

Does Personality Predict Occupational Gravitation?

A DISSERTATION
SUBMITTED TO THE FACULTY OF
UNIVERSITY OF MINNESOTA
BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Dr. Paul R. Sackett

February 2018

Acknowledgements

Writing a dissertation is not an undertaking to be taken lightly. Ironically, one cannot fully grasp this statement until they've written one themselves. Although challenging at times, I've come out the other side both an improved scholar and person, and for that, I am grateful. Graduate school was not a journey I took alone— I have many people to thank who helped me along the way.

Paul— Your calm demeanor yet unrivaled productivity astounds me. Thank you for your patience, guidance, and genuine interest in me as a student and person. Anytime I walked into your office with a question or concern, you always put aside whatever you were working on and made me feel as if I was your most important priority. To put it simply, you made the challenging task of completing a PhD as painless as it could be. Not all graduate students are so lucky.

Mom and Dad— I without a doubt hit the parents jackpot. You have filled my life with unconditional love, support, and encouragement. That kind of belief makes a person want to do great things. So thank you for inspiring me to be great. I love you and hope I can be half the parents you are someday.

Abby, Mike, and Julia— Thank you for your unwavering love and support. I could not ask for three more awesome people in my corner on a daily basis. I am so very proud to call you my sister, brother-in-law, and niece. I have the world's best cheering section, and I want everybody to know it. Baby J, I hope to serve in a similar cheering capacity for your life's greatest achievements.

Grandma and Grandpa— Having you both here to celebrate this accomplishment with me means everything. You are two of my absolute favorite people in the world, and I am thankful every day for the time we get to share together.

Scott— Words cannot express my gratitude. I would not be doing what I am today if our lives had not serendipitously intersected. Thank you for your guidance and support during the ups and downs of graduate school. You made an immensely positive difference, and I will forever consider you one of my best friends.

Joey— Buddy, what can I say. Bone chewing, walks, and white lightning sessions provided the perfect distraction during all those hours of procrastination. I'm excited to begin our next adventure in Pensacola, FL. Hooyah, Navy Beans!

Committee Members (Drs. John Campbell, Nathan Kuncel, and Aaron Sojourner)— Thank you for your thoughtful and valuable comments on previous versions of this dissertation. Your efforts resulted in a much improved final product.

Dedication

This dissertation is dedicated to my family. I love you all.

Abstract

The current dissertation investigated the role of personality in occupational gravitation. Two directions of occupational gravitation were proposed and tested— lateral and vertical gravitation. Results revealed that individuals found improved person-occupation personality fit over time as measured by the indices of Openness, Conscientiousness, Openness-Conscientiousness, and Big Five fit. Effect sizes ranged from .12 *SD* to .38 *SD*. Findings also indicated that Extraversion and Agreeableness fit worsened over time, and Emotional Stability fit remained constant. Analyses further showed that improved fit over time was driven by vertical and not lateral gravitation. Extraversion (+), Openness (-), Agreeableness (-), and Conscientiousness (+) predicted upward job zone movement, and this job zone movement resulted in improved fit. That is, job zone mediated the relationship between age and person-occupation personality fit.

Table of Contents

Chapter 1: Introduction.....	1
Chapter 1.1: Occupational Gravitation	3
Chapter 1.1: “Personalities” of Occupations	3
Chapter 1.1: Emergence of FFM	4
Chapter 1.1: Development of Meta-Analytic Methods	9
Chapter 1.1: Increased Attention to Trait-Criterion Matching	10
Chapter 1.1: Personality-Oriented Work Analysis (POWA)	12
Chapter 1.1: U.S. Armed Forces Classification Efforts	20
Chapter 1.2: Occupational Gravitation and Person-Occupation (P-O) Fit	22
Chapter 1.2: Empirical Evidence for Occupational Gravitation	24
Chapter 1.2: Vocational Interest Fit and Occupational Gravitation	24
Chapter 1.2: Cognitive Ability Fit and Occupational Gravitation	28
Chapter 1.2: Preliminary Research on Personality Fit and Occupational Gravitation	30
Chapter 1.3: Lateral vs. Vertical Gravitation	33
Chapter 2: Method	36
Chapter 2: Sample 1: NLSY79 Children and Young Adults	37
Chapter 2: Occupational Data: Occupation Information Network (O*NET)	40
Chapter 2: Analyses	40
Chapter 3: Results	44
Chapter 4: Discussion	56

References	63
Appendix	73

Chapter 1

Introduction: Does Personality Predict Occupational Gravitation?

Vocational psychology has long been interested in how individuals select occupations and subsequently make career decisions throughout their working lives. That is, the field seeks to understand how individuals initially choose which occupation they will pursue and what causes some people to remain in their originally chosen occupations throughout their careers and what causes others to leave their originally chosen occupations and gravitate to different ones. Past research has shown that individuals gravitate to occupations that are aligned with their vocational interests and abilities. However, little is known about the role personality plays in initial occupational choice and subsequent gravitation.

The goal of this dissertation is to provide the first empirical, longitudinal investigation into whether personality contributes to occupational gravitation. To achieve this aim, longitudinal data analyses will be carried out on a nationally representative data sets to determine whether individuals, over time, gravitate to occupations that are aligned with their personality. The following dissertation is organized into four chapters— 1) Introduction, 2) Method, 3) Results, and 4) Discussion. Chapter 1 provides an introduction for the dissertation project to follow and is divided into three sections. Section 1 discusses the “personalities” of occupations. Several lines of evidence are presented to support the idea of occupations having unique personalities. Section 2 provides a summary of the existing occupational gravitation literature. Research on occupational gravitation driven by vocational interests and cognitive ability will be discussed, and preliminary research investigating personality and occupational

gravitation will be touched upon as well. Section 3 will propose two new terms to the literature, which will serve as a foundation for a more complete, comprehensive organizing framework for the topic of occupational gravitation. Currently, occupational gravitation is discussed as a singular phenomenon. However, gravitation can occur in two different directions. 1) Individuals can switch to an entirely different career that is more aligned with their personal make-up, or 2) individuals can move up (or down) within a career path due to their unique combination of knowledge, skills, abilities, and other characteristics (KSAOs). The former type of gravitation will be termed “lateral gravitation,” whereas the latter type of gravitation will be coined “vertical gravitation.” Lateral gravitation is the type of gravitation seen when an individual switches occupations based on misaligned vocational interests. These are the career changers. For example, an individual finds themselves in a strongly Enterprising occupation like sales and chooses to switch to a Realistic occupation like civil engineering, because it fits much better with his or her vocational interests and the type of work he or she enjoys doing. Vertical gravitation, on the other hand, is the type of gravitation seen when an individual moves up or down the occupational complexity hierarchy based on cognitive ability. These are the career advancers. For example, an individual enters the sales profession at the entry level and over the course of their career finds him or herself promoted from salesperson → sales manager → regional sales director → national sales director. The ultimate goal of the current dissertation is to investigate whether personality contributes to lateral gravitation, vertical gravitation, neither, or both. Chapter 2 will introduce the two studies carried out for the current dissertation and provide a detailed description of the methodology used. Chapter 3 will present the results

from both studies. The fourth and final chapter will summarize the preceding chapters, discuss implications of the results found in Chapter 3, and provide concluding remarks on the key findings and contributions of this dissertation.

