what each level of skill is meant to represent. For example, the description attached to category two in the math question is “count the amount of change to be given to a customer,” while the description attached to category six in math is “develop a mathematical model to simulate and resolve an engineering problem.” In the descriptive analysis, “general skill” refers to the sum of all skill measures. I then standardize the measure. This is done to facilitate a clearer interpretation of the descriptive regressions.

Personality traits. In the 2014 wave of LISA's survey, all respondents were obligated to respond to a 15-item inventory that aimed to capture the Big Five personality traits. This inventory was specifically designed for large-scale representative surveys.[13] Each dimension of personality is represented by three items.

For this study, I focus on the questions related to three specific dimensions of the Big Five personality traits: openness to experience, extraversion, and agreeableness. Openness to experience refers to an individual's inclination to embrace intellectual, aesthetic, or cultural encounters. Extraversion pertains to the orientation of one's interests and energies towards the external world of people and things, rather than the internal realm of subjective experiences. It is characterized by positive affect and sociability. Agreeableness reflects a person's tendency to behave in a cooperative and unselfish manner towards others. I focus on these dimensions because they have significant effects in the descriptive wage regressions discussed later in this study. The average of each set of three items is calculated and scored on a scale between one and seven, with higher scores indicating the trait is a better descriptor of the person. I standardize each dimension to be mean zero and standard deviation one

[13] See Lang, John, Lüdtke, Schupp, and Wagner (2011) for an in-depth discussion of how this 15-item inventory was designed and its robustness in relation to the original Big Five inventory.

and use these measures in the descriptive analysis.[14]

2.2 Construction of Labour Market Histories

To construct worker labor market histories in four-month periods, I begin with their monthly labor market histories. Firstly, I determine the employment status of workers based on certain criteria. If a worker is employed and works full-time hours or if they have a non-missing wage but their labor force status is unknown, they are classified as employed. According to Statistics Canada, a job is considered full-time if it requires a minimum of 30 hours of work per week. In the LISA dataset, workers report their wages only if they were employed during the reference week of the survey. Additionally, workers are classified as employed if they are absent from work due to reasons such as vacation, personal matters, work schedule, paternity leave, elder care, or childcare responsibilities. It is worth noting that these instances of being absent from work are typically of short duration.

Conversely, workers are classified as nonemployed if their monthly labor market history indicates that they are either unemployed, employed but work part-time, not in the labor force, employed but absent from work due to illness or disability, or employed but absent from work without a specified reason. Finally, if a worker is employed for at least two out of the four months in question, they are classified as employed; otherwise, they are classified as unemployed.

2.3 Sample Selection Criteria

The analysis focuses on waves 2 to 4 of the LISA dataset, covering the years 2014 to 2018 with a biennial frequency. To create a panel dataset, I organize the data at the person-year-period level. Here, "period" refers to a four-month period within a year or a *quadrimester*. Therefore, there are three periods per year.

This paper seeks to understand the influence of personality trait heterogeneity within the

[14]The descriptions of the Big Five personality traits were largely drawn from Almlund et al. (2011).

skill and job search channels on the life cycle wages of low-educated adult men. Low-educated adult men are defined as those with no more than a high school diploma. I restrict the analysis to this sample of workers because these workers are often situated towards the lower end of the income distribution and face increased volatility in the labour market compared to higher-educated workers. Consequently, these individuals are likely to derive substantial benefits from labour market interventions such as on-the-job training or job search assistance throughout their careers. Therefore, discerning the specific channels through which personality trait heterogeneity exerts the most significant influence is crucial for identifying the most effective labour market policies to enhance wages across the life cycle.

To comprehensively explore the impact of personality trait heterogeneity on women's life cycle wages, it is essential to consider factors such as marriage, fertility, and childcare dynamics. However, incorporating these elements into the current model, which will be discussed in Section 4, would significantly increase computational complexity and complicate the overall analysis. Therefore, women are excluded from the analysis.

In summary, the analysis sample comprises adult men with low levels of education aged between 20 and 65. These individuals have fully completed the survey, possess non-missing labor force status, possess no more than 50 years of actual work experience, and reside in Canada.

3 Describing the Role of Personality in Life Cycle Wages

Table 1 presents the OLS estimates for the impact of personality traits on life cycle wages. The analysis includes three personality traits: extraversion, openness to experience, and agreeableness. Each trait is examined within three sub-samples: early-career (age $\in [20, 35)$), mid-career (age $\in [35, 50)$), and late-career (age $\in [50, 65]$). The regression model involves regressing log wages on discretized indicators for each personality trait. The indicators divide workers into three categories based on their trait levels: "trait level $\leq -1SD$," "trait level $\in (-1SD, 1SD)$," and "trait level $\geq 1SD$." These categories represent workers who are highly below average (at least one standard deviation below average), around average (above -1 standard deviation and below 1 standard deviation), and highly above average (at least one standard deviation above average) in the respective trait. This analysis aims to investigate the impact of personality traits on wages over the life cycle.

Focusing on the early-career impacts of personality traits, as shown in the first three columns of the table, I observe significant and contrasting effects of Extraversion and Openness to Experience on wages. In column (1), the coefficient $\mathbb{I}(Extra \geq 1SD)$ indicates a notable wage premium associated with high levels of extraversion. Holding all else constant, highly extroverted early-career workers earn, on average, 18 percentage points (pp) more than their highly introverted counterparts. On the other hand, column (2) reveals that highly open to experience early-career workers experience a substantial wage penalty at –27 pp relative to their highly un-open to experience early-career counterparts. Last, the wage effects linked to different levels of agreeableness are not statistically significant at conventional levels.

Examining the mid-career impacts of personality traits (columns 4–6), I find significant effects on wages related to agreeableness and openness to experience. Being a highly agreeable mid-career worker is associated with a substantial wage penalty compared to being highly disagreeable. Additionally, there is a wage premium for mid-career workers with an average level of openness to experience relative to those who are highly un-open to experience. Notably, the impacts of extraversion are not significant at conventional levels during the mid-career phase.

Analyzing the late-career impacts (columns 7–9), we find that openness to experience has the most substantial effects on wages. Late-career workers who are highly open to experience earn, on average, 15.91 pp more than their highly un-open to experience counterparts. This is in contrast to the early-career phase, where high levels of openness to experience were associated with a wage penalty.

Overall, this regression analysis demonstrates that personality traits have economically and statistically significant impacts on wages. Moreover, the effects of personality traits vary throughout the life cycle. For instance, high levels of openness to experience are initially associated with a wage penalty but become a wage premium later in the career.[15]

These findings enrich existing literature by delving into how personality traits affect wages, job search outcomes, and skill development over workers' careers. Studies such as Nyhus and Pons (2005) and Heineck (2011) have examined the influence of personality traits on wage levels, generally uncovering modest wage advantages or disadvantages associated with different personality traits. For instance, Heineck (2011) notes that for both men and women, openness to experience correlates positively with hourly earnings, while agreeableness is negatively associated with wages. Heineck (2011) also touches upon how job tenure interacts with personality traits, suggesting that being open to experience is beneficial with increasing tenure, aligning with my findings.

Furthermore, these insights build on research exploring how personality traits contribute to gender wage disparities, as seen in works by Nyhus and Pons (2012), Collischon (2021), and Flinn et al. (2021). For example, Flinn et al. (2021) observe associations between personality traits and hourly wages by gender, but they do not delve into how these traits influence these wage gaps over the life cycle. They find that agreeableness negatively impacts men's wages significantly, while openness to experience and extraversion are significantly associated with wages at conventional significance levels. My contribution lies in uncovering specific wage gaps linked to personality traits, which vary across traits and throughout the life cycle.

[15] The observed effects remain significant even after controlling for all personality trait indicators, occupation groups, and year effects. These regressions are shown in Appendix B.

Table 1: Life Cycle Wage Impacts of Personality Traits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sub-sample:	Early-Career	Early-Career	Early-Career	Mid-Career	Mid-Career	Mid-Career	Late-Career	Late-Career	Late-Career
Dependent Variable:	ln wage	ln wage	ln wage	ln wage	ln wage	ln wage	ln wage	ln wage	ln wage
I(Extra ∈ (-1SD,1SD))	0.17***			−0.03			0.09*		
	(0.05)			(0.09)			(0.05)		
I(Extra ≥ 1SD)	0.18*			−0.01			0.06		
	(0.11)			(0.10)			(0.07)		
I(Open ∈ (-1SD,1SD))		−0.18*			0.16***			0.13***	
		(0.10)			(0.06)			(0.05)	
I(Open ≥ 1SD)		−0.27**			0.07			0.16**	
		(0.11)			(0.07)			(0.07)	
I(Agree ∈ (-1SD,1SD))			−0.01			−0.14*			−0.09
			(0.07)			(0.08)			(0.06)
I(Agree ≥ 1SD)			−0.02			−0.24***			−0.11
			(0.09)			(0.08)			(0.07)
Constant	6.54***	6.83***	6.69***	6.86***	6.72***	6.97***	6.71***	6.67***	6.86***
	(0.04)	(0.10)	(0.06)	(0.08)	(0.05)	(0.07)	(0.04)	(0.04)	(0.05)
N	3,200	3,200	3,200	3,100	3,100	3,100	4,400	4,400	4,400

Notes: Standard errors are in parentheses. Standard errors are clustered by individual identifiers. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

In Table 2, I examine the relationship between personality traits and the skill and search channels. The table includes both OLS and logistic regression estimates.[16] The first column of the table regresses the worker's general skill level on personality traits, along with a quadratic experience term. The remaining columns display the relationship between personality traits and outcome variables related to the search channel. Specifically, these outcomes pertain to the probabilities of transitioning from unemployment to employment (U2E), from employment to employment (E2E), and from employment to unemployment (E2U).[17]

[16] To facilitate easier comparisons with prior research, I did not conduct individual regressions for each age group or with discretized personality traits. Analyzing these specifications separately by age groups and controlling for discretized personality traits, as demonstrated in Table 1, does not change the conclusions drawn from the analysis. The detailed results of these regressions are displayed in Appendix B.

[17] I do not control for general skill in the regression specifications shown in columns (2)–(4) because I only observe this measure for workers who are employed during the reference period of the survey.

Table 2: The Relationship Between Personality and the Search and Skill Channels

	(1)	(2)	(3)	(4)
	OLS	Logit	Logit	Logit
Dependent variable:	General skill level	U2E	E2E	E2U
Openness	0.14***	–0.02	0.24***	–0.07
	(0.03)	(0.07)	(0.018)	(0.06)
Extraversion	0.02	–0.01	–0.00	0.00
	(0.03)	(0.08)	(0.07)	(0.06)
Agreeableness	–0.04	–0.06	0.03	0.03
	(0.03)	(0.08)	(0.06)	(0.07)
Constant	–0.13	–1.71***	–2.68***	–2.90***
	(0.08)	(0.09)	(0.16)	(0.06)
$exp + exp^2$	Y		Y	
N	6,700	5,600	22,500	22,500

Notes: Standard errors are displayed in parentheses. Standard errors are clustered by individual identifiers. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Upon examining the results, I find that openness to experience is a statistically significant trait within the skill and search channels. However, the remaining traits do not exhibit significant effects at conventional levels for the other search outcomes. Specifically, a worker's general skill level and the probability of transitioning from E2E increase with higher levels of openness to experience. It is noteworthy that these findings align with results found in other studies in the literature, which also tend to observe insignificant effects of personality traits on U2E and E2U transitions (Flinn et al., 2021).

Taking stock. The regression analyses have uncovered interesting relationships between personality traits and wages. Notably, the impact of personality traits on wages varies across traits and changes significantly throughout the life cycle. Additionally, skill and on-the-job search outcomes are significantly associated with personality traits. Drawing from research in human capital and job search literature, which highlights that skill accumulation and job search are the most important sources of post-schooling wage growth, this is prima facie evidence that personality traits may affect life cycle wages through these mechanisms.[18] However, it remains unclear how personality traits impact wages through these mechanisms or which mechanisms are most influenced by personality traits. Understanding this influence is crucial for understanding wage determination over the life cycle and for assessing the effectiveness of policies such as on-the-job training or job search assistance. Therefore, I will utilize a life cycle skill and job search model that integrates personality traits into both channels to address these questions.

4 Model

This section presents a partial-equilibrium life cycle labour search model. The economy is populated by firms and finitely lived workers. Time is discrete and one model period corresponds to four months in a year. Workers work for $t = 1, 2, ..., 135$ periods (45 years) and discount the future at rate $1/R$, where R is the gross interest rate. Workers differ by their level of general skill, as well as openness to experience, extraversion, and agreeableness, which are measured using the Big Five personality trait questionnaire. I extend standard life cycle frameworks by letting these traits influence workers' rate of general skill accumulation and success at job search in the model.

4.1 Workers

Workers are risk neutral. Workers are characterized by their stocks of general skill and personality traits, $\Theta_{it} = (ln\theta_{it}^{gen},\ \theta_i^O,\ \theta_i^E,\ \theta_i^A)$, and their labour market status, either employed (E) or unemployed (U). Personality traits vary across individuals and are fixed over time. Upon entering the labour market in $t = 1$, workers draw their initial latent stocks of general

[18] For example, see Rubinstein and Weiss (2006), Yamaguchi (2010), Bowlus and Liu (2013), and Bagger et al. (2014).

skill and immutable personality traits from the distribution $\Gamma(\Theta_{i1})$.