Chapter 1.1

Occupational Gravitation

The occupational gravitation hypothesis proposes that individuals, throughout their working careers, will sort themselves into occupations that are aligned with their personalities, interests, and abilities (Wilk, Desmarais, & Sackett, 1995) . Gravitation is a dynamic labor force process that occurs over time as individuals enter and leave occupations in search of the one that is best suited for their unique portfolio of personal characteristics. That is, individuals gravitate to occupations for which there is good person-occupation fit. Past research has shown that vocational interests and cognitive ability predict occupational gravitation, but less is known about the role of personality. The current dissertation seeks to shed light on whether personality contributes to occupational gravitation. However, before this can occur, it must first be established that occupations do in fact have unique “personalities” to which individuals can gravitate to.

“Personalities” of Occupations

There is a vast body of industrial-organizational (I-O) psychology literature which supports the idea that occupations have personalities. One piece of evidence that provides support for this claim is personality-performance relationships across occupations. If occupations have unique personality profiles, then personality traits should differentially predict performance across varying occupations.

Initial findings with regard to personality-performance relationships within the I-O field were rather pessimistic. In an early review of the validity of personality measures in personnel selection, Guion and Gottier (1965) concluded that “it is difficult in the face of this summary to advocate, with a clear conscience, the use of personality measures in most situations as a basis for making employment decisions” (p. 160). Although this conclusion went generally unchallenged for the next 25 years, by the mid 1980’s to early 1990’s, the conversation surrounding personality and performance was quickly changing. There was a new optimism regarding the use of personality measures for the purposes of personnel selection. This new optimism was largely the result of three main developments within the literature: 1) emergence of the Five-Factor Model (FFM) of personality, 2) development of meta-analytic methods, and 3) increased attention given to trait-criterion matching.

Emergence of FFM. Original research aimed at establishing an organizing framework of personality dates back to German researchers in the early 20th century. Klages (1926) suggested that an analysis of language would be useful in understanding personality. This call caused Baumgarten (1933) to carry out the first psycholexical classification of personality-descriptive terms in the German language. Baumgarten’s work influenced Allport and Odbert (1936) who completed the same task with the English language. Allport and Odbert’s ambitious attempt to understand the structure of personality through language laid the foundation for the lexical hypothesis which states, “those individual differences that are most salient and socially relevant in people’s lives will eventually become encoded in their language; the more important such a difference, the more likely it is to become expressed as a single word” (John, Angleitner, &

Ostendorf, 1988, p. 174). The two researchers examined more than 550,000 words in *Webster's New International Dictionary* (1925) in search for all words that “distinguish the behavior of one human being from that of another” (Allport & Odbert, 1936, p. 24). Their work identified 17,953 adjectives which could be used to describe an individual's personality. This list was then paired down to approximately 4,500 adjectives which were determined to be descriptive of observable and enduring personality traits.

With the advancement of factor analytic methods, Raymond B. Cattell (1947) conducted a series of studies in which he attempted to reduce Allport and Odbert's original adjective list into a smaller, interpretable set of dimensions. Cattell began by abstracting 171 synonym groups from Allport and Odbert's larger set of adjectives based on the words' semantic similarities. Bipolar rating scales were constructed to represent each synonym group, and intercorrelations from a peer-rating study revealed 35 clusters which he labeled as the “standard reduced personality sphere.” Cattell performed factor analysis on the 35 identified clusters and concluded that 12 underlying factors were present. In subsequent self-rating studies, Cattell identified an additional four factors which he believed could only be accessed through self-report data. These additional four factors combined with original 12 factors served as the basis for the construction of Cattell's well-known personality inventory, the 16PF (Sixteen Personality Factors) Questionnaire (Cattell, 1997). As research progressed over time, however, these 12 factors turned out to be unreplicable.

In one of the first studies building off Cattell's work, Fiske (1949) carried out an investigation for the Michigan VA Selection Research Project on a sample of incoming clinical psychology students. The personality inventory utilized was a 22-trait scale

adapted from a longer scale previously created by Cattell. Factor analysis revealed five factors that replicated across self, peer, and observer ratings. Fiske referred to the five factors he found as “recurrent” to emphasize the similarity of structure across the three samples. Similarly, in a series of studies conducted for the U.S. Air Force on academy cadets and junior and senior officers, Tupes and Christal (Tupes, 1957; Tupes & Christal, 1958, 1961) found support for a five-factor structure. They labeled the five factors as Surgency, Emotional Stability, Agreeableness, Dependability, and Culture—remarkably analogous to how we label the Big Five today. Tupes and Christal (1961) also reanalyzed Cattell’s earlier work (based on published correlations) and found good support for the five factors rather than the much more complex structure Cattell has previously reported. The only drawback to Tupes & Christal’s work was that it was published as an obscure Air Force technical report which caused their findings to have only a minor impact as they failed to reach mainstream personality researchers.

Luckily, Norman (1963) was aware of the technical report and replicated Tupes & Christal’s findings in the well-known *Journal of Abnormal and Social Psychology*. Among four different samples of students at the University of Michigan, Norman found support for five factors. Borgatta (1964) and Smith (1967) found the same five factors in studies of their own, each giving the factors slightly different yet relevant labels. By the end of the 1960s, it seemed enough evidence had been amassed to render a growing consensus regarding the factor structure of personality, however in 1968, Walter Mischel put a moratorium on major segments of personality research, including personality structure, when he ignited the person-situation debate in his book *Personality and Assessment*. Mischel’s book led to reduced research activity in the 1970s, but by the

early 80s top personality researchers in the field were revisiting research on the five recurring dimensions of personality (Digman & Takemoto-Chock 1981; Goldberg, 1981, 1982; John, 1989; McCrae & Costa, 1985, 1987). By 1990, cumulated knowledge in the field led to widespread acceptance of these five factors as the universal, underlying structure of personality. They became known as the “Five-Factor Model” of personality.” Today the five dimensions are commonly labeled as Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness.

Since the formal acceptance of the “Big Five” in the 1990s, there has been ongoing debate among scholars regarding the underlying facets of personality that are subsumed within each of the five broader dimensions. Virtually all facets, which comprise the five domains, were not derived empirically, but rationally constructed by the developers of the various measures of personality. Consequently, the nature, number, and names of these facet-level traits have been openly contested. DeYoung, Quilty, and Peterson (2007) made a major contribution to the progress of this discussion through their empirical discovery of meso-level traits called *aspects*, located between the domain and facet levels of the personality hierarchy. Each of the five domains can be subdivided into two related, yet independent aspects that may have distinct biological substrates.

Neuroticism, oftentimes referred to as the reverse-coded Emotional Stability, is a factor made up of two aspects labeled Volatility and Withdrawal. Volatility encompasses the outward expression of negative affect, such as anger, irritability, and difficulty controlling emotions. The Withdrawal aspect of Neuroticism represents negative affect directed inward, including traits like depression, vulnerability, and anxiety.

Extraversion is made up of two aspects labeled Assertiveness and Enthusiasm. The Assertiveness aspect includes the leading and influencing aspects of having a strong, “take charge” personality. Enthusiasm, on the other hand, represents positive emotionality as well as outgoing friendliness and sociability.

The factor of Openness to Experience includes the aspects of Openness and Intellect. The Openness aspect represents the portion of Openness to Experience that includes an appreciation for art, nature, and beauty, and a vivid imagination. The aspect of Intellect includes the portion of Openness to Experience that focuses on creativity, mental quickness, and the desire and ability to think through complex ideas. The Intellect aspect of personality most closely resembles intelligence or cognitive ability.

The dimension of Agreeableness is made up of the aspects Compassion and Politeness. Compassion represents an emotional affiliation with others which includes empathy, sympathy, warmth, and understanding toward others. The Politeness aspect of Agreeableness instead focuses on more cognitively reasoned interactions with others, including the facet-level traits of cooperation, compliance, and straightforwardness.

The fifth dimension of Conscientiousness is characterized by the aspects of Industriousness and Orderliness. Industriousness is the achievement-striving, hardworking, self-disciplined, and dutiful aspect of Conscientiousness that many think of when envisioning the trait. Finally, Orderliness is defined by being organized, tidy, and detail-oriented. Individuals who score high on Orderliness also have a desire for routine in their lives (DeYoung et al., 2007).

The establishment of the Five-Factor Model (FFM) served as a critical advancement in personality psychology. This advancement also played a significant role

in the history of I-O psychology— specifically, the FFM was vital in elucidating the relationship between personality and job performance. Firstly, the FFM provided an organizing framework and common language in which researchers can speak to one another when discussing personality. Secondly, the FFM framework allowed for knowledge accumulation of trait-criterion relationships for each of the five factors. That is, rather than correlating a set of random, disjointed personality facets with job performance or investigating the validity of overall “personality” with job performance, the FFM allowed for a more nuanced investigation into how each of the five factors related to performance on the job. As a result, meaningful personality-job performance relationships that had previously been obscured in the pre-FFM era were revealed.

Development of Meta-Analytic Methods. The second reason initial conclusions in the I-O community regarding personality-performance relationships were so dire is that statistical meta-analytic methods had not been developed yet. Before meta-analysis, there was no systematic way to quantitatively summarize all studies that had been conducted on a particular predictor-criterion relationship like personality and job performance. As a result of this, most bodies of research were a confusing mix of conflicting significant and null findings. It was hard to come to any meaningful conclusions as to whether true, underlying relationships existed. That state of affairs was so frustrating that it led Cronbach (1975), a famous research methodologist, to lament that cumulative knowledge was likely impossible in psychology. In a turn of events, in 1977, Schmidt and Hunter presented a statistical meta-analytic method (originally referred to more narrowly as validity generalization) that changed the landscape of I-O research. Meta-analysis provided a method for quantitatively summarizing an entire

literature while accounting for the statistical artifacts that were leading to much of the confusing variation from study to study. Specifically, Schmidt and Hunter's method can account for sampling error, measurement error, and other statistical artifacts like range restriction and dichotomization of continuous measures. This advancement allowed researchers to summarize the personality-performance literature which was previously believed to be fraught with inconsistencies and conclude that reliable, consistent relationships between personality and job performance did exist. As Sackett (2003) concluded, meta-analysis revolutionized thinking in I-O psychology, and provided, for the first time, a true framework for building cumulative knowledge in the field.

Increased Attention to Trait-Criterion Matching. The third reason personnel selection experts originally believed personality was not useful in predicting future job performance was the lack of attention that was given to predictor-criterion matching in early personality-job performance studies. Without the Big Five as an organizing framework, there was almost no rhyme or reason as to how the relationship between personality and job performance was investigated. That is, there was little to no theorizing as to which personality traits should be related to performance in which occupations. Unlike cognitive ability measures which have been shown to consistently predict performance across all settings and occupations, personality encompasses a more diverse set of traits that are less highly interrelated than specific abilities (DeYoung, 2011). Therefore, it should not be expected that validities of personality measures would generalize across settings and occupations like they do with cognitive ability. That is, the situational specificity hypothesis holds for personality measurement in personnel selection. As a result, the validity of personality was historically underestimated because

traits were being examined in contexts in which they were not theoretically expected to predict performance. (The solution to this problem emerged with the development of personality-oriented work analysis which will be discussed in the next section).

Barrick and Mount's (1991) seminal meta-analytic article on personality and job performance was the first article that incorporated all three of the major post-Guion and Gottier (1965) developments that were just discussed. Specifically, Barrick and Mount used Schmidt and Hunter's meta-analytic procedure (1977, 1990) to summarize the entire existing literature on personality and job performance. They did so within the framework of the Five-Factor Model of personality and while giving special consideration to the occupational context in which each primary study was conducted (i.e., trait-criterion matching). As of this writing, Barrick and Mount's paper has been cited 7,693 times and has been given credit for reinvigorating personality research in I-O psychology (Rothstein, 2003). Their findings also provided one of the first pieces of evidence for the "personalities" of occupations. Results revealed that across all occupations and criteria, conscientiousness is a valid predictor of job performance ($r = .22$). However, the Big Five dimension of extraversion was found to be predictive of performance only in occupations that had a large interpersonal component, like sales and management. Barrick, Mount, and Judge (2001) summarized 15 personality-performance meta-analysis 10 years later and found the same pattern of relationships to hold. Conscientiousness was predictive of all criteria across all occupations ($r = .24$), whereas extraversion was predictive of performance in people-oriented occupations like management ($r = .21$) and police work ($r = .12$). Across both studies, results for the other Big Five dimensions were less consistent. Emotional Stability, Agreeableness, and Openness to Experience

predicted performance in some occupations but failed to predict in others. Collectively, these results illustrate that certain personality traits are more important for successful performance in some occupations than others.

Personality-Oriented Work Analysis (POWA). A second literature which supports the assertion that occupations have differing personalities is the research on personality-oriented work analysis (POWA). As touched upon earlier, POWA originated from calls for increased trait-criterion matching within the personality domain of personnel selection due to evidence of situational specificity (Tett, Jackson, & Rothstein, 1991). As Rothstein and Jelley (2003) summarize,

Unlike the case of general mental ability, it is simply not possible to use meta-analytic results from personality studies to develop validity generalization arguments to justify the selection of a particular personality measure across all or most jobs. Clearly, personality measures compared to measures of general mental ability are relatively more situationally specific...

p. 255

One of the most critical implications of this quote for selection purposes is that personality traits assessed during the selection process must be matched to the work tasks and requirements of the job in question. Thus, we have the origination of POWA.

POWA is a specific type of the more general method of work analysis (WA). Morgeson and Dierdorff (2011) define WA as, “the systematic investigation of (a) work role requirements and (b) the broader context within which work roles are enacted” (p. 4). Traditionally, work analysis is divided into two broad categories: work-oriented and

worker-oriented. In work-oriented work analysis, the focus is on describing the tasks that are carried out of the job. In worker-oriented work analysis, the primary goal is to describe the knowledge, skills, abilities, and other attributes (KSAOs) required to perform the job. POWA falls under the worker-oriented category as its purpose is to describe the personality traits that are required for successful performance on the job. There are two general methodological approaches to conducting POWA. First, the *trait approach* asks subject matter experts (SMEs) the extent to which a personality trait increases, or decreases, performance on the job. Second, the *behavioral approach* asks SMEs to rate a set of behavioral statements (that tap underlying personality traits) on the extent to which each is not required, helpful, or essential to successful performance on the job in question.

An example of a work analysis tool that was developed using the *trait approach* is the Performance Improvement Characteristics (PIC) inventory (Hogan & Rybicki, 1998). The PIC is a work analysis instrument used to assess which personality traits are important for successful job performance. The PIC was derived directly from the Hogan Personality Inventory (Hogan & Hogan, 1992), a measure of personality that is modeled after the Big Five and is used by organizations as a selection and/or development tool. The PIC was designed to directly translate work-analysis results into recommendations regarding which HPI scales should be used for selection purposes for varying occupations. The PIC asks SMEs to rate 48 trait-based items on the extent to which each would improve performance on the job in question, ranging from 0 (*does not improve performance*) to 3 (*substantially improves performance*). Example items include, “Is steady under pressure,” “Is curious about how things work,” and “Likes excitement.”

The 48 trait-based items are organized into seven PIC scales which mirror the seven scales of the HPI. These scales are: Adjustment, Ambition, Sociability, Interpersonal Sensitivity, Prudence, Inquisitive, and Learning Approach. The result of the PIC work analysis is a profile reflecting how important each of the seven personality scales are to successful job performance.