Skill accumulation occurs by learning-by-doing. Workers accumulate general skill while employed and do not accumulate general skill while unemployed.[19] The worker's skill accumulation rate is influenced by his learning ability and age. The law of motion for general skill is,

$$ln\theta_{it+1}^{gen} = ln\theta_{it}^{gen} + \left(\frac{\alpha_i}{1 + exp(\gamma \times (t-1))}\right) \times \mathbb{I}(\mathrm{E}_t = 1), \tag{1}$$

where $\alpha_i \in (0,1)$.[20] I depart from existing literature by allowing the ability parameter (α_i) to be influenced by the worker's personality traits, while γ is common across workers and influences how steeply general skill accumulation will decline with age. Therefore, workers with certain personality traits may have advantages in accumulating general skills.

Job search is random. The probabilities of contacting an outside firm are λ_{it}^E and λ_i^U in employment and unemployment, respectively. If employed, match separation occurs with probability η_i. The search parameters are exogenous and are also influenced by the worker's personality traits. Thus, personality traits influence how quickly workers climb the job ladder over their life cycle. When unemployed, a worker's income is $b \times \theta_{it}^{gen}$. Here, b is the return to general skill in unemployment and is common across workers.

4.2 Firms

Firms are risk neutral and there is free entry into the labour market. Firms differ in their general skill match productivity. The skill match productivity distribution is denoted as,

[19] Utilizing unique skill measures that describe how a worker's skill has changed over time contained in LISA, Trivieri (2021) empirically documents that almost no workers report skill declines over time.

[20] This functional form for skill accumulation is an adapted version of the one utilized in Gregory (2023). I chose this functional form over alternative parameterizations for two primary reasons. First, it guarantees that skill growth decelerates with age until workers reach a point where they can no longer accumulate skills, reflecting diminished learning effectiveness or incentives as retirement approaches. Thereby, replicating the skill accumulation patterns observed for other reduced-form specifications and endogenous skill accumulation specifications like Ben-Porath (1967). Second, it enables the straightforward incorporation of personality trait heterogeneity into the skill accumulation process.

$G(p)$, and log-normally distributed. That is, $ln(p) \sim N(\mu_p, \sigma_p^2)$. A match between a worker (Θ_{it}) and a firm (p) produces output equal to the product of the firm's match productivity and the worker's general skill supplied to the firm,

$$y(p, \Theta_{it}) = \overbrace{p}^{\text{firm productivity}} \times \underbrace{\theta_{it}^{gen}}_{\text{gen skill}} . \tag{2}$$

4.3 Bargaining and Employment Contracts

I assume employment contracts are renegotiated by mutual consent only and are set through a Rubinstein (1982) style bargaining game as in Cahuc, Postel-Vinay, and Robin (2006).[21] Workers can use a contact with one employer as a threat point in a bargaining game with another. When two firms with productivity levels p and q compete for the worker's services, the worker bargains using the less productive firm as the outside option, say $q \leq p$, and ends up employed by the more productive firm (p). When unemployed, the worker bargains with unemployment as their outside option. The worker has bargaining power $\beta = 0.5$, which is standard in the literature.

Joint worker-firm match value. The joint worker-firm match value is

$$\begin{aligned} P_t(p, \Theta_{it}) = \Bigg\{ \overbrace{p\theta_{it}^{gen}}^{\text{match output}} + \frac{1}{R}\Bigg[& \overbrace{P_{t+1}(p, \Theta_{it+1})}^{\text{stay in match}} + \overbrace{\eta_i \left[U_{t+1}(\Theta_{it+1}) - P_{t+1}(p, \Theta_{it+1})\right]}^{\text{worker} \rightarrow \text{U ; firm} \rightarrow \text{vacancy}} \\ & + \underbrace{(1-\eta_i)\lambda_{it}^E \beta \int_p^\infty \left[P_{t+1}(x, \Theta_{it+1}) - P_{t+1}(p, \Theta_{it+1})\right] dG(x)}_{\text{match dissolves; worker} \rightarrow \text{new firm } (x)\text{; current firm } (p) \rightarrow \text{vacancy}} \Bigg] \Bigg\}. \end{aligned} \tag{3}$$

At the beginning of the period, the worker-firm match generates an output flow $p\theta_{it}^{gen}$. The firm's value of a vacancy is equal to zero. The first term within the square brackets is the continuation value of the joint worker-firm pair remaining intact at the end of the period. With probability η_i the worker-firm match dissolves, and the worker and firm transit to

[21]The outcomes in this framework are observationally equivalent to those in Dey and Flinn (2005).

unemployment and the vacancy state, respectively. With probability $(1-\eta_i)\lambda_i^E(1-G(p))$, a worker contacts an outside firm with match productivity level, $x > p$, and transits to the new firm in the next period yielding the worker's bargaining share times the new joint value of the worker-firm pair net the old value of the joint worker firm pair. In this case, the firm transits to the vacancy state.

Value of unemployment. The value of unemployment for a worker is

$$U_t(\Theta_{it}) = \overbrace{b\theta_{it}^{gen}}^{\text{U income}} + \frac{1}{R}\left[\overbrace{U_{t+1}(\Theta_{it+1})}^{\text{stay in U}} + \overbrace{\lambda_i^U \beta \int_{p^\star}^{\infty} \left[P_{t+1}(x, \Theta_{it+1}) - U_{t+1}(\Theta_{it+1})\right] dG(x)}^{\text{worker} \to \text{E}}\right], \quad (4)$$

where $p^\star$ is the worker's reservation value such that $P_t(p^\star, \Theta_{it}) = U_t(\Theta_{it})$. At the beginning of the period, the worker consumes his unemployment income and his general skill level remains stagnant. With probability $(1-\lambda_i^U)$ the worker does not contact a firm and remains unemployed. Similarly, with probability $(1-\lambda_i^U)G(p^\star)$, the worker meets a firm with a match productivity level below their reservation value and remains unemployed. With probability $\lambda_i^U(1-G(p^\star))$, they contact a firm with a match productivity level higher than his reservation value, $p^\star$. In this case, the worker moves from unemployment to employment at the new firm in the next period.

Value of the wage contract. The value of the wage contract, $V_t(p, q, \Theta_{it})$, to a worker employed at a firm with match productivity level p, with outside option q, and general skill and personality traits Θ_{it}, solves

$$\begin{aligned} V_t(p, q, \Theta_{it}) = w_{it} + \frac{1}{R}\Bigg[& \overbrace{\eta_i U_{t+1}(\Theta_{it+1})}^{\text{worker} \to \text{U}} + \overbrace{(1-\eta_i)(1-\lambda_{it}^E(1-G(q)))V_{t+1}(p, q, \Theta_{it+1})}^{\text{no offer or discard outside offer}} \quad (5) \\ & + \underbrace{(1-\eta_i)\lambda_{it}^E \int_q^p V_{t+1}(p, x, \Theta_{it+1}) dG(x)}_{\text{renegotiate wage contract}} + \underbrace{(1-\eta_i)\lambda_{it}^E \int_p^\infty V_{t+1}(x, p, \Theta_{it+1}) dG(x)}_{\text{switch firms with full surplus extraction from old firm}} \Bigg]. \end{aligned}$$

At the beginning of the period, the worker receives their wage. At the end of the period, the worker-firm match dissolves with probability η_i, and the worker transits to unemployment. With probability $(1-\eta_i)(1-\lambda_i^E(1-G(q)))$, the worker either does not receive an offer or receives an offer that they cannot use to improve their employment contract, implying they continue working for the current firm. If the worker contacts an outside firm with match productivity $x \in (q, p]$, then the contract is renegotiated, the worker's outside option increases from q to x, and the worker continues working for the current firm. This case is captured by the second last term in equation (5). Finally, if the worker meets a firm with a match productivity level $x > p$, as captured by the last term in equation (5), then the current match dissolves, the worker transits to the new firm x receiving a contract with the new firm that yields value $V_t(x, p, \Theta_{it})$.

Optimal wages. Employment contracts consist of a wage level, w_{it}, that dictates the surplus split,

$$\underbrace{V_t(p, q, \Theta_{it})}_{\text{Value of wage contract}} = \underbrace{\beta P_t(p, \Theta_{it}) + (1-\beta) P_t(q, \Theta_{it})}_{\text{Nash Bargaining Solution}}, \tag{6}$$

when a worker is bargaining with a firm, p, using their next best alternative, $q \leq p$. Importantly, while the wage increases with general skill accumulation throughout the worker-firm match, the total share of the match surplus delivered to the worker remains constant until the following renegotiation.

The optimal wage in all periods $t < T$ is

$$
\begin{aligned}
w_{it} = \beta P_t(p, \Theta_{it}) + (1-\beta) P_t(q, \Theta_{it}) \\
- \frac{1}{R}\Big[\eta_i U_{t+1}(\Theta_{it+1}) + (1-\eta_i)(1-\lambda^E_{it}(1-G(q)))V_{t+1}(p, q, \Theta_{it+1}) \qquad (7) \\
+ (1-\eta_i)\lambda^E_{it}\int_q^p V_{t+1}(p, x, \Theta_{it+1})dG(x) + (1-\eta_i)\lambda^E_{it}\int_p^\infty V_{t+1}(x, p, \Theta_{it+1})dG(x)\Big].
\end{aligned}
$$

The first terms on the RHS capture the share of the match surplus delivered to the worker, resulting from the worker's current match and their history of outside job offers. The terms in the brackets reflect the value of all future outside offers, which lowers the worker's starting wage. The wage level is influenced by personality traits through the skill and search channels.

Terminal values. In the final period T, the joint worker-firm match value, the value of unemployment, the value of the employment contract, and the wage become

$$P_T(p, \Theta_{iT}) = p\theta^{gen}_{it}, \qquad (8)$$

$$U_T(\Theta_{iT}) = b\theta^{gen}_{it}, \qquad (9)$$

$$V_T(p, q, \Theta_{iT}) = w_{iT}, \qquad (10)$$

$$w_{iT} = (\beta p + (1-\beta)q)\,\theta^{gen}_{it}. \qquad (11)$$

In the terminal period, the worker consumes their income, either from unemployment or their wages, and the joint match value equals current period output. The optimal wage is a weighted sum of the current firm's match productivity level and the worker's outside option multiplied by the stock of their human capital.

4.4 Model Parameterizations

The search and skill parameters lie in the unit interval. To ensure this is the case and to allow the parameters to vary with personality traits, I make the following parametric assumptions for $\zeta \in \{\lambda_i^U,\ \eta_i,\ \alpha_i\}$

$$\zeta_i = \frac{exp\left(\zeta_0 + \sum_{\rho \in PT} \zeta_\rho \theta_i^\rho\right)}{1 + exp\left(\zeta_0 + \sum_{\rho \in PT} \zeta_\rho \theta_i^\rho\right)}, \tag{12}$$

where, $\rho \in PT \equiv \{O,\ E,\ A\}$ corresponds to the personality traits. Similar parametric assumptions were made on the search and bargaining parameters in Flinn et al. (2021).

I parameterize the probability of contacting a firm (λ_{it}^E) as,

$$\lambda_{it}^E = \frac{exp\left(\lambda_0^E + \tilde{\lambda^E}^\top \mathbf{Z}\right)}{1 + exp\left(\lambda_0^E + \tilde{\lambda^E}^\top \mathbf{Z}\right)}, \tag{13}$$

where $\mathbf{Z}$ is a matrix containing personality traits, mid- and late-career age group indicators, and interactions of personality trait-age group indicators. I allow the probability of contacting a firm while employed to depend on age and personality traits to help capture heterogeneity in search effort over the life cycle across different workers.

5 Estimation and Identification

This section describes the identification and estimation of the model's parameters. First, I externally estimate the joint latent distribution of skills using LISA's general skill and personality trait measurements. I simulate draws from this estimated distribution, which serve as initial conditions for each worker in my simulated data set. Then, I use indirect inference to estimate the remaining parameters in the model.

5.1 Distribution of Latent Skills

I use LISA's measurements of skill and personality traits in the 2014 cross-section to estimate the distribution of latent skills in the initial sample period, $\Gamma(\Theta_{i1})$. I address the bias introduced by measurement error inherent in these (or any other) measures of latent skills using a factor analytic approach.[22] This method allows me to combine all available information contained in LISA's measurements of skill and personality traits to identify the underlying joint distribution of latent skills.[23]

I parameterize $\Gamma(\Theta_{i1})$ with a multivariate normal distribution so that $\Theta_{i1} \sim N(\vec{\mu}, \Sigma)$. Here, $\Theta_{i1} = (ln\theta_{i1}^{gen},\ \theta_i^O,\ \theta_i^E,\ \theta_i^A)^\top$. I estimate this distribution on a sample of workers between the ages of 20 and 65 using maximum likelihood. This estimation is conducted prior to estimating the main model parameters discussed in subsequent sections. Subsequently, I generate simulated draws from this estimated distribution and employ them as initial conditions for workers in my simulated dataset.

I assume there is a dedicated measurement system, where each measure only proxies one latent skill. I also assume each measure is age-invariant.[24] All the measures in the system are discrete. The discrete measures related to general skill contain eight ordinal categories (i.e., $Q = 8$), while the personality trait measures contain seven ordinal categories (i.e., $Q = 7$). Let $M_{i,j}^\ell$ denote the $j = 1, ..., J$ available measurements relating the latent skills $\ell \in \{gen,\ O,\ E,\ A\}$.