As of 2009, Hogan had administered the PIC to over 12,000 SME's representing over 400 jobs. Hogan classifies each job into one of seven job families: Managers & Executives, Professionals, Technicians & Specialists, Operations & Trades, Sales & Customer Support, Administrative & Clerical, and Service & Support. One-way ANOVA results reveal that all seven PIC scales vary significantly by job family ($p < .01$), providing support for the claim that occupations do indeed have differing personalities. In a study assessing the predictive validity of the PIC, Meyer, Foster, and Anderson (2006) found that personality-performance correlations were higher when HPI scales were weighted in accordance to which PIC scales were deemed important for successful job performance. For each job studied, the authors created a weighted personality algorithm based on the PIC work-analysis results. When a weighted personality algorithm was used to predict performance in the job it was created for, it was considered to be an *aligned algorithm*. On the other hand, when a weighted personality algorithm was used to predict performance in a job it was not created for, it was considered to be a *misaligned algorithm*. Across six studies ($N = 826$), results revealed that *aligned algorithms* ($r = .24$) predicted performance better than *misaligned algorithms* ($r = .07$). That is, performance was better predicted by the PIC profile algorithm that was generated specifically for the job in question than algorithms that were created for other

jobs. The authors argue their results support the importance of conducting a personality-oriented work analysis and the ability of the PIC to reliably differentiate the personality dimensions required for jobs.

An example of a work analysis tool that was developed using the *behavioral approach* is the Personality-Related Position Requirements Form (PPRF) (Raymark, Schmit, & Guion, 1997). Like the PIC, the PPRF is an instrument used to assess which personality traits are important for successful job performance. The PPRF asks SMEs to rate 107 personality-linked behavioral statements on the extent to which each are required for the job, ranging from 0 (*not required*) to 2 (*essential*). Example items include, “Work with one or more co-workers to complete assigned tasks,” “Stay cool in responding to potentially dangerous situations,” and “Solicit and consider differing options or points of view before making a decision.” The behavioral statements on the PPRF are organized into the Big Five factors as well as 12 narrower traits subsumed under the Big Five. The 12 subdimensions are: General Leadership, Interest in Negotiation, Achievement Striving, Friendly Disposition, Sensitivity to Interest of Others, Cooperative or Collaborative Work Tendency, General Trustworthiness, Adherence to a Work Ethic, Thoroughness and Attentiveness to Detail, Emotional Stability, Desire to Generate Ideas, and Tendency to Think Things Through.

To test whether their newly developed personality-oriented work analysis questionnaire could reliably distinguish between jobs, Raymark et al. (1997) collected subdimension ratings for 260 jobs. These jobs were then classified into 12 broad occupational groups. Correlations among the 12 subdimensions across jobs showed that the subdimension ratings were independent of one another— that is, a high rating on one

subdimension did not necessarily correlate with a high rating on another subdimension. Results also revealed that ratings on the 12 personality subdimensions were differentiated across the 12 occupational groups. For example, management occupations received the highest General Leadership ratings. Customer service and cashier occupations received the highest ratings for Friendly Disposition, whereas janitors received the lowest ratings for this subdimension. Similarly, the occupational group of accountants and auditors were rated highest on the subdimensions of Thoroughness and Attentiveness to Details as well as Tendency to Think Things Through. Also noteworthy was the lack of differentiation for some subdimensions across occupational groups. At least two of the three Conscientiousness subdimensions had mean scores greater than 1 for each of the occupational subgroups. Similar to the findings of Barrick and Mount (1991), this result suggests Conscientiousness is a personality dimension important for performance across all occupations.

A final work analysis project that is relevant to POWA and deserves attention is the Occupational Information Network (O*NET; Peterson, Mumford, Borman, Jeanneret, & Fleishman, 1999). O*NET is an occupational database managed by the U.S. Department of Labor which provides detailed, descriptive information for over 800 detailed occupations. Each occupation is assigned a six-digit occupational code. These 800+ detailed occupations (e.g., psychology teachers, postsecondary) are further classified into 461 broad occupations (e.g., social science teachers, postsecondary), 97 minor groups (e.g., postsecondary teachers), and 23 major groups (e.g., education, training, and library occupations). Information available through O*NET includes ability, skill, knowledge, and training and education requirements of occupations as well

as generalized work activities, work context, organizational context, occupational values, and work styles for occupations. The descriptor category that is most applicable to the current dissertation is the O*NET work styles.

Work styles are a set of personality traits, organized into 7 higher-order and 16 lower-order dimensions, which were deemed relevant for job performance by O*NET developers. The 7 higher-order dimensions (and associated lower-order dimensions) are as follows: 1) achievement orientation (achievement/effort, persistence, initiative), 2) social influence (leadership), 3) interpersonal orientation (cooperation, concern for others, social orientation), 4) adjustment (self-control, stress tolerance, adaptability/flexibility), 5) conscientiousness (dependability, attention to detail, integrity), 6) independence, and 7) practical intelligence (innovation, analytical thinking). Occupational experts or incumbents have provided importance ratings for all occupations where they rate on a scale of 1-5 how important (1 = “Not Important” to 5 = “Extremely Important”) each work style is to successful job performance.

Because work style descriptors were rated as differentially important for varying occupations, O*NET developers believed the ratings could be useful in three ways. First, work style requirements of occupations could be useful in personnel selection for purposes of identifying applicants with potential for high job performance. Second, work styles could be used by vocational counselors for person-occupation matching. And third, developers believed work styles could directly help job seekers identify occupations they would be well-suited for, leading to self-selection into occupations in which they are likely to succeed.

In an effort to assess the utility of O*NET work styles, Coaster and Christiansen (2009) conducted a synthetic validity meta-analysis in which they integrated O*NET work styles information with published personality validation studies. The authors' literature search yielded 154 primary studies. The number of studies found for each FFM dimension were: Conscientiousness ($k = 136$), Extraversion ($k = 114$), Agreeableness ($k = 107$), Openness to Experience ($k = 85$), and Emotional Stability ($k = 76$). To begin their analyses, each job that appeared in one of the primary validation studies was assigned a six-digit O*NET code. For each job, the 16 work styles importance ratings were mapped to the FFM and turned into a Big Five profile. Based on the first two digits of the O*NET code, all jobs were then classified into one of 23 job families. To determine whether distinct personality profiles emerged, the authors investigated Big Five profiles and meta-analytic validity estimates for each of the 23 job families. Work style ratings and validity estimates yielded differentiated personality profiles across job families, extending previous research supporting occupational differences in trait profiles (Barrick & Mount, 1991; Hurtz & Donovan, 2000; Tett et al., 1991).

In a second analysis, Coaster and Christiansen examined the relationship between work style ratings for jobs and FFM validity coefficients. They wanted to determine whether work style importance ratings for each of the Big Five dimensions predicted personality-job performance relationships across their chosen validation studies. That is, do Extraversion work style ratings predict Extraversion validity coefficients across studies? Mixed results were found. Correlations between work style ratings and validity coefficients were as follows: Extraversion (.15), Openness to Experience (.14), Agreeableness (.01), Emotional Stability (-.03), and Conscientiousness (-.16). Overall,

work style ratings did not do a great job of predicting which Big Five dimensions would be related to performance in the validation studies.

Taken as a whole, POWA has led to a more nuanced use of personality in personnel selection. Instead of using broadband personality measures, organizations are making more efficient use of their testing time and cost limitations and are administering tailored assessments which include a selection of personality scales that are particularly important for the job in question. Linking job tasks to personality dimensions (and facets) through POWA is a fundamental and vital part of this effort.

U.S. Armed Forces Classification Efforts. A third and final piece of evidence that supports occupations having unique personalities are the personality-based classification efforts that are taking place in the U.S. Armed Forces (specifically, the U.S. Army). Moving beyond the knowledge that personality dimensions predict job performance for some jobs better than others, the Army has begun a program of research working to classify soldiers to military occupational specialties (MOS) based upon personality.

The Tailored Adaptive Personality Assessment System (TAPAS) is the current personality measure used for soldier selection by the U.S. Army (Dragow, Stark, Chernyshenko, Nye, Hulin, & White, 2012). The TAPAS assessment is comprised of 21 facets of the Big Five personality factors plus Physical Conditioning, which have been shown to be predictive of military outcomes. Previous research has shown the TAPAS to be predictive of various Army criteria, including physical fitness levels, attrition, Can-Do performance (e.g., job knowledge tests), and Will-Do performance (e.g., performance

ratings, disciplinary incidents) (Campbell & Knapp, 2001; Chernyshenko, Stark, Woo & Conz, 2008; Knapp & Heffner, 2009; Knapp, Owens, Allen, 2011).

Taking the TAPAS research one step further, Nye, Drasgow, Chernyshenko, Stark, Kubisiak, White, and Jose (2012) set out to investigate the usefulness of the TAPAS for *differential classification*. The authors note that a selection instrument is “*not* useful for classification if it provides essentially the same rank-order of individuals across all jobs” (p. 67). That is, the TAPAS may be useful for selection into the Army, but if it predicts the same level of performance across jobs, then no benefit for classification would exist. Nye et al. (2012) looked at predicted performance and measured criterion performance across 4 MOS— 1) Infantry, 2) Military Police, 3) Combat Medic, and 4) Motor Transport Operators.

A TAPAS composite score was created to best predict performance in each of the 4 MOS. The authors then first compared TAPAS composite scores across MOS to determine the extent to which they yielded the same rank-ordering of individuals. They then examined whether MOS-specific TAPAS composite scores could identify soldiers that may perform better in a different MOS than the one to which they were assigned.

In terms of the rank-ordering of individuals, predictive validity analyses revealed that the TAPAS differentially predicted criterion scores across MOS. Further, TAPAS scores best predicted the Will-Do criterion composite across MOS. This finding is consistent with job performance theory which views personality as an antecedent for motivation to perform well on the job (Campbell, 1990; Judge & Ilies, 2002). When looking at MOS classification, the authors compared predicted performance scores in soldiers’ current MOS to their performance potential in the three other MOS. Results

showed that 41-51% of soldiers in a particular MOS would have been classified into a different MOS based on TAPAS scores alone. Additionally, 18-25% of all soldiers were predicted to perform one full *SD* higher in a MOS other than the one to which they were assigned. The authors do temper their results by saying other factors in the classification process such as soldier job preference and needs of the Army are not incorporated into these results. In spite of this, findings do suggest that personality is differentiated enough across MOS that it could be useful to classify soldiers to jobs based on their TAPAS scores. Better job performance and lower attrition rates are realistic outcomes for the Army if the TAPAS is used for classification purposes.

Chapter 1.2

Occupational Gravitation and Person-Occupation (P-O) Fit

After providing support for occupations having unique personalities to which individuals can gravitate to, it is important to discuss how occupational gravitation fits within the broader person-environment (P-E) fit literature, more specifically the person-occupation (P-O) fit literature.

The notion of P-O fit can be traced back to the work of Frank Parsons in the early twentieth century. Dubbed as the “father of vocational guidance,” Parsons was the first to provide a schema for understanding initial occupational choice and subsequent career decision-making with his *Tripartite Model* of vocational selection (Parsons, 1909). Parson’s proposed that wise occupational choices hinged on three pieces of information. First, individuals must have an understanding of themselves, including their own knowledge, skills, abilities, personality, interests, and values. Second, individuals must have an understanding of the occupational demands and requirements of various

occupations, including the knowledge, skills, abilities, and other personal characteristics (KSAOs) that lead to success on the job. Finally, individuals must understand the relationship between the first two pieces of information. Essentially, Parsons was describing the phenomenon of P-O fit— he believed a good match between the characteristics of a person and the characteristics of his or her occupation would lead to positive, harmonious employment outcomes, whereas a poor match between the characteristics of a person and the characteristics of his or her occupation would lead to negative, unharmonious employment outcomes. One of the outcomes of poor fit would be occupational gravitation.

According to the gravitation hypothesis (Wilk, Desmarais, & Sackett, 1995), individuals gradually and continually move to more fitting occupational environments. This process of continual improved fit occurs through cycles of attraction, selection, and attrition (Schneider, Goldstein, & Smith, 1995). That is, individuals are attracted to, select themselves into, and are selected into occupational environments that align with their personal characteristics. Due to imperfect labor market information, people may initially select into a poor fitting occupation, but through the dynamic processes of attrition and gravitation, they will move to more suitable occupational environments over time.

Researchers can assess occupational fit on a number of different dimensions, including vocational interests, cognitive ability, and personality. If a person is ill-fit to his or her occupation on one of these dimensions, theory predicts that he or she will exit the occupation and gravitate to an occupation that is a better fit. Previous research has investigated whether this prediction plays out in people's real working lives. The

majority of occupational gravitation research has focused on dimensions of occupational fit other than personality— namely, vocational interests and cognitive ability. Empirical evidence on vocational interest fit predicting occupational gravitation will be presented first. This literature centers around Holland's (1985, 1997) Theory of Vocational Choice, which will be discussed. The relationship between cognitive ability fit and occupational gravitation will be discussed second. Newer, emerging research on the relationship between personality fit and occupational gravitation will be discussed last.

Empirical Evidence for Occupational Gravitation

Vocational Interest Fit and Occupational Gravitation. Vocational interests reflect a person's preferences for behaviors, situations, contexts in which activities occur, and/or the outcomes associated with the preferred activities (Su, Rounds, & Armstrong, 2009). The basic premise behind Holland's (1985, 1997) Theory of Vocational Choice is that people are attracted to, perform better, are more satisfied with, and persist in occupations that are congruent with their vocational interests. Holland's theory has become ubiquitous in the person-occupation fit literature, in large part, because it provides an organizing framework for both individuals and occupations. Holland proposed that both individuals and occupational environments can be categorized into six vocational types: Realistic, Investigative, Artistic, Social, Enterprising, and Conventional— collectively known as the RIASEC hexagon model.

Realistic (R) individuals tend to have mechanical and athletic abilities. They tend to enjoy working with their hands and solving concrete problems. Prototypic Realistic occupations include farmers, chefs, and commercial airline pilots.

Investigative (I) individuals tend to have math and science abilities. Oftentimes, they enjoy working alone and solving complex problems that incorporate abstract theories and ideas. Common Investigative occupations include veterinarians, pharmacists, and molecular and cellular biologists.

Artistic (A) individuals tend to have a great deal of artistic ability and imagination. They get satisfaction out of creating original work. Actors, artists, and musicians are typical Artistic occupations.

Social (S) individuals tend to have strong social skills and enjoy doing work that helps others solve problems. Prototypic Social occupations include social workers, teachers, and counselors.

Enterprising (E) individuals tend to have leadership and speaking abilities and enjoy using those abilities to influence others. They oftentimes value economic gain and political achievement. Common Enterprising occupations include lawyers, politicians, and chief executives.

Conventional (C) individuals tend to have clerical abilities and enjoy organizing data and information in systematic ways. Bank tellers, accountants, and administrative assistants are typical Conventional occupations.