I relate the latent skills to the discrete measures using an ordered model

$$M_{i,j}^\ell = \begin{cases} 1 & \text{if} \quad \delta_j^\ell \theta_i^\ell + \epsilon_{i,j}^\ell < \kappa_{1,j}^\ell \\ q & \text{if} \quad \kappa_{q-1,j}^\ell < \delta_j^\ell \theta_i^\ell + \epsilon_{i,j}^\ell < \kappa_{q,j}^\ell, \text{ for } 1 < q < Q, \\ Q & \text{if} \quad \kappa_{Q-1,j}^\ell < \delta_j^\ell \theta_i^\ell + \epsilon_{i,j}^\ell \end{cases} \tag{14}$$

[22] For example, see Cunha and Heckman (2008).

[23] By skills, I mean general skills and personality traits.

[24] This implies that the expected level of measured skill for workers of different ages would be the same if they have the same level of latent skill (Agostinelli and Wiswall, 2017).

where the κ's are cutoffs, the δ's are the factor loading's (or scale parameters), and the ϵ's are idiosyncratic measurement errors. I assume $\epsilon^{\ell}_{i,j} \sim N(0,1)$.[25] The measurement errors are also assumed to be independent of latent skills and each other.

Finally, the scale of the latent skills needs to be set based on normalization restrictions. For the latent general skill level, I normalize the factor loading on the level of mathematics required at work to be equal to one. For the personality traits, I normalize the factor loadings on "originality," "talkative," and "rudeness" (reverse scored) all equal to one. Lastly, for each latent variable in Θ_i, I normalize its unconditional mean to zero. All these parameters are identified by ratios of covariances of different measures and the means of the measurements.

5.2 Self-Reported Skill Changes

I use LISA's novel self-reported skill change measurement to help inform the model about skill accumulation.[26] This is a measure of how a worker's overall skill level has changed over two years. Specifically, workers are asked to choose one of four possible categories that best describes *how* their overall skill level has changed, which are, "(1) Decreased," "(2) Did not change," "(3) Increased somewhat," or "(4) Increased a lot." Therefore, even if a worker's skill requirements at work do not change, this measure provides information about whether the worker acquired more skill to better perform the skill requirements at their job. In estimation, I combine the no skill change and skill depreciation categories together because less than one percent of workers report skill decreases.

Let $M^{\Delta gen}_{i,t}$ denote the discrete-ordinal self-reported skill change variable for worker i that is age t. κ^{Δ}_k for $k = 1, 2$, $ln\theta^{gen}_{i,t} - ln\theta^{gen}_{i,t-6}$, and $\epsilon^{\Delta}_{i,t}$ represent the cutoff points, the two-year

[25] As discussed in Agostinelli and Wiswall (2020), when dealing with ordinal measurements researchers must make a parametric assumption on their distribution to identify the parameters governing the measurements.

[26] In Appendix D, I further highlight the benefits of using LISA's Self-Reported Skill Changes in estimation to help inform the model's skill formation process. The skill change variable is consistent with standard human capital theory, in that it produces the age and education skill accumulation profiles predicted by Becker (1964) and Ben-Porath (1967) and also captures significant variation in wage growth. See Trivieri (2021) and Bowlus et al. (2023).

change in a worker's general skill level, and idiosyncratic measurement error, respectively,

$$M_{i,t}^{\Delta gen} = \begin{cases} 1 & \text{if} \quad ln\theta_{i,t}^{gen} - ln\theta_{i,t-6}^{gen} + \epsilon_{i,t}^{\Delta} < \kappa_1^{\Delta}, \\ 2 & \text{if} \quad \kappa_1^{\Delta} < ln\theta_{i,t}^{gen} - ln\theta_{i,t-6}^{gen} + \epsilon_{i,t}^{\Delta} < \kappa_2^{\Delta}, \\ 3 & \text{if} \quad \kappa_2^{\Delta} < ln\theta_{i,t}^{gen} - ln\theta_{i,t-6}^{gen} + \epsilon_{i,t}^{\Delta}. \end{cases} \tag{15}$$

I assume that $\epsilon_{i,t}^{\Delta} \sim N(0,1)$ and that the measurement errors are uncorrelated contemporaneously across measures as well as uncorrelated with latent skill changes. Given a level of general skill drawn from the initial latent skill distribution, I can construct the self-reported skill change measure in the simulated data for employed workers of any age. The cutoffs are identified from the frequency distribution of self-reported skill changes and internally estimated.

5.3 Structural Model Parameters

In this section, I discuss the estimation and identification of the structural model parameters. There are a total of 28 structural parameters that I need to estimate, which are the mean and variance of the log-normal match productivity distribution (denoted as μ_p and σ_p^2), self-reported skill change cutoffs (κ_k^{Δ} for $k = 1, 2$), parameters determining ability (α_i), and search-related parameters determining (λ_i^U, λ_i^E, η_i). Except for the parameters determining η_i, I estimate all these parameters using indirect inference.

Within the model, skill accumulation takes place exclusively on-the-job, the accumulation rate diminishes with age, and the level of skill a worker possesses is influenced by their personality traits. Notably, conditional on age and being employed, the rate of skill accumulation is primarily determined by a worker's ability (α_i) and is independent of job-to-job transitions because skills are general and fully transferable across firms.

As a result, the auxiliary model includes coefficients taken from an OLS regression of the general skill level on quadratic experience and personality traits. These moments contain valuable information on the rate of skill accumulation as well as how personality traits affect the level of general skill. Additionally, I include average wage levels by age and the frequency distribution of self-reported skill changes in the auxiliary model. These moments provide additional information on the evolution of wages over the life cycle that is important for identifying the ability parameters (α_i) and they also convey information useful for identifying the mean and variance of the match productivity distribution, as well as the cutoffs for self-reported skill changes (μ_p, σ_p, and κ_k^{Δ} for $k = 1, 2$).

Moving on, the probability of contacting a firm while in unemployment (λ_i^U) varies with observed personality traits and remains constant over the life cycle. Therefore, to identify these parameters, I include coefficients from a logistic regression of U2E conditional on the level of openness to experience, extraversion, and agreeableness in the auxiliary model.

When it comes to the probability of contacting a firm while employed (λ_{it}^E), this varies with observed personality trait heterogeneity and age. To identify these parameters, I include the fraction of workers transiting E2E by age in the auxiliary model. This fraction is highest early in the life cycle and lowest later in life, providing crucial information for identifying the life cycle-related parameters in λ_{it}^E.

Furthermore, I also target the life cycle wage profiles for each personality type. In other words, I regress log wages on discretized personality trait indicators fully interacted with age group indicators (early-, mid-, and late-career indicators). These regressions are conducted separately for each personality trait, with the personality trait indicators defined in the same manner as described in Section 3. These moments capture significant variation in the life cycle impact of personality traits on wage levels, influenced by on-the-job search throughout a worker's career. They are thus instrumental in identifying the personality trait-age indicator parameters in the probability of contacting a firm while employed. Additionally, these moments offer further information useful for identifying the personality trait parameters in the skill channel, which also affect how personality traits influence life cycle wages.

The probability of match separation (η_i) has a direct empirical counterpart, which is the

E2U rate conditional on personality traits. Specifically, I utilize the coefficients displayed in column (4) of Table 2 as the parameters determining each worker's probability of match separation in the model.

Bargaining power. In estimation, I set the worker's bargaining power (β) equal to 0.5, a practice well-established in the literature, e.g., Yamaguchi (2010) and Flinn et al. (2017). This normalization is necessary due to the absence of data on firms. The reason for this is that, in this model, skills are accumulated during employment and are fully transferable across different firms. Without access to firm-specific data or additional modelling assumptions, it is challenging to separately identify the bargaining power parameter from the skill accumulation and search parameters with only wage data.[27]

5.4 Indirect Inference Estimator

To estimate the structural model parameters as outlined in Section 5.3 (i.e., parameters determining α_i, λ_{it}^E, λ_i^U, and the cutoffs κ_k^Δ for $k = 1, 2$), I employ a technique known as indirect inference. Indirect inference is a simulation-based estimation method used when the likelihood function of an economic model is either analytically intractable or too complex to evaluate directly (Gourieroux et al., 1993).

In this approach, a vector of structural parameters denoted as $\boldsymbol{\rho}$ serves as the starting point. Indirect inference involves selecting a set of key statistics, denoted as $\hat{M}$, that the model aims to replicate.[28] For a given parameter vector $\boldsymbol{\rho}$ that is being estimated, the model is utilized to generate a corresponding vector of target moments denoted as $M(\boldsymbol{\rho})$.

To obtain the parameter estimates, $\hat{\boldsymbol{\rho}}$, I utilize an optimization algorithm, which searches across the parameter space to identify the vector that minimizes a criterion function, as

[27] As a robustness check, I have estimated a version of this model with worker's bargaining power equal to 0.25. The conclusions of the counterfactual exercises discussed in Section 7 remain the same.

[28] In this paper, $\hat{M}$ includes all the moments discussed in Section 5.3.

expressed in the equation:

$$\hat{\boldsymbol{\rho}} = \arg\min_{\boldsymbol{\rho}} \left[\left(\hat{M} - M(\boldsymbol{\rho}) \right)^{\top} W \left(\hat{M} - M(\boldsymbol{\rho}) \right) \right], \tag{16}$$

where W is a positive-definite diagonal weighting matrix. Using a diagonal weighting matrix helps to avoid finite sample biases in two-step GMM-type models. See for example Altonji and Segal (1996). The variance of $\hat{\boldsymbol{\rho}}$ is calculated using the formula for the asymptotic variance that corrects for simulation error and detailed in Gourieroux et al. (1993).

Summary of estimation procedure. The model parameters are estimated in two stages. Initially, the joint latent distribution of skills is externally estimated using the method outlined in Section 5.1. Subsequently, the remaining structural model parameters are estimated using Indirect Inference. During the Indirect Inference stage, when forward-simulating life cycle decisions of workers, a vector of initial conditions is sampled from the estimated joint latent distribution of skills. These initial conditions are required for simulating life cycle labor market outcomes in the model. Without the simulated life cycle labor market outcomes, I would not be able to construct the simulated moment counterparts ($M(\boldsymbol{\rho})$) outlined in Equation (16).

6 Estimation Results and Model Fit

In this section, I discuss the estimation results of the model parameters. The section concludes with a discussion of the fit of the estimated model to moment counterparts in the data.

6.1 Parameter Estimates

Table 3 presents the estimated distribution of latent skills in the initial sample period. This table is divided into two panels. The first panel illustrates the standard deviations of these latent skills, highlighting that openness to experience has the highest variability (standard deviation of 1.19), while general skill and agreeableness exhibit the least variability, with standard deviations of 0.5 and 0.61, respectively.

In the second panel of Table 3, I showcase the correlation matrix of these latent skills. The personality traits are positively correlated with each other. General skills are positively correlated with openness to experience and extraversion but negatively correlated with agreeableness. However, the correlations between general skills and personality traits are relatively weak. This is consistent with the descriptive evidence shown in Table 2 of Section 3.

Table 3: Distribution of Skills in the Initial Sample Period

Standard Deviation	General Skill	Openness to Experience	Extraversion	Agreeableness
	0.50	1.19	0.99	0.61
Correlation Matrix	General Skill	Openness to Experience	Extraversion	Agreeableness
General Skill	1.00			
Openness to Experience	0.15	1.00		
Extraversion	0.05	0.42	1.00	
Agreeableness	–0.07	0.33	0.32	1.00

Table 4 displays internally estimated parameter estimates, with standard errors provided below in parentheses where applicable. All parameters are statistically significant at the one percent level except for the coefficients related to personality traits in η_i, which are not statistically significant at conventional levels.

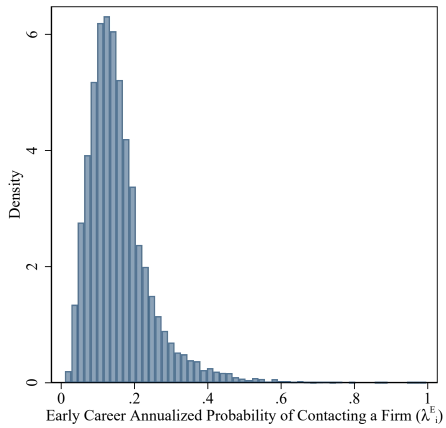
The first row of Table 4 shows that a worker's ability is positively correlated with their levels of openness to experience and extraversion. However, the magnitude of the coefficient for extraversion is relatively small. In contrast, a worker's ability is negatively correlated with their level of agreeableness. Comparing the magnitudes of the coefficients for openness to experience and agreeableness, it is evident that the penalty associated with agreeableness is more substantial than the premium associated with openness to experience.

Moving on to the estimated coefficients governing the probability of contacting a firm in employment, a key insight is that the impact of personality traits varies significantly with age. For example, for early-career workers, the probability of contacting a firm increases extraversion (represented by λ_2^E), all else equal, while there is a strong negative correlation associated with openness to experience (represented by λ_1^E). However, in the late-career phase, high levels of extraversion (as per λ_9^E) are associated with a significant penalty in contacting firms, while high levels of openness to experience (as per λ_7^E) are associated with an advantage in contacting firms.

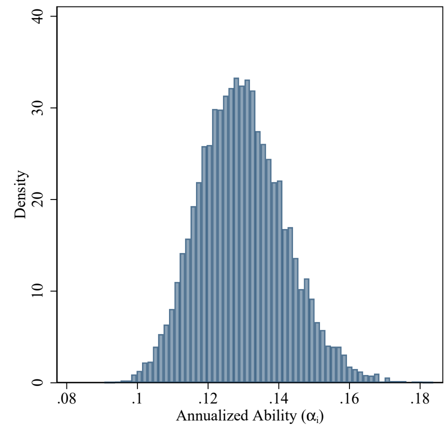
Table 4: Parameter Estimates

	Ability (α_i)	Match Separation (η_i)	Probability of contacting a firm in UE (λ_i^U)	Probability of contacting a firm in E (λ_{it}^E)
Constant	α_0	η_0	λ_0^U	λ_0^E
	–3.100	–2.900	–1.781	–3.050
	(0.006)	(0.062)	(0.000)	(0.002)
Openness	α_1	η_1	λ_1^U	λ_1^E
	0.079	–0.065	–0.032	–0.510
	(0.004)	(0.059)	(0.000)	(0.002)
Extraversion	α_2	η_2	λ_2^U	λ_2^E
	0.026	0.001	0.008	0.710
	(0.005)	(0.062)	(0.000)	(0.002)
Agreeableness	α_3	η_3	λ_3^U	λ_3^E
	–0.156	0.027	–0.009	0.151
	(0.009)	(0.073)	(0.000)	(0.002)
Mid-career				λ_4^E
				0.060
				(0.005)
Late-career				λ_5^E
				0.020
				(0.005)
Open × Mid-career				λ_6^E
				0.200
				(0.003)
Open × Late-career				λ_7^E
				0.700
				(0.007)
Extra × Mid-career				λ_8^E
				–0.560
				(0.006)
Extra × Late-career				λ_9^E
				–1.050
				(0.006)
Agree × Mid-career				λ_{10}^E
				–0.199
				(0.007)
Agree × Late-career				λ_{11}^E
				–0.280
				(0.007)
	Mean Match Productivity (μ_p)	Std Dev Match Productivity (σ_p)	Skill Change Cutoff 1 (κ_1)	Skill Change Cutoff 2 (κ_2)
	6.180	0.298	0.001	0.900
	(0.002)	(0.002)	(0.000)	(0.000)
Preset Parameters:	discount rate ($1/R$)	Bargaining weight (β)	Match Productivity in UE (b)	Common skill growth parameter (γ)
	0.99	0.50	5.73	0.04

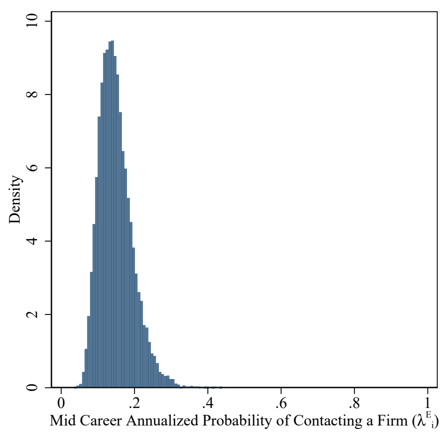
Note: standard errors are displayed in parentheses.



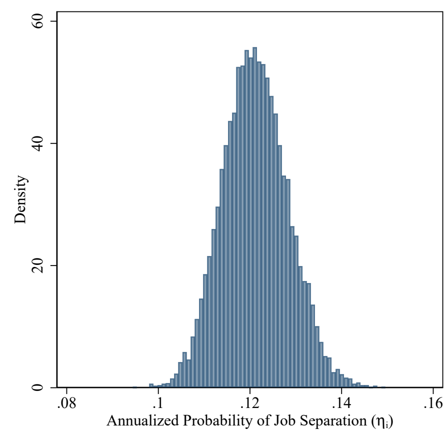
(a) Early-Career Contact Probability in E Distribution



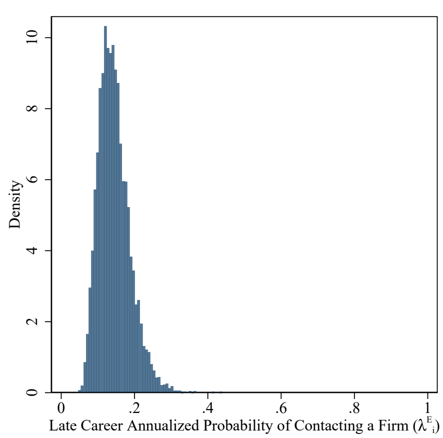
(b) Ability Distribution



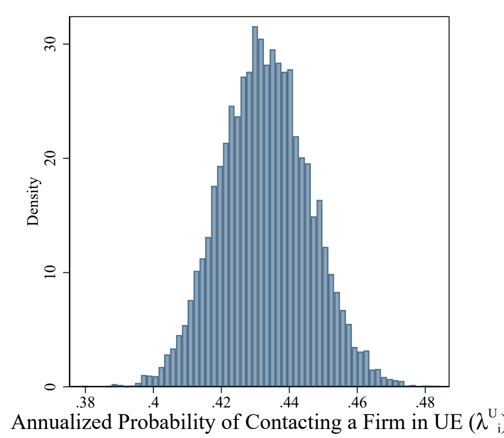
(c) Mid-Career Contact Probability in E Distribution



(d) Probability of Job Separation Distribution



(e) Late-Career Contact Probability in E Distribution



(f) Contact Probability in UE Distribution

Figure 1: Annualized Parameter Distributions

In contrast to the parameters governing skills and the probability of contacting a firm in employment, the personality trait parameters related to the probability of contacting a firm in unemployment and the probability of job separation are not statistically and almost always not economically significant. The coefficients for personality traits in these cases are quite small and, in some instances, nearly zero, except for the openness to experience coefficient in the probability of match separation (η_1), which equals -0.065 but is not statistically significant at any conventional level.

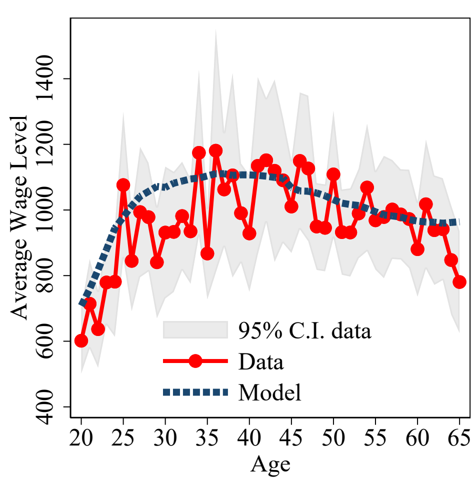
In Figure 1, I plot the parameter distributions to further illustrate how the estimates from Table 4 translate into the main model parameters. Panels (a), (c), and (e) depict the parameter distributions of the annualized probability of contacting a firm in employment for early-, mid-, and late-career age groups, respectively. Notably, this parameter varies the most for early-career workers with a standard deviation of 0.09 and the least for late-career workers with a standard deviation of 0.045. Additionally, the average annualized parameter value for the probability of contacting a firm in employment decreases with age, which plays an additional role in contributing to the decline in the fraction of workers transitioning E2E over the life cycle.

The parameter distributions for worker ability, the probability of match separation, and the probability of contacting a firm in unemployment are depicted in panels (b), (d), and (f), respectively. These parameter distributions all exhibit bell-shaped distributions with a similar level of dispersion. Moreover, the range of parameter values is fairly tight for each of these distributions in comparison to the distributions of the probability of contacting a firm in employment. Overall, the average parameter values for ability, match separation, and the probability of contacting a firm in unemployment are 0.13, 0.12, and 0.43, respectively.

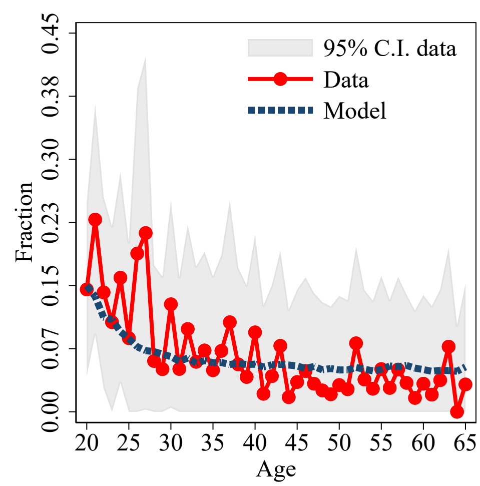
6.2 Model Fit

Figure 2 depicts average wages and the annualized fraction of workers transitioning E2E over the course of a career. In these figures, the shaded grey area represents the 95% confidence interval for the data, the red solid line reflects the actual mean values, and the blue dashed lines represent the mean values generated by the model.

In Panel (a) of Figure 2, I plot the age-earnings profile for both the data and the model. The model aligns well with the actual data, capturing the expected pattern, which is that wages increase at a decreasing rate over the life cycle, exhibiting a concave profile. Panel (b) shows that the model also effectively replicates the E2E transition rates throughout a career. These rates are highest at the start of one's career and gradually decline with age, reflecting workers climbing the job ladder over time.



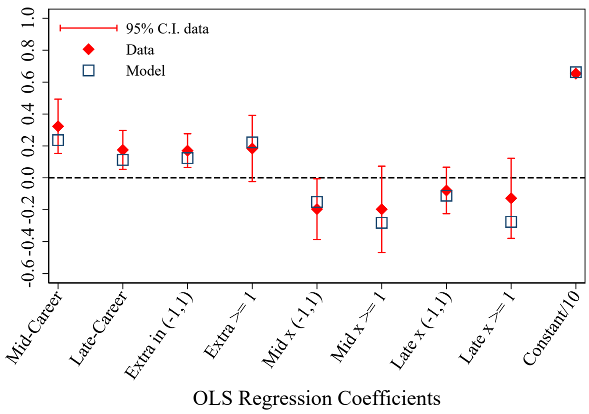
(a) Life Cycle Wages



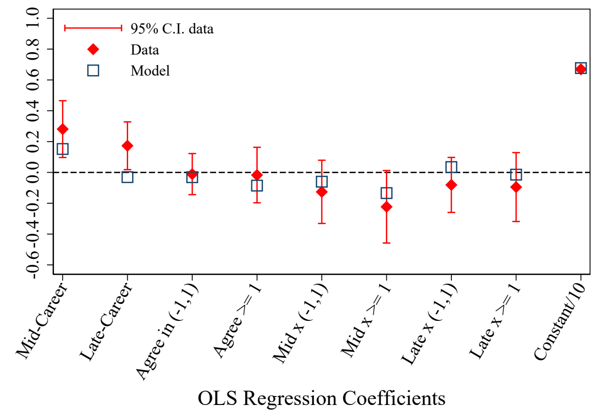
(b) Annualized E2E Rate

Figure 2: Model Fit of Average Wages and E2E Rates Over the Life Cycle

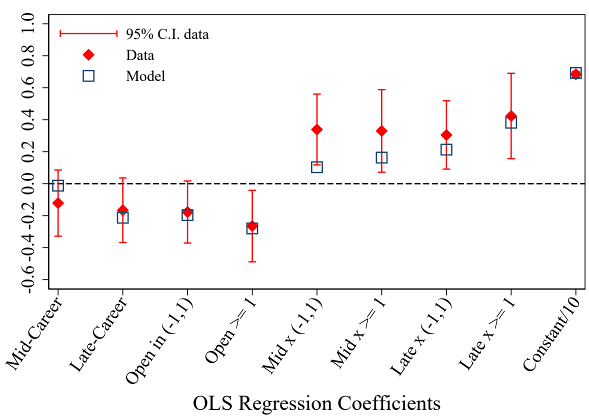
Figure 3 presents the model's fit with key regression moments targeted during estimation. In each panel, blue hollow squares represent point estimates from the model, red diamonds represent the moments from the data, and red lines outline the 95% confidence intervals from the data.