Individuals are likely to have vocational interests that align with more than one of the areas listed above. In fact, it is traditional within Holland's theory for individuals to be assigned a 3-letter RIASEC code that describes their vocational type. The first letter in the code signifies the area in which a person's strongest interests lie, followed by the RIASEC categories with the second and third strongest interests, respectively. For example, an individual with an SAI code will have more social, artistic, and investigative

interests than conventional, realistic, and enterprising interests. Fittingly, this individual is more likely to find a better fit in occupations that include social, artistic, and investigative activities. Holland labeled fit between an individual and his/her occupation as “congruence.” Congruence is theorized to lead to positive work-related outcomes, including occupational stability. Incongruence on the other hand, or a lack of person-occupation fit, is predicted to lead to negative work-related outcomes, and in turn, occupational gravitation. That is, individuals will find the occupational environment dissatisfying and will eventually leave the occupation and gravitate to a new occupation that provides a better match.

A number of studies have investigated whether interest-occupation fit predicts occupational gravitation. Research has produced mixed results. Bruch and Krieshok (1981) tracked 158 male freshmen engineering students for two years. They found that students with higher levels of interest-major fit were significantly more likely to persist in classes than those who with lower levels of interest-major fit. In a study of over 600 college aged women, Rose and Elton (1982) tracked interest congruence and major persistence. Congruence was defined as a match between participants’ highest score on the Vocational Preference Inventory (VPI) and the primary Holland code for their intended major as a freshman in college. Participants were labeled “stable” if they remained within their major over 4 years of studies. They were labeled “unstable” if they switched majors during that time. Results showed that 39% of the women in the stable group had originally made congruent major choices, whereas only 19% of women in the unstable group had originally made congruent major choices.

In studies focusing on individuals in the work force, Gottfredson and Holland (1990) examined the congruence in relation to career change with a sample of 126 bank tellers tracked over a 4-month period. They found a positive, albeit weak, association between congruence and career persistence ($r = .13, p < .05$). Similarly, Meir, Esformes, and Friedland (1994) studied a sample of 774 people seeking employment in technology, business, and organizational fields. Congruence was positively correlated with career persistence for those employed in business ($r = .23, p < .05$) and technology ($r = .19, p < .05$), but not for those employed in organizational occupations ($r = .05, p > .05$).

In a study failing to find support for a relationship between interest-occupation fit and occupational gravitation, Salomone and Sheehan (1985) studied 917 nonprofessional workers. Findings revealed no significant relationship between interest congruence and career persistence and change. However, the authors' analytic strategy included a median split where they divided participants into "high congruent" and "low congruent" groups. The range restriction and significant loss of variance associated with this decision may have obscured underlying relationships.

In more recent research, Donohue (2006) studied a sample of 212 career changes (participants who expressed an intent to change careers and had engaged in preliminary career change activity) and 249 career persisters (participants who indicated an intent to remain in their current career). Results showed that career persisters had higher levels of interest-occupation fit than career changers, however the effect was small to medium in size. Further, findings revealed that career changers' level of interest-occupation fit was higher for their intended career than for their current career.

Donohue (2014) assessed 285 professionals and then followed up 18 months later to assess career persistence/change status (241 persisters, 44 changers). Persisters were found to be more congruent with their original occupation than changers, and changers moved to occupations that were more congruent than their original careers. Further, results showed that interest congruence may be better at predicting direction of occupational change (i.e., to an occupation that is more congruent) than distinguishing between those who will switch occupations (i.e., career changers) and those who won't (i.e., career persisters).

Wille, Tracey, Feys, and De Fruyt (2014) investigated interest-occupation congruence within and across time. General findings showed levels of interest-occupation fit were significantly above chance levels at both the beginning of career and 15 years later. That is, vocational interests seem to play a role in initial occupational choice and subsequent career decisions. The authors did not single out career changers, but in a test of the gravitational hypothesis, they did not find that Time 2 occupations correlated more highly with Time 1 interests than Time 1 occupations did.

Studies have investigated interest-occupation fit at time points ranging from the very beginning of people's careers (i.e., initial college major choice) all the way through the mid-points of people's careers (i.e., 15 years after college graduation). Overall, there is some support for interest-occupation fit playing a role in initial occupational choice as well as subsequent occupational gravitation.

Cognitive Ability Fit and Occupational Gravitation.

Wilk, Desmarais, and Sackett (1995) conducted one of the only studies to specifically investigate the relationship between ability-occupation fit and occupational

gravitation. In two large datasets, the authors tested the premise that, over time, individuals will gravitate to jobs commensurate with their ability level. In Study 1, they tested the relationship between ability, as measured by the Armed Services Vocational Aptitude Battery (ASVAB), and job complexity measured at two points in time, five years apart. Descriptive results revealed that individuals with higher cognitive ability moved into jobs that required higher levels of cognitive ability while individuals with lower cognitive ability moved into jobs that required lower levels of cognitive ability. Further, after controlling for age and job complexity at Time 1, the authors found that cognitive ability was a significant predictor of job complexity at Time 2. In a second study, the authors hypothesized that the longer a person remains in a job, the more likely it is he or she meets the cognitive ability requirements for that job. Given this, it was predicted that groups of people with long job tenure should be more homogenous in cognitive ability than groups of people with short job tenure. Findings showed that groups high in job experience were less variable in cognitive ability than groups with less job experience, albeit the differences were rather small.

In a related topic to occupational gravitation, Timothy Judge has built up a line of research on career success. Judge defines extrinsic career success as having three main criteria: 1) salary or income, 2) ascendancy or number of promotions, and 3) occupational status (Judge & Kammeyer-Mueller, 2007). Judge, Higgins, Thoresen, and Barrick (1999) found that childhood intelligence predicted subsequent extrinsic career success to a strong degree. Children with high level of cognitive ability earned higher salaries and attained occupations with higher occupational status in adulthood. Subsequent studies have found similar results. In a sample of 4,537, Furnham and Cheng (2017) found that

childhood cognitive ability was positively related to both adult earning ability and occupational prestige. Meta-analytic findings also showed that childhood intelligence predicted occupation and income in adulthood (Strenze, 2007). In studies that measured intelligence before the age of 19 and criteria after the age of 29, childhood intelligence had a corrected correlation of .45 (sample size = 43,304) with occupation and .23 (sample size = 29,152) with income in adulthood.

Taken as a whole, findings presented in this section illustrate that people gravitate to jobs that are commensurate with their cognitive ability, and over a career, this leads to individuals with higher levels of cognitive ability achieving higher incomes and occupational prestige.

Preliminary Research on Personality Fit and Occupational Gravitation. As previously mentioned, there has historically been less research investigating the link between personality and occupational gravitation. However, some indirect evidence exists, and in recent years, a handful of studies have begun to give attention to the topic. In an indirect look at the phenomenon of personality predicting occupational gravitation, Ones and Viswesvaran (2003) predicted that individuals would be attracted to and self-select into occupations that align with their personalities. As a result of this, they hypothesized that applicants for specific jobs would be less variable in terms of personality than applicants in the workforce in general. That is, standard deviations in specific jobs would be smaller than standard deviations of national norms. Results revealed that job-specific applicant pools (23,231 applicants for 111 jobs) were slightly less variable (by about 4%) than national norms (40,474).

In a study that measured individuals' Big Five personalities and the vocational interest profile of occupations, Judge et al. (1999) found that, after controlling for cognitive ability, Openness to Experience positively predicted gravitation to Artistic jobs and negatively predicted gravitation to Conventional jobs. Extraversion negatively predicted gravitation to Realistic jobs, and Agreeableness predicted gravitation to Social jobs (+) and Investigative jobs (-). Surprisingly, Conscientiousness and Neuroticism did not predict gravitation to any of the RIASEC job codes. As a note of caution, these analyses were performed on a small sample ($N = 109$), and the authors were directly comparing personality-interest gravitation and not personality-personality gravitation. Although they did not directly compare Big Five personality of individuals to Big Five personality of occupations, the relationship between personality and vocational interests allows for some indirect evidence that individuals' Big Five personalities would predict gravitation to the Big Five personalities of occupations as well (Barrick, Mount, & Gupta, 2003). Additionally, similar to the cognitive ability findings, Judge et al. also found that low Neuroticism, low Agreeableness, high Extraversion, and high Conscientiousness were related to extrinsic career success (composite of occupational status and income level).

In more recent studies, Satterwhite, Fleenor, Braddy, Feldman, and Hoopes (2009) investigated whether the forces of attraction-selection-attrition (ASA) lead to a "modal personality" within occupations. Building off the predictions of Schneider's (1987) ASA framework and Holland's (1985, 1997) Theory of Vocational Choice, the authors hypothesized that within-occupation personality variability would be significantly smaller than between-occupation personality variability. In a sample of 6,582

incumbents in 8 occupations across 8 organizations, MANOVA results revealed that personality variance within occupations was indeed smaller than personality variance across occupations.

In another study, Carless and Arnup (2011) studied individual difference factors that predicted career change. The authors predicted that Openness to Experience and Extraversion would both positively be related to career change. They had no strong theoretical prediction for how Conscientiousness would influence career change, so they investigated this variable in an exploratory fashion. In a sample of 4,547 full-time Australian employees, results showed a significant, positive relationship between career change and the personality variables of Openness to Experience and Extraversion. Out of the full sample, 696 individuals changed careers between Time 1 and Time 2, whereas 3,851 individuals remained in the same career at both data collections (career stayers). No significant differences in Conscientiousness were found between career changers and career stayers.

Using data from the same longitudinal Australian sample, NieB and Zacher (2015) investigated whether Big Five personality variables predicted upward job change (or gravitation) to managerial and professional positions. The authors hypothesized that Openness to Experience and Extraversion would predict upward job mobility, and they explored the other three Big Five variables (Conscientiousness, Agreeableness, Emotional Stability) in an exploratory fashion as these variables could theoretically be expected to predict upward job change in a positive or negative direction. Similar to O*NET job zones, the authors used the Australian and New Zealand Standard Classification of Occupations (ANZSCO) which provides a 1-5 skill level rating for each

occupation based on the range and complexity of tasks performed in that occupation. Like O*NET job zones, the skill level rating is operationalized as “the level and amount of formal education and training, previous experience, and on-the-job training required for working in the occupation” (NieB & Zacher, 2015, p. 10). Managerial and professional occupations are assigned the highest possible skill level rating (i.e., 1).

The original sample consisted of 3,489 individuals. The authors then coded individuals as having made an upward job change (1) if they had changed their occupation from non-managerial and non-professional positions to managerial and professional positions and remained there for the duration of the data collection (2005 to 2009). Individuals were coded as having not made an upward job change (0) if they originated in a non-managerial and non-professional positions associated with a lower skill level rating and remained there for the duration of the study. This coding procedure resulted in a smaller sample of 1,957 (247 upward job changers and 1,710 non-upward job changers). Regression analyses revealed that Openness to Experience significantly predicted upward job changes into managerial and professional positions. The odds ratio effect size showed that a 1-unit increase in Openness to Experience (~1 SD) resulted in a 39% higher likelihood of attaining an upward job change. No significant effects were found for any of the other Big Five personality variables.

Although the line of research investigating personality and occupational gravitation is not as voluminous as the work on vocational interests or as clear cut as the cognitive ability literature, findings to date do provide support for personality contributing to the occupational changes that occur throughout people’s working lives.

Chapter 1.3

Lateral vs. Vertical Gravitation. The preceding review of the occupational gravitation literature highlights a troublesome issue that exists in the literature as a whole. Previous research and writing have discussed occupational gravitation as a singular phenomenon, when in reality, two different directions of occupational gravitation exist. As discussed in the opening paragraphs of this paper, 1) individuals can switch to an entirely different career that is more aligned with their personal make-up, or 2) individuals can move up (or down) the occupational complexity hierarchy due to their unique combination of knowledge, skills, abilities, and other characteristics (KSAOs). These two directions of occupational gravitation are very different, but equally important in understanding how individuals navigate their working lives. Thus, the goal of the current dissertation is two-fold. First, I will present a more comprehensive, organizing terminology that will add clarity to the occupational gravitation literature by specifying the direction of gravitation that is taking place. Second, I will carry out a longitudinal investigation in an attempt to elucidate the role personality plays in occupational gravitation.

“Lateral gravitation” is the direction of occupational gravitation that takes place when individuals switch to an entirely different career that is more aligned with their personal characteristics. It is the direction of gravitation that occurs when an individual switches occupations based on misaligned vocational interests. These are the career changers. For example, an individual finds themselves in a strongly Enterprising occupation like sales and chooses to switch to a Realistic occupation like civil engineering, because it fits much better with his or her vocational interests and the type of

work he or she enjoys doing. The vocational interest literature provides evidence that interests can predict college major choice, occupational choice, and any subsequent gravitation that occurs due to poor interest-occupation fit (Bruch & Krieshok, 1981; Donohue, 2006, 2014; Wille et al., 2014).

“Vertical gravitation” is the direction of occupational gravitation that takes place when individuals move up (or down) the occupational complexity hierarchy due to their unique combination of KSAOs. It is the direction of gravitation that occurs when an individual moves up or down the occupational complexity hierarchy based on cognitive ability. These are the career advancers. For example, an individual enters the sales profession at the entry level and over the course of their career finds him or herself promoted from salesperson → sales manager → regional sales director → national sales director. Accumulated research evidence provides support for cognitive ability predicting upward (or downward) gravitation (Judge et al., 1999; Wilk et al., 1995).

This brings us to personality and occupational gravitation. The main question of inquiry is whether personality predicts lateral gravitation, vertical gravitation, neither, or both. Does personality behave like vocational interests and drive lateral gravitation, or does personality behave like cognitive ability and contribute to vertical gravitation? For lateral gravitation, like with vocational interests, one can imagine that individuals are able to select into and gravitate to occupations that align well with their personality. For example, extremely extraverted individuals would likely find working in a quiet, isolated environment all day to be very dissatisfying, and it would not be surprising if they sought out an occupation that satisfied their need for interpersonal interaction. This would be a personality-occupation fit effect.

However, it also could be the case that personality is not varied enough across occupations to drive switching. Unlike vocational interests, which are distinct and varied groupings, what if there is one “ideal work personality” profile that is inherent to all occupations and cuts across all lines of work?. So instead of driving switching between occupations like vocational interests do, personality predicts vertical gravitation, in that those individuals with the ideal work personality find themselves gravitating upward in the occupational complexity hierarchy. Sackett and Walmsley (2014) found evidence that employers seek applicants who are high in Conscientiousness, Agreeableness, Emotional Stability, and Extraversion. If these personality traits are sought after and rewarded in all work environments, then personality would not so much drive switching across occupations, but it would drive movement up (or down) the occupational complexity hierarchy. This would be a personality main effect.

It is unclear if personality contributes to lateral gravitation, vertical gravitation, neither, or both. Theoretically one could make the case for both lateral and vertical gravitation being driven by personality, but it will be valuable to empirically test this question in a large-scale longitudinal sample and see what the results reveal.