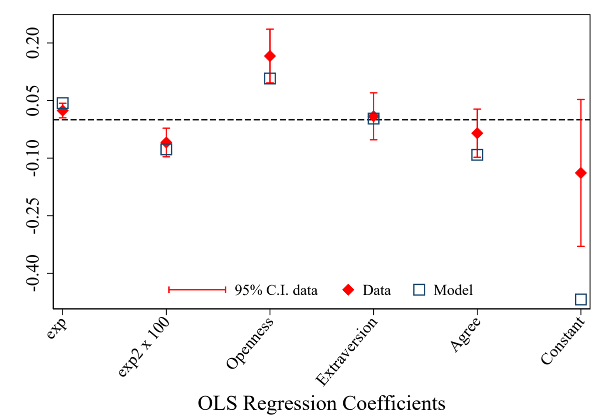
(a) wages regressed on full interactions of discretized extraversion-age groups



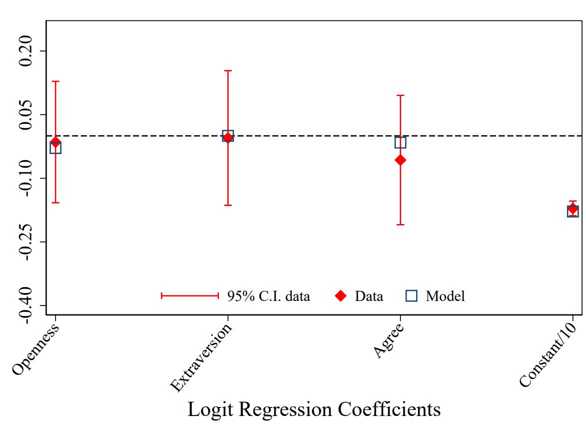
(b) wages regressed on full interactions of discretized agreeable-age groups



(c) wages regressed on full interactions of discretized openness-age groups



(d) gen skill regressed on personality traits and quadratic experience



(e) U2E regressed on personality traits

Figure 3: Model Fit of Regressions

Panel (a) in Figure 3 displays estimates of log wages conditional on discretized levels of extraversion fully interacted with age group indicators. Panel (b) similarly shows estimates for log wages, but for discretized levels of agreeableness fully interacted with age group indicators. Panel (c) provides estimates for log wages in relation to levels of openness to experience, once again fully interacted with age group indicators.[29] Panels (d) and (e) show the coefficients from the general skill OLS regression and the coefficients from the U2E logistic regression, respectively.

An analysis of Figure 3 reveals that the simulated moments from the model closely match their data counterparts. Point estimates from the model typically fall within the 95% confidence interval from the data and closely align with the point estimates from the data. There are a few exceptions, notably in panel (c), where the model tends to slightly underestimate the openness to experience level-age group interactions, and in panel (d) where the model underestimates the constant from the general skill regression.

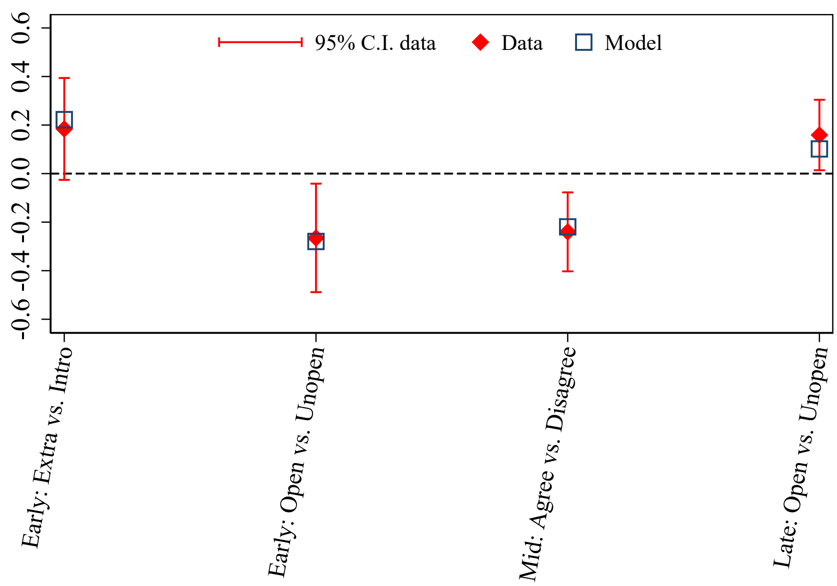


Figure 4: Life Cycle Wage Impacts of Personality Traits

[29]Recall, the discretized personality trait variables have three categories, which correspond to very low (personality trait ≤ -1), medium (personality trait $\in (-1, 1)$), and very high (personality trait ≥ 1). Additionally, Mid-Career equals one if workers are aged 35–50 and zero otherwise. Late-Career equals one if workers are aged 50–65 and zero otherwise.

Figure 4 illustrates the model's fit with the life cycle wage impacts of personality traits, as discussed in Section 3 of this paper. The model successfully replicates the wage gaps observed over the life cycle. This is to be expected, given how well the model was able to match the coefficients of wages regressed on discretized personality traits interacted with age group indicators displayed in panels (a)–(c) of Figure 3.

Table 5: Model Fit of Self-Reported Skill Changes

	Data (%)	Model (%)
No skill change	48.44	48.01
Small skill change	27.36	32.01
Large skill change	24.20	19.98

Lastly, Table 5 presents the distribution of self-reported skill changes in both the data and the model. The model effectively reproduces this distribution, with the percentage of workers reporting no skill change closely matching that in the data. While the model slightly overstates and understates the percentages of workers reporting small and large skill changes, respectively, the differences are generally small.

7 The Impact of Personality Traits Over the Life Cycle

In this section, I utilize the estimated model to determine the impact of heterogeneity in personality traits on the observed life cycle wage gaps that occur between individuals with high and low levels of each personality trait. Specifically, I seek to determine which channels of the model are primarily responsible for generating the observed life cycle wage gaps due to personality traits. Then, I investigate the overall impact of personality trait heterogeneity within the model's skill and search channels on wages and wage inequality over the life cycle. The section concludes with a discussion of the counterfactual results.

7.1 Determinants of Personality Trait Related Wage Gaps

To explore how personality trait heterogeneity within the model's skill and search channels may generate the observed wage gaps documented in Table 1, I conduct simulations using four different versions of the model. The first simulation represents the baseline model, incorporating personality trait heterogeneity in both the skill and search channels (i.e., the skill and search parameters vary with a worker's personality trait levels). In the second model version, I eliminate personality trait heterogeneity solely in the skill channel (i.e., $\alpha_i = \bar{\alpha}$ for all workers). The third model version eliminates personality trait heterogeneity solely in the search channel (i.e., $\eta_i = \bar{\eta}$, $\lambda_i^U = \bar{\lambda^U}$, $\lambda_{it}^E = \bar{\lambda_t^E}$ for all workers). Finally, the fourth scenario eliminates personality trait heterogeneity in both the skill and search channels (i.e., $\alpha_i = \bar{\alpha}$, $\eta_i = \bar{\eta}$, $\lambda_i^U = \bar{\lambda^U}$, $\lambda_{it}^E = \bar{\lambda_t^E}$ for all workers). It is important to note that workers still engage in labour market search and skill accumulation in each of the simulation scenarios. The aim of this exercise is to explore how these gaps change across each scenario and consequently identify the key channels contributing to these disparities over the life cycle.

Table 6 presents the results of the exercise. The last three columns in each row under the "Percent Change in Wage Gap" header show the percentage change in the wage gap compared to the baseline scenario. For instance, a –0.4 percent change under the "No Ability Heterogeneity" column in the first row indicates that the wage gap in the scenario with no personality trait differences in the skill channel is 0.4 percent smaller than the baseline scenario's wage gap (22.2 log points). Rows 1 and 2 of Table 6 track the early-career wage gaps for extraversion and openness to experience, respectively, in each simulation scenario. Rows 3 and 4 show the mid-career wage gap changes for agreeableness and late-career changes for openness to experience across scenarios, respectively.

Rows 1 and 2 in Table 6 show that removing personality trait differences solely in the skill channel has no discernible impact on the early-career wage gaps associated with extraversion and openness to experience. In contrast, eliminating personality trait heterogeneity in the search channel results in a notable reduction in the early-career wage gaps for extraversion and openness to experience, with decreases of 50.25 percent and 36.34 percent, respectively, compared to the baseline model that includes personality trait heterogeneity in both the skill and search channels. Fully eliminating heterogeneity in all channels reduces the early-career extraversion and openness to experience wage gaps by 56.3 percent and 39.5 percent, respectively. This means that there are still large portions of the gap due to correlations between workers initial general skill level and the personality traits. Overall, these exercises highlight that personality trait heterogeneity in the search channel contributes much more to these early-career wage disparities compared to the role played by personality trait heterogeneity in the skill channel.

Turning our attention to the mid-career wage gap between highly agreeable and highly disagreeable individuals, as shown in row 3, a slightly different story emerges. Eliminating personality trait differences in the skill channel causes the wage gap to decrease by approximately 5 percent, which is not substantial but the reduction is larger in comparison to the changes in the early-career gaps. Once again, the search channel causes a more significant reduction in the mid-career agreeableness wage gap relative to the skill channel. However, fully eliminating heterogeneity in both channels leads to the largest reduction in the wage gap, which is displayed in the final column of the third row. This suggests the interaction of heterogeneity in both channels plays a role in shaping this gap.

Table 6: The Impact of Personality Trait Heterogeneity on Life Cycle Wage Gaps

	Life Cycle Wage Gaps:	**Baseline Wage Gap:**	**Percent Change in Wage Gap** No Ability Heterogeneity	No Search Heterogeneity	No Ability and No Search Heterogeneity
1.	Early-Career Extraversion	22.2 pp	–0.4%	–50.26%	–56.3%
2.	Early-Career Openness to Experience	–28.0 pp	3.5%	–36.34%	–39.5%
3.	Mid-Career Agreeableness	–22.0 pp	–5.2%	–13.90%	–26.0%
4.	Late-Career Openness to Experience	10.2 pp	–18.3%	3.6%	–10.5%

Notes: The wage gaps represent the difference between the average wages of workers whose personality traits are more than one standard deviation above the average, compared to those whose personality traits are more than one standard deviation below the average. For instance, in row 1, the average wages are 22.2 log points higher for early-career workers who are highly extraverted compared to those who are highly introverted.

Finally, the last row in the table shows that personality trait heterogeneity within the skill and search channels do not explain a substantial portion of this wage gap. Instead, this gap is primarily influenced by differences in initial skill levels, which are correlated with personality traits. However, in contrast to the previous wage gaps, the skill channel contributes more to shaping the wage gap. When heterogeneity in the skill channel is eliminated, there is an 18 percent reduction in the wage gap.

Interestingly, when heterogeneity in the search channel is eliminated, there is a slight increase in the wage gap between highly open and highly closed workers compared to the baseline simulation scenario. This effect is primarily driven by the probability of contacting a firm during employment, rather than other search parameters. Specifically, individuals with high levels of openness to experience face a disadvantage in establishing contact with firms during the first 15 years of their career, as indicated by $\lambda_1^E = -0.51$. In this framework, the more frequently a worker can connect with new firms, the faster they progress up the career ladder compared to those who have less frequent firm contact. Therefore, setting $\lambda_1^E = 0$ eliminates this disadvantage experienced by highly open workers during the initial 15 years of their career, allowing them to engage with firms at the same rate as highly closed workers. This translates into higher wages later in their life cycle.

In summary, this exercise demonstrates that the search channel tends to play a more important role than the skill channel in generating these life cycle wage gaps. Specifically, given the small magnitudes of the personality trait coefficients in the probability of contacting a firm in unemployment and in the probability of job separation, these wage differences are driven primarily by differences in workers' ability to contact firms more frequently on-the-job.

7.2 The Overall Impact of Personality Traits on Life Cycle Wages

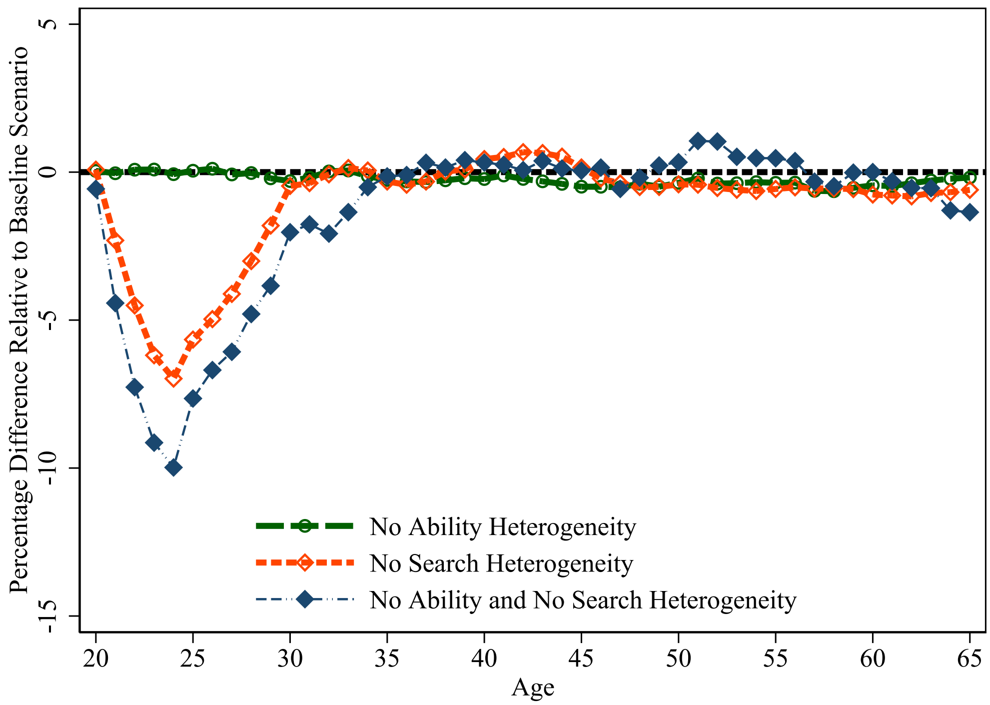
Given the findings in Section 7.1, it is natural to explore what the overall impacts of personality trait heterogeneity within the skill and search channels are on average wages and wage inequality over the life cycle. To delve into this, I calculate average wage levels (the standard deviation of wage levels) by age for each simulation scenario employed in the previous exercise. Subsequently, I calculated the percentage difference between average wages (the standard deviation of wages) in scenarios with no skill heterogeneity, no search heterogeneity, and in scenarios with no skill and search heterogeneity, compared to average wages (the standard deviation of wages) from the baseline simulation. The outcomes of this exercise are depicted in Figure 5.

In Figure 5(a) (Figure 5(b)), the green line with hollow circles shows the relative percentage difference between average wages (the standard deviation of wages) when there is no variation in personality traits within the skill channel, compared to the baseline scenario. Meanwhile, the orange dashed line with hollow diamonds illustrates the percentage difference between average wages (the standard deviation of wages) in scenarios without search heterogeneity relative to the baseline simulation. The blue dashed line with solid diamonds represents the percentage difference between average wages (the standard deviation of wages) in scenarios without both search and skill heterogeneity. It is crucial to note that if any of these lines intersect with the black dashed line, it indicates that average wages (the standard deviation of wages) in such a scenario is equal to that of the baseline scenario.

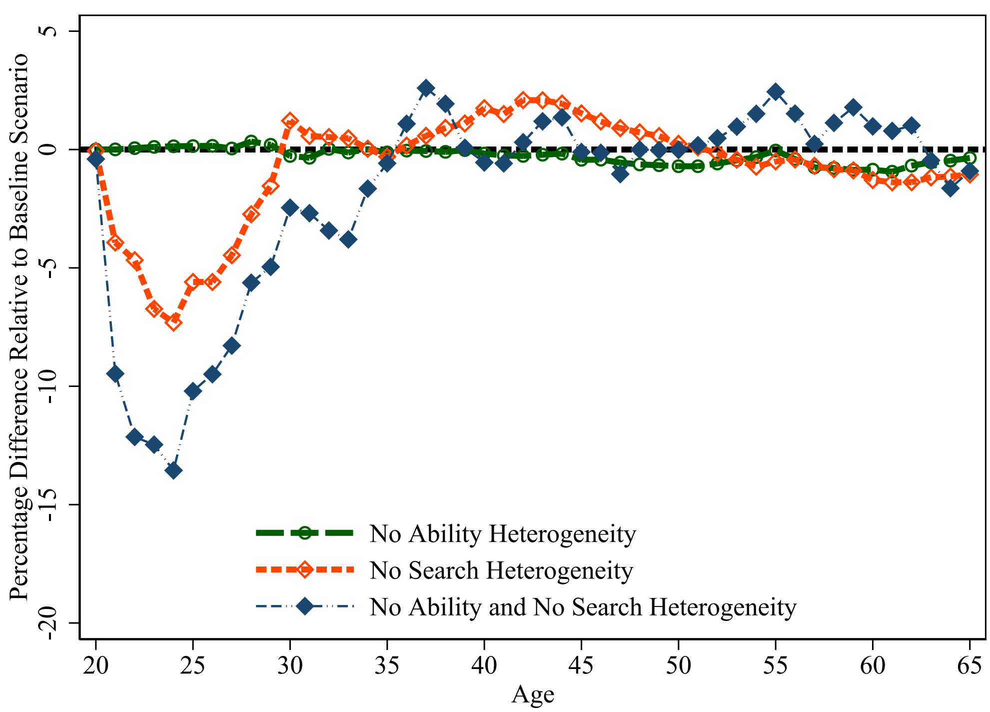
Consistent with earlier findings, personality trait heterogeneity within the skill channel has minimal impact on average wages and the standard deviation of wages. In Figure 5(a) and (b), the green line with hollow circles closely tracks and overlaps with the black dashed line throughout the entire life cycle. In contrast, personality trait heterogeneity within the search channel exerts a significant influence on average wages and wage inequality over the life cycle, as illustrated by the orange line with hollow diamonds in Figures 5(a) and (b).

Fully removing personality trait differences in the skill and search channels has the most significant impact on both average wages and the standard deviation in wages compared to all other scenarios in the simulation, indicating an interaction effect between the search and skill channels. In Figure 5(a), when personality trait heterogeneity is eliminated in both channels, it consistently leads to lower average earnings over the first 15 years of a worker's career compared to the standard simulation scenario (depicted by the blue dashed line with solid diamond markers). The difference in average wages between this scenario and the baseline widens over the initial 5 years, peaking at a 10 percent gap by age 25. Afterward, this wage gap gradually diminishes and aligns with average wages in the baseline scenario by age 35.

The decrease in average earnings observed in the final simulation scenario, illustrated in Figure 5(a), corresponds directly with a decrease in the standard deviation of wages (shown by the blue line with solid diamonds) as depicted in Figure 5(b). Initially, there is a steady decline in wage variation over the first five years, echoing the pattern seen in Figure 5(a), reaching approximately 15 percent lower than the baseline simulation scenario's standard deviation of wages. Subsequently, the standard deviation of wages follows the trend observed for average wages, gradually narrowing and completely converging with the baseline scenario by age 35.



(a) The Impact of Personality Trait Heterogeneity on Average Wages



(b) The Impact of Personality Trait Heterogeneity on the Std Dev of Wages

Figure 5: The Overall Impact of Personality Traits Over the Life Cycle

Two main factors are driving the trends observed in Figure 5. First, individuals at the lower end of the wage distribution, who previously faced significant disadvantages in interacting with firms while on the job due to their personality traits in the baseline simulation, experience a noticeable improvement in the final simulation scenario. This improvement allows them to have more frequent interactions with firms, accelerate up the job ladder more quickly, and consequently experience faster wage growth during the initial five years of their career compared to the baseline scenario.

Conversely, individuals at the higher end of the wage distribution, who previously benefited from substantial advantages in on-the-job interactions with firms due to their personality traits, no longer have these advantages in the final simulation scenario. Consequently, they engage with firms less frequently and, as a result, do not experience as rapid wage growth as they did in the baseline scenario.

Furthermore, the decrease in earnings at the higher end of the wage distribution outweighs the increase in earnings for individuals at the lower end of the wage distribution, contributing to the decline in average wages over the initial years depicted in Figure 5(a). Taken together, these opposing dynamics lead to a narrowing of the wage distribution during the first 15 years of workers' careers in the final simulation scenario.

7.3 Discussion

This analysis highlights the significant impact of personality trait differences within the search and skill channels on average wages and wage inequality over individuals' lifetimes. Notably, these impacts vary throughout the life cycle, being most pronounced during the initial 15 years of workers' careers. However, after 15 years, their overall impact on average wages becomes negligible for this demographic of workers.

Furthermore, the findings suggest potential policy avenues to enhance wage outcomes for workers. Specifically, policies aimed at reducing search frictions may hold promise in improving wages for early-career individuals with low levels of extraversion or high levels of openness to experience, as indicated by the results of both counterfactual exercises. Such policies could potentially be more effective than programs such as on-the-job training. Future research should delve into the relative costs and benefits associated with these policy interventions in a richer model framework that endogenizes search effort and skill investment decisions. This framework would provide a clearer understanding of the feasibility and efficacy of such interventions in improving wage outcomes for these workers.

8 Concluding Remarks

In this study, I develop and estimate a life cycle model of skills, labour search, and bargaining. The model incorporates two distinct types of skills: (1) general skills, acquired through work experience, and (2) immutable personality traits, which exert influence on key parameters within the search and skill channels. Utilizing a selected sample of low-educated Canadian adult men from the Longitudinal and International Study of Adults, I employ the estimated model to determine how personality traits contribute to significant wage differentials associated with these traits across the life cycle, inferring their impact through the primary model channels. Additionally, I explore the overall ramifications of personality trait heterogeneity on life cycle wage inequality.

The analyses underscore the role of personality traits in shaping wages over the life cycle. Notably, the observed wage gaps linked to personality traits predominantly arise from the heterogeneity in these traits within the on-the-job search channel, rather than the skill channel in the model, although the skill channel does play a larger role in explaining wage gaps later in the life cycle. Furthermore, personality trait heterogeneity has a non-trivial impact on average wages and wage inequality during the initial 15 years of a worker's career.

Overall, the findings suggest that there could be opportunities for policy interventions to enhance wage growth outcomes for low-educated workers. Specifically, policies aimed at reducing search frictions during the initial 15 years of a worker's career may prove more effective in fostering wage growth for this demographic compared to interventions like on-the-job training, especially for individuals who are highly introverted or highly open to experience. However, the impact of such policies is uncertain without understanding the relative costs of improving workers' search abilities versus their ability to acquire skills. Therefore, future research should explore the returns associated with various policies in this context, as well as the costs associated with search and skill acquisition.

Importantly, these findings are specific to a sample of low-educated adult Canadian men, and it remains plausible that outcomes may differ for individuals with higher education levels or for women. Additionally, unexplored personality traits, such as conscientiousness and emotional stability, may play pivotal roles in different samples. Therefore, future research should also delve deeper into these aspects to provide a more comprehensive understanding of the role of personality trait heterogeneity in shaping life cycle wages.

References

Francesco Agostinelli and Matthew Wiswall. Identification of dynamic latent factor models: The implications of re-normalization in a model of child development, 2017.

Francesco Agostinelli and Matthew Wiswall. Estimating the technology of children's skill formation, 2020.

Mathilde Almlund, Angela Lee Duckworth, James Heckman, and Tim Kautz. Personality psychology and economics, 1 2011. ISSN 15740692.

Joseph G Altonji and Lewis M Segal. Small-sample bias in gmm estimation of covariance structures. *Journal of Business and Economic Statistics*, 14:353–366, 1996.

Jesper Bagger, François Fontaine, Fabien Postel-Vinay, and Jean-Marc Robin. Tenure, experience, human capital, and wages: A tractable equilibrium search model of wage dynamics. *American Economic Review*, 104:1551–1596, 2014.

Gadi Barlevy. Identification of search models using record statistics. *Review of Economic Studies*, 75:29–64, 1 2008. ISSN 0034-6527. doi: 10.1111/j.1467-937X.2007.00459.x. URL https://academic.oup.com/restud/article-lookup/doi/10.1111/j.1467-937X.2007.00459.x.

Gary S. Becker. Human capital theory. 1964.

Yoram Ben-Porath. The production of human capital and the life cycle of earnings. *Journal of Political Economy*, 1967. URL http://www.journals.uchicago.edu/t-and-c.

Audra Bowlus, Chris Robinson, and Tommas Trivieri. New evidence on skill portfolio evolution and wages over the lifecycle from the canadian longitudinal international study of adults. 2023.

Audra J. Bowlus and Huju Liu. The contributions of search and human capital to earnings growth over the life cycle. *European Economic Review*, 64:305–331, 11 2013. ISSN 00142921. doi: 10.1016/j.euroecorev.2013.10.002.

Nils Braakmann. The role of psychological traits for the gender gap in full-time employment and wages: Evidence from germany. *SSRN Electronic Journal*, 12 2011. ISSN 1556-5068. doi: 10.2139/ssrn.1357346. URL https://papers.ssrn.com/abstract=1357346.

Ken Burdett, Carlos Carrillo-Tudela, and Melvyn Coles. Wage inequality: A structural decomposition. *Review of Economic Dynamics*, 19:20–37, 1 2016. ISSN 10942025. doi: 10.1016/j.red.2015.10.004.

Pierre Cahuc, Fabien Postel-Vinay, and Jean-Marc Robin. Wage bargaining with on-the-job search: Theory and evidence. *Econometrica*, 74:323–364, 3 2006. ISSN 0012-9682. doi: 10.1111/j.1468-0262.2006.00665.x. URL http://doi.wiley.com/10.1111/j.1468-0262.2006.00665.x.

Deborah A. Cobb-Clark and Stefanie Schurer. The stability of big-five personality traits, 1 2012. ISSN 1556-5068. URL https://papers.ssrn.com/abstract=1919414.

Matthias Collischon. Personality traits as a partial explanation for gender wage gaps and glass ceilings. *Research in Social Stratification and Mobility*, 73, 2021.

Flavio Cunha and James J. Heckman. Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. *Journal of Human Resources*, 43:738–782, 2008. ISSN 0022166X. doi: 10.3368/jhr.43.4.738.

Matthew S. Dey and Christopher J. Flinn. An equilibrium model of health insurance provision and wage determination. *Econometrica*, 73:571–627, 3 2005. ISSN 0012-9682. doi: 10.1111/j.1468-0262.2005.00588.x. URL http://doi.wiley.com/10.1111/j.1468-0262.2005.00588.x.

Rosemary K. Elkins, Sonja C. Kassenboehmer, and Stefanie Schurer. The stability of personality traits in adolescence and young adulthood. *Journal of Economic Psychology*, 60: 37–52, 6 2017. ISSN 01674870. doi: 10.1016/j.joep.2016.12.005.

Christopher Flinn, Ahu Gemici, and Steven Laufer. Search, matching and training. *Review of Economic Dynamics*, 25:260–297, 4 2017. ISSN 10942025. doi: 10.1016/j.red.2017.02.003. URL www.elsevier.com/locate/red.

Christopher Flinn, Petra Todd, and Weilong Zhang. Labor market returns to personality: A job search approach to understanding gender gaps. pages 1–73, 2021.

Christopher J. Flinn, Petra E. Todd, and Weilong Zhang. Personality traits, intra-household allocation and the gender wage gap. *European Economic Review*, 109:191–220, 10 2018. ISSN 00142921. doi: 10.1016/j.euroecorev.2017.11.003.