Chapter 2

Method

Data for this dissertation exist in two separate datasets. The first dataset is an individual sample which includes personality, cognitive ability, and longitudinally-tracked occupational data for each participant. The second dataset is an occupational database that includes personality, job zone, and vocational interest variables for each occupation.

Sample 1: NLSY79 Children and Young Adults— The individual dataset includes participants from the NLSY79 Children and Young Adults sample. Participants in this longitudinal sample are all children born to the nationally-representative NLSY79 female respondents. Children ages 15 and older were surveyed on a biennial basis from 1994-2012. For participants with full data on all variables of interest, the total N was 6,596 with 3,339 males and 3,257 females. The ethnicity breakdown of the sample was 22.5% Hispanic, 34.7% African-American, and 42.8% Non-Hispanic, Non-African American. At the time of the last data collection in 2012, the mean age of the sample was 27.7 years old ($SD = 4.6$) with a minimum of 20 years old and a maximum of 42 years old.

Big Five Personality— Participants' personality was assessed using the Ten Item Personality Inventory (TIPI) (Gosling, Rentfrow, & Swann, 2003). The TIPI is a ten-item measure of the Big Five personality domains— 2 items are used to assess each of the 5 dimensions. Each item is rated on a 7-point scale that ranges from 1 (strongly disagree) to 7 (strongly agree). Sample items for the Big Five include “Anxious, easily upset” (Neuroticism), “Extraverted, enthusiastic” (Extraversion), “Open to new experiences, complex” (Openness to Experience), “Sympathetic, warm” (Agreeableness), and “Dependable, self-disciplined” (Conscientiousness). If participants had personality data available from more than one data collection, the earliest personality data (i.e., data in which the participant was youngest at time of collection) was used for all analyses. Mean age at the time of personality data collection was 23.1 years old ($SD = 3.5$) with a minimum of 18 years old and a maximum of 38 years old.

Cognitive Ability— Participants' cognitive ability was assessed using the Peabody Individual Achievement Test (PIAT) (Dunn & Markwardt, 1970). Participants were assessed in childhood on the PIAT subtests of Mathematics, Reading Recognition, and Reading Comprehension. Age-normed, standard scores are reported for each subtest. The average score across the three subtests was used as the measure of cognitive ability. If participants had PIAT data available from more than one data collection, the latest ability data (i.e., data in which the participant was oldest at time of collection) was used for all analyses. Mean age at the time of ability data collection was 13.0 years old ($SD = 1.8$) with a minimum of 5 years and a maximum of 18 years.

Occupation— Participants' occupations were tracked on a biennial basis from 1998-2012 (8 data collections). Occupations were recorded using the 4-digit 2002 Census occupational code. A participant had to report working in the given occupation an average of 30 hours per week or more for the data point to be included in analyses. Occupational codes in the individual dataset were crosswalked and mapped to the Standard Occupational Classification (SOC) coding system that appears in the O*NET occupational dataset.

Occupational Data: Occupational Information Network (O*NET; Peterson et al., 1999)— O*NET is an occupational database managed by the U.S. Department of Labor which provides detailed, descriptive information for over 800 detailed occupations. Each occupation is assigned a six-digit occupational code. These 800+ detailed occupations (e.g., psychology teachers, postsecondary) are further classified into 461 broad occupations (e.g., social science teachers, postsecondary), 97 minor groups (e.g.,

postsecondary teachers), and 23 major groups (e.g., education, training, and library occupations).

O*NET Work Styles (Personality)— The O*NET content model defines work styles as “personal characteristics that can affect how well someone performs a job.” The 16 personality traits that were deemed relevant for job performance by O*NET developers are (in alphabetical order): 1) Achievement/Effort, 2) Adaptability/Flexibility, 3) Analytical Thinking, 4) Attention to Detail, 5) Concern for Others, 6) Cooperation, 7) Dependability, 8) Independence, 9) Initiative, 10) Innovation, 11) Integrity, 12) Leadership, 13) Persistence, 14) Self-Control, 15) Social Orientation, and 16) Stress Tolerance. For each of the 16 work styles, Occupational experts or incumbents have provided importance ratings for all occupations where they rate on a scale of 1-5 how important (1 = “Not Important” to 5 = “Extremely Important”) each work style is to successful job performance.

O*NET work styles were not developed within a Big Five framework, and instead developers classified the 16 lower-order dimensions into 7 higher-order dimensions. These 7 higher-order dimensions are: 1) Achievement Orientation, 2) Social Influence, 3) Interpersonal Orientation, 4) Adjustment, 5) Conscientiousness, 6) Independence, and 7) Practical Intelligence. To best match the O*NET work styles data to the Big Five personality data that is available in the individual datasets, the author and a second I-O PhD coder classified the 16 work styles into a Big Five framework, rather than using the 7-dimension framework provided by O*NET.

Based on this exercise, a composite of Self-Control and Stress Tolerance will be used to measure Neuroticism, a composite of Social Orientation and Leadership will be

used to measure Extraversion, a composite of Adaptability/Flexibility, Analytical Thinking, and Innovation will be used to measure Openness to Experience, a composite of Concern for Others and Cooperation will be used to measure Agreeableness, and a composite of Achievement/Effort, Attention to Detail, Dependability, Initiative, and Persistence will be used to measure Conscientiousness. The work styles of Independence and Integrity were determined to be compound trait in nature and thus were not assigned to any of the Big Five dimensions.

O*NET Job Zones— O*NET job zones provide information on the level of experience, education, and job training needed for each occupation in the O*NET database. Two trained I-O psychologists review each occupation and assign it a rating ranging from 1 (Little or No Preparation Needed) to 5 (Extensive Preparation Needed). On education levels alone, Job Zone 1 is associated with needing less than a high school diploma, and Job Zone 5 is associated with needing more than a bachelor's degree. Similar to the cognitive complexity hierarchy used by Wilk et al. (1995), O*NET job zones will serve as a measure of occupational complexity and will be used to test the vertical gravitation hypothesis.

O*NET Vocational Interests— O*NET vocational interests provide information on each of Holland's six RIASEC interests for every occupation in the O*NET database. Three trained I-O psychologists review each occupation and assign it a rating for each RIASEC interest ranging from 1 to 7 based on how descriptive and characteristic the occupation is of each work environment. The average rating from the three raters serves as the score for each of the six RIASEC interests. Each occupation is then provided a high-point code which signifies the interest that received the highest average rating. That

is, if an occupation's highest rating was for the Realistic work environment, it would be assigned "R" as its high-point code and would be coded in the database as a Realistic occupation. The six RIASEC interest categories do a good job of grouping together similar and distinct occupations. RIASEC high-point codes of occupations will be used to test the lateral gravitation hypothesis.

Analyses

Analyses began by computing person-occupation fit indices between individuals and their recorded occupations at ages 1819, 2021, 2223, 2425, 2627, 2829, 3031, 3233, 3435. Since individual personality variables and occupation personality variables were measured on different scales, personality variables in both datasets were standardized into z-scores. Occupation personality variables were then merged into the individual dataset so each individual had a set of Big Five occupation variables for each of their recorded occupations. Initial fit calculations were then carried out at the individual Big Five level.

For each occupation available for an individual, a fit difference score was calculated by subtracting the occupation's Emotional Stability (ES), Extraversion (EX), Openness (O), Agreeableness (A), and Conscientiousness (C) z-score values from the individual's Emotional Stability, Extraversion, Openness, Agreeableness, and Conscientiousness z-score values. This procedure created five fit scores for each person-occupation pairing in the dataset. For example, if an individual had occupation data available at three ages (e.g., 1819, 2223, 2425), they would have 15 individual Big Five fit scores— ES1819fit, EX1819fit, O1819fit