Lewis R. Goldberg. The development of markers for the big-five factor structure. *Psychological Assessment*, 4:26–42, 1992. ISSN 10403590. doi: 10.1037/1040-3590.4.1.26. URL /record/1992-25730-001.

Samuel D. Gosling, Peter J. Rentfrow, and William B. Swann. A very brief measure of the big-five personality domains. *Journal of Research in Personality*, 37:504–528, 12 2003. ISSN 00926566. doi: 10.1016/S0092-6566(03)00046-1.

C. Gourieroux, A. Monfort, and E. Renault. Indirect inference. *Journal of Applied Econometrics*, 8:S85–S118, 12 1993. ISSN 10991255. doi: 10.1002/jae.3950080507. URL https://onlinelibrary.wiley.com/doi/full/10.1002/jae.3950080507https://onlinelibrary.wiley.com/doi/abs/10.1002/jae.3950080507https://onlinelibrary.wiley.com/doi/10.1002/jae.3950080507.

Victoria Gregory. Firms as learning environments: Implications for earnings dynamics and job search. *Working Paper*, 2023.

Guido Heineck. Does it pay to be nice? personality and earnings in the uk. *Industrial and Labor Relations Review*, 64:1020–1038, 10 2011. ISSN 00197939. doi: 10.1177/001979391106400509. URL https://journals.sagepub.com/doi/abs/10.1177/001979391106400509?

Frieder R. Lang, Dennis John, Oliver Lüdtke, Jürgen Schupp, and Gert G. Wagner. Short assessment of the big five: Robust across survey methods except telephone interviewing. *Behavior Research Methods*, 43:548–567, 6 2011. ISSN 1554351X. doi: 10.3758/s13428-011-0066-z. URL www.geronto.uni-erlangen.de.

Jeremy Lise and Fabien Postel-Vinay. Multidimensional skills, sorting, and human capital accumulation. *American Economic Review*, 2020. URL https://ideas.repec.org/p/red/sed015/386.html.

Claudio Michelacci and Josep Pijoan-Mas. Intertemporal labour supply with search frictions. *Review of Economic Studies*, 79:899–931, 2012. ISSN 00346527. doi: 10.1093/restud/rdr042.

Gerrit Mueller and Erik Plug. Estimating the effect of personality on male and female earnings. *Industrial and Labor Relations Review*, 60:3–22, 6 2006. ISSN 00197939. doi: 10.1177/001979390606000101. URL https://journals.sagepub.com/doi/10.1177/001979390606000101.

Ellen K. Nyhus and Empar Pons. The effects of personality on earnings. *Journal of Economic Pyschology*, 26, 2005. URL https://www.sciencedirect.com/science/article/pii/S0167487004000546.

Ellen K. Nyhus and Empar Pons. Personality and the gender wage gap. *Applied Economics*, 44, 2012.

Leonora Risse, Lisa Farrell, and Tim R L Fry. Personality and pay: do gender gaps in confidence explain gender gaps in wages? *Oxford Economic Papers*, 70:919–949, 2018.

Ariel Rubinstein. Perfect equilibrium in a bargaining model. *Econometrica*, 50:97, 1 1982. ISSN 00129682. doi: 10.2307/1912531.

Yona Rubinstein and Yoram Weiss. *Post Schooling Wage Growth: Investment, Search and Learning*, volume 1. Elsevier, 1 2006. ISBN 9780444513991. doi: 10.1016/S1574-0692(06)01001-4.

Gerard Saucier. Mini-markers: A brief version of goldberg's unipolar big-five markers. *Journal of Personality Assessment*, 63:506–516, 1994. ISSN 15327752. doi: 10.1207/s15327752jpa6303_8. URL https://www.tandfonline.com/doi/abs/10.1207/s15327752jpa6303_8.

Petra E. Todd and Weilong Zhang. A dynamic model of personality, schooling, and occupational choice. *Quantitative Economics*, 11:231–275, 1 2020. ISSN 1759-7323. doi: 10.3982/QE890. URL http://qeconomics.org/ojs/index.php/qe/article/view/QE890.

Tommas Trivieri. Skill changes, skill increasing activities, and wage growth. *Working Paper*, 2021.

Shintaro Yamaguchi. Job search, bargaining, and wage dynamics. *Journal of Labor Economics*, 28:595–631, 7 2010. ISSN 0734306X. doi: 10.1086/651954.

Appendices

A Description of Skill and Personality Trait Measurements

Latent Variable	Measurement	Variable Code	Description	Scale Range
General Skill	Reading	SKSW_Q10	What level of reading comprehension [is/was] needed to perform your [current job/former job]?	0 to 7
General Skill	Writing	SKSW_Q20	What level of writing [is/was] needed to perform your [current job/former job]?	0 to 7
General Skill	Communication	SKSW_Q30	What level of communicating with supervisors, peers, or subordinates [is/was] needed to perform your [current job/former job]?	0 to 7
General Skill	Mathematics	SKSW_Q40	What level of mathematics [is/was] needed to perform your [current job/former job]?	0 to 7
General Skill	Manual Dexterity	SKSW_Q50	What level of manual dexterity [is/was] needed to perform your [current job/former job]?	0 to 7
General Skill	Strength	SKSW_Q60	What level of physical strength [is/was] needed to perform your [current job/former job]?	0 to 7
Openness to experience	open1	BFII_Q20	I see myself as someone who is original, comes up with new ideas.	1 to 7
Openness to experience	open2	BFII_Q45	I see myself as someone who values artistic, aesthetic experiences.	1 to 7
Openness to experience	open3	BFII_Q70	I see myself as someone who has an active imagination.	1 to 7
Extraversion	extra1	BFII_Q10	I see myself as someone who is talkative.	1 to 7
Extraversion	extra2	BFII_Q35	I see myself as someone who is outgoing and sociable.	1 to 7
Extraversion	extra3	BFII_Q60	I see myself as someone who is reserved. (reverse scored)	1 to 7
Agreeableness	agree1	BFII_Q01	I see myself as someone who is sometimes rude to others. (reverse scored)	1 to 7
Agreeableness	agree2	BFII_Q25	I see myself as someone who has a forgiving nature.	1 to 7
Agreeableness	agree3	BFII_Q50	I see myself as someone who is considerate and kind to almost everyone.	1 to 7

B Additional Descriptive Regressions

Table 7: Additional regressions describing the impacts of personality traits over the life cycle

Dependent variable: ln wage level	(1) Early-career	(2) Mid-career	(3) Late-career	(4) Early-career	(5) Mid-career	(6) Late-career
I(Extra $\in$ (-1SD,1SD))	0.1871***	–0.0304	0.0712	0.1518***	–0.0244	0.0650
	(0.0575)	(0.0788)	(0.0529)	(0.0461)	(0.0616)	(0.0457)
I(Extra $\geq$ 1SD)	0.2187**	–0.0008	0.0300	0.2137***	0.0060	0.0085
	(0.0972)	(0.0912)	(0.0715)	(0.0655)	(0.0763)	(0.0611)
I(Open $\in$ (-1SD,1SD))	–0.1967**	0.1844***	0.1426***	-0.0951	0.1984***	0.1359***
	(0.0959)	(0.0630)	(0.0464)	(0.0688)	(0.0540)	(0.0418)
I(Open $\geq$ 1SD)	–0.2933**	0.1177	0.1993**	–0.1958**	0.0979	0.1828**
	(0.1176)	(0.0765)	(0.0786)	(0.0767)	(0.0659)	(0.0757)
I(Agree $\in$ (-1SD,1SD))	0.0062	–0.1484*	–0.1208**	–0.0245	–0.1241*	–0.0850*
	(0.0607)	(0.0781)	(0.0582)	(0.0476)	(0.0635)	(0.0503)
I(Agree $\geq$ 1SD)	0.0182	–0.2532***	–0.1629**	–0.0168	–0.2229***	–0.1082*
	(0.0870)	(0.0789)	(0.0688)	(0.0712)	(0.0634)	(0.0600)
Management				0.6560***	0.5223***	0.5332***
				(0.0985)	(0.0977)	(0.0706)
Business, Finance, and Administration				0.1744***	0.2036***	0.2664***
				(0.0484)	(0.0642)	(0.0615)
Natural and applied science				0.5199***	0.5312***	0.4969***
				(0.0631)	(0.0898)	(0.0835)
Health				0.1089	0.4146	0.1619
				(0.1402)	(0.3123)	(0.1288)
Education, law & social, community & government				0.4529***	0.4173***	0.3150**
				(0.0828)	(0.0804)	(0.1362)
Art, culture, recreation & sports				0.4168***	0.4180***	-0.2348
				(0.1497)	(0.1453)	(0.3276)
Sales and Services				0	0	0
				–	–	–
Trades, transport and equipment operators				0.4038***	0.2069***	0.2314***
				(0.0470)	(0.0584)	(0.0490)
Natural resources/agriculture				0.6337***	0.5072**	0.2675***
				(0.1286)	(0.2215)	(0.0918)
Manufacturing and utilities				0.1979***	0.1394**	0.1490**
				(0.0526)	(0.0664)	(0.0580)
2014				0.0562*	0.0762**	0.0228
				(0.0340)	(0.0321)	(0.0265)
2016				0.0668	0.0448	0.0648**
				(0.0428)	(0.0369)	(0.0308)
2018				0.1049**	0.0835**	0.0388
				(0.0413)	(0.0369)	(0.0363)
constant	6.6911***	6.8542***	6.7163***	6.2949***	6.5496***	6.4677***
	(0.0880)	(0.0954)	(0.0665)	(0.0719)	(0.0897)	(0.0748)
N	3,200	3,100	4,400	3,200	3,100	4,400

Table 8: The Relationship Between Personality and the Search and Skill Channels

Dependent:	OLS General Skill	Logit I(U2E=1)	Logit I(E2E=1)	Logit I(E2U=1)
I(Extra $\in$ (-1SD,1SD))	–0.0272	0.3994*	–0.0066	0.1815
	(0.0788)	(0.2311)	(0.1836)	(0.1663)
I(Extra $\geq$ 1SD)	–0.0172	0.1069	–0.0594	–0.0999
	(0.1016)	(0.2800)	(0.2268)	(0.2134)
I(Open $\in$ (-1SD,1SD))	0.2895***	-0.0977	0.0732	–0.2591
	(0.0954)	(0.2088)	(0.1790)	(0.1576)
I(Open $\geq$ 1SD)	0.4167***	-0.3171	0.7117***	–0.3038
	(0.1122)	(0.2872)	(0.2622)	(0.2181)
I(Agree $\in$ (-1SD,1SD))	–0.0564	-0.2508	0.1158	–0.3670**
	(0.0717)	(0.2325)	(0.1693)	(0.1587)
I(Agree $\geq$ 1SD)	–0.1601*	–0.2388	0.1644	0.1890
	(0.0906)	(0.2561)	(0.1906)	(0.1881)
constant	–0.3029**	–1.7091***	–2.9617***	–2.6421***
	(0.1304)	(0.2609)	(0.2355)	(0.2189)
exp + exp2	Y		Y	
N	6,700	5,600	22,500	22,500

C Value Function Derivations

Note,

$$\begin{aligned}
\underbrace{V_t(p,q,\Theta_{it})}_{\text{Value of wage contract}} &= \underbrace{\beta P_t(p,\Theta_{it}) + (1-\beta)P_t(q,\Theta_{it})}_{\text{Nash Bargaining Solution}}, \\
\underbrace{V_t(p,p^\star,\Theta_{it})}_{\text{Value of wage contract}} &= \underbrace{\beta P_t(p,\Theta_{it}) + (1-\beta)U_t(\Theta_{it})}_{\text{Nash Bargaining Solution in unemployment}}
\end{aligned}$$

where $P_t(p,\Theta_{it})$, $V_t(p,q,\Theta_{it})$, and $U_t(\Theta_{it})$ are the joint match value, the value of a wage contract, and the value of unemployment, respectively. With this in hand, we can derive the value of unemployment as follows,

$$
\begin{aligned}
U_t(\Theta_{it}) &= b\theta_{it}^{gen} + \frac{1}{R}\Big[(1-\lambda_i^U)U_{t+1}(\Theta_{it+1}) + \lambda_i^U G(p^\star)U_{t+1}(\Theta_{it+1}) + \lambda_i^U \int_{p^\star}^{\infty} V_{t+1}(x,p^\star,\Theta_{it+1})dG(x)\Big] \\
&= b\theta_{it}^{gen} + \frac{1}{R}\Big[U_{t+1}(\Theta_{it+1}) - \lambda_i^U U_{t+1}(\Theta_{it+1}) + \lambda_i^U G(p^\star)U_{t+1}(\Theta_{it+1}) \\
&\qquad\qquad + \lambda_i^U \int_{p^\star}^{\infty} V_{t+1}(x,p^\star,\Theta_{it+1})dG(x)\Big] \\
&= b\theta_{it}^{gen} + \frac{1}{R}\Big[U_{t+1}(\Theta_{it+1}) - \lambda_i^U (1-G(p^\star))U_{t+1}(\Theta_{it+1}) + \lambda_i^U \int_{p^\star}^{\infty} V_{t+1}(x,p^\star,\Theta_{it+1})dG(x)\Big] \\
&= b\theta_{it}^{gen} + \frac{1}{R}\Big[U_{t+1}(\Theta_{it+1}) - \lambda_i^U \int_{p^\star}^{\infty} U_{t+1}(\Theta_{it+1})dG(x) + \lambda_i^U \int_{p^\star}^{\infty} V_{t+1}(x,p^\star,\Theta_{it+1})dG(x)\Big] \\
&= b\theta_{it}^{gen} + \frac{1}{R}\Big[U_{t+1}(\Theta_{it+1}) + \lambda_i^U \int_{p^\star}^{\infty} V_{t+1}(x,p^\star,\Theta_{it+1}) - U_{t+1}(\Theta_{it+1})dG(x)\Big] \\
&= b\theta_{it}^{gen} + \frac{1}{R}\Big[U_{t+1}(\Theta_{it+1}) \\
&\qquad + \lambda_i^U \int_{p^\star}^{\infty} U_{t+1}(\Theta_{it+1}) + \beta(P_{t+1}(x,\Theta_{it+1}) - U_{t+1}(\Theta_{it+1})) - U_{t+1}(\Theta_{it+1})dG(x)\Big] \\
&= b\theta_{it}^{gen} + \frac{1}{R}\Big[U_{t+1}(\Theta_{it+1}) + \lambda_i^U \beta \int_{p^\star}^{\infty} [P_{t+1}(x,\Theta_{it+1}) - U_{t+1}(\Theta_{it+1})]dG(x)\Big].
\end{aligned}
$$

Similarly, the joint worker-firm match value is derived as follows,

$$
\begin{aligned}
P_t(p,\Theta_{it}) = p\theta_{it}^{gen} + \frac{1}{R}\Big[&(1-\eta_i)(1-\lambda_{it}^E)P_{t+1}(p,\Theta_{it+1}) + (1-\eta_i)\lambda_{it}^E G(p)P_{t+1}(p,\Theta_{it+1}) + \eta_i U_{t+1}(\Theta_{it+1}) \\
&+ (1-\eta_i)\lambda_{it}^E \int_p^\infty [V_{t+1}(x,p,\Theta_{it}) + 0\,]dG(x)\Big] \\
= p\theta_{it}^{gen} + \frac{1}{R}\Big[&(1-\eta_i)(1-\lambda_{it}^E)P_{t+1}(p,\Theta_{it+1}) + (1-\eta_i)\lambda_{it}^E G(p)P_{t+1}(p,\Theta_{it+1}) + \eta_i U_{t+1}(\Theta_{it+1}) \\
&+ (1-\eta_i)\lambda_{it}^E \int_p^\infty [\beta P_{t+1}(x,\Theta_{it+1}) + (1-\beta)P_{t+1}(p,\Theta_{it+1})\,]dG(x)\Big] \\
= p\theta_{it}^{gen} + \frac{1}{R}\Big[&(1-\eta_i)(1-\lambda_{it}^E)P_{t+1}(p,\Theta_{it+1}) + (1-\eta_i)\lambda_{it}^E G(p)P_{t+1}(p,\Theta_{it+1}) + \eta_i U_{t+1}(\Theta_{it+1}) \\
&+ (1-\eta_i)\lambda_{it}^E \int_p^\infty [P_{t+1}(p,\Theta_{it+1}) + \beta(P_{t+1}(x,\Theta_{it+1}) - P_{t+1}(p,\Theta_{it+1}))\,]dG(x)\Big] \\
= p\theta_{it}^{gen} + \frac{1}{R}\Big[&(1-\eta_i)P_{t+1}(p,\Theta_{it+1}) + \eta_i U_{t+1}(\Theta_{it+1}) \\
&- (1-\eta_i)\lambda_{it}^E P_{t+1}(p,\Theta_{it+1}) + (1-\eta_i)\lambda_{it}^E G(p)P_{t+1}(p,\Theta_{it+1}) \\
&+ (1-\eta_i)\lambda_{it}^E \int_p^\infty [P_{t+1}(p,\Theta_{it+1}) + \beta(P_{t+1}(x,\Theta_{it+1}) - P_{t+1}(p,\Theta_{it+1}))\,]dG(x)\Big] \\
= p\theta_{it}^{gen} + \frac{1}{R}\Big[&P_{t+1}(p,\Theta_{it+1}) + \eta_i[U_{t+1}(\Theta_{it+1}) - P_{t+1}(p,\Theta_{it+1})] \\
&- (1-\eta_i)\lambda_{it}^E(1-G(p))P_{t+1}(p,\Theta_{it+1}) \\
&+ (1-\eta_i)\lambda_{it}^E \int_p^\infty [P_{t+1}(p,\Theta_{it+1}) + \beta(P_{t+1}(x,\Theta_{it+1}) - P_{t+1}(p,\Theta_{it+1}))\,]dG(x)\Big] \\
= p\theta_{it}^{gen} + \frac{1}{R}\Big[&P_{t+1}(p,\Theta_{it+1}) + \eta_i[U_{t+1}(\Theta_{it+1}) - P_{t+1}(p,\Theta_{it+1})] \\
&- (1-\eta_i)\lambda_{it}^E \int_p^\infty P_{t+1}(p,\Theta_{it+1})dG(x) \\
&+ (1-\eta_i)\lambda_{it}^E \int_p^\infty [P_{t+1}(p,\Theta_{it+1}) + \beta(P_{t+1}(x,\Theta_{it+1}) - P_{t+1}(p,\Theta_{it+1}))\,]dG(x)\Big] \\
= p\theta_{it}^{gen} + \frac{1}{R}\Big[&P_{t+1}(p,\Theta_{it+1}) + \eta_i[U_{t+1}(\Theta_{it+1}) - P_{t+1}(p,\Theta_{it+1})] \\
&+ (1-\eta_i)\lambda_{it}^E \int_p^\infty \beta\,[P_{t+1}(x,\Theta_{it+1}) - P_{t+1}(p,\Theta_{it+1})\,]dG(x)\Big] \\
= p\theta_{it}^{gen} + \frac{1}{R}\Big[&P_{t+1}(p,\Theta_{it+1}) + \eta_i[U_{t+1}(\Theta_{it+1}) - P_{t+1}(p,\Theta_{it+1})] \\
&+ (1-\eta_i)\lambda_{it}^E \beta \int_p^\infty [P_{t+1}(x,\Theta_{it+1}) - P_{t+1}(p,\Theta_{it+1})\,]dG(x)\Big].
\end{aligned}
$$

D Model Fit

Table 9: Life cycle wage levels

Age	Model	Data	S.E.
21	50.53	112.70	69.53
22	109.43	35.37	59.83
23	171.40	177.68	66.11
24	236.17	179.96	85.66
25	270.04	474.47	113.84
26	304.32	243.29	78.15
27	333.16	392.11	101.28
28	348.16	376.73	87.41
29	363.36	239.23	86.95
30	360.52	329.70	102.43
31	373.29	331.77	93.42
32	379.87	380.97	84.43
33	386.27	333.38	81.39
34	388.92	572.68	128.18
35	395.47	265.80	71.14
36	402.50	579.17	189.88
37	402.23	461.03	89.40
38	397.15	504.86	158.78
39	398.78	388.57	77.29
40	398.55	327.86	90.65
41	397.25	533.25	137.72
42	394.67	550.33	96.70
43	390.95	518.88	141.72
44	388.51	489.75	97.55
45	359.53	409.32	72.11
46	349.91	548.85	106.41
47	348.71	525.22	113.18
48	343.51	348.93	67.42
49	334.96	344.86	67.48
50	322.92	507.02	98.67
51	312.54	331.22	66.20
52	308.28	330.70	68.57
53	305.30	388.82	69.68
54	296.07	468.00	99.07
55	286.23	367.34	76.80
56	276.49	377.74	95.04
57	273.50	400.77	76.91
58	270.34	385.88	70.18
59	262.63	371.64	76.68
60	257.83	279.99	73.76
61	255.09	416.20	100.37
62	254.44	337.81	85.05
63	251.42	340.74	79.21
64	253.72	246.52	84.92
65	255.64	179.74	79.26
Constant	708.32	601.49	51.00

Table 10: Life cycle E2E transition rates

Age	**Model**	**Data**	**S.E.**
21	-0.013	0.084	0.070
22	-0.037	-0.004	0.059
23	-0.040	-0.039	0.059
24	-0.055	0.014	0.064
25	-0.063	-0.058	0.059
26	-0.073	0.043	0.100
27	-0.077	0.068	0.108
28	-0.078	-0.086	0.058
29	-0.081	-0.095	0.057
30	-0.084	-0.018	0.063
31	-0.090	-0.095	0.056
32	-0.086	-0.047	0.063
33	-0.092	-0.086	0.058
34	-0.089	-0.073	0.060
35	-0.092	-0.097	0.057
36	-0.091	-0.074	0.058
37	-0.094	-0.039	0.074
38	-0.092	-0.090	0.059
39	-0.094	-0.104	0.056
40	-0.093	-0.051	0.060
41	-0.097	-0.125	0.054
42	-0.094	-0.104	0.055
43	-0.093	-0.067	0.058
44	-0.094	-0.129	0.053
45	-0.095	-0.112	0.057
46	-0.098	-0.097	0.057
47	-0.096	-0.111	0.055
48	-0.100	-0.120	0.054
49	-0.098	-0.125	0.053
50	-0.100	-0.114	0.054
51	-0.100	-0.119	0.054
52	-0.097	-0.064	0.059
53	-0.099	-0.107	0.054
54	-0.101	-0.118	0.053
55	-0.100	-0.095	0.057
56	-0.095	-0.118	0.053
57	-0.096	-0.095	0.056
58	-0.095	-0.111	0.054
59	-0.098	-0.129	0.053
60	-0.100	-0.112	0.054
61	-0.102	-0.125	0.054
62	-0.101	-0.109	0.055
63	-0.101	-0.068	0.060
64	-0.102	-0.146	0.052
65	-0.097	-0.113	0.061
Constant	0.150	0.146	0.052

Table 11: Extraversion life cycle wage profile

Dependent variable: ln wage level	**Model**	**Data**	**S.E.**
mid-career	0.24	0.32	0.09
late-career	0.11	0.18	0.06
$\mathbb{1}$(extra $\in$ (-1,1))	0.12	0.17	0.05
$\mathbb{1}$(extra $\geq$ 1)	0.22	0.18	0.11
mid-career $\times$ $1(extra \in (-1{,}1))$	-0.15	-0.20	0.10
mid-career $\times$ $1(extra \geq 1)$	-0.28	-0.20	0.14
late-career $\times$ $1(extra \in (-1{,}1))$	-0.11	-0.08	0.07
late-career $\times$ $1(extra \geq 1)$	-0.28	-0.13	0.13
Constant	6.62	6.53	0.04

Table 12: Openness to experience life cycle wage profile

Dependent variable: ln wage level	**Model**	**Data**	**S.E.**
mid-career	-0.01	-0.12	0.11
late-career	-0.21	-0.17	0.10
$\mathbb{1}$(open $\in$ (-1,1))	-0.20	-0.18	0.10
$\mathbb{1}$(open $\geq$ 1)	-0.28	-0.26	0.11
mid-career $\times$ $1(open \in (-1{,}1))$	0.10	0.34	0.11
mid-career $\times$ $1(open \geq 1)$	0.16	0.33	0.13
late-career $\times$ $1(open \in (-1{,}1))$	0.21	0.31	0.11
late-career $\times$ $1(open \geq 1)$	0.38	0.42	0.14
Constant	6.92	6.84	0.10

Table 13: Agreeableness life cycle wage profile

Dependent variable: ln wage level	**Model**	**Data**	**S.E.**
mid-career	0.15	0.28	0.09
late-career	-0.03	0.17	0.08
$\mathbb{1}$(agree $\in$ (-1,1))	-0.03	-0.01	0.07
$\mathbb{1}$(agree $\geq$ 1)	-0.09	-0.02	0.09
mid-career $\times$ $1(agree \in (-1{,}1))$	-0.06	-0.13	0.10
mid-career $\times$ $1(agree \geq 1)$	-0.13	-0.22	0.12
late-career $\times$ $1(agree \in (-1{,}1))$	0.03	-0.08	0.09
late-career $\times$ $1(agree \geq 1)$	-0.01	-0.09	0.11
Constant	6.77	6.69	0.06

Table 14: General skill regression

Dependent variable: General skill level	**Model**	**Data**	**S.E.**
exp	0.04	0.02	0.01
$exp^2 \times 1000$	-0.77	-0.59	0.19
openness to experience	0.11	0.17	0.04
extraversion	0.00	0.01	0.03
agreeableness	-0.09	-0.04	0.03
Constant	-0.47	-0.14	0.10

Table 15: Logistic U2E regression

Dependent variable: U2E	**Model**	**Data**	**S.E.**
openness to experience	-0.03	-0.01	0.07
extraversion	0.00	-0.01	0.08
agreeableness	-0.02	-0.06	0.08
Constant	-1.78	-1.71	0.09

Table 16: Life cycle personality trait wage gaps

Dependent variable: ln wage	**Model**	**Data**	**S.E.**
Early-career extraversion gap	0.22	0.18	0.11
Early-career openness to experience gap	-0.28	-0.26	0.11
Mid-career agreeableness gap	-0.22	-0.24	0.08
Late-career openness to experience gap	0.10	0.16	0.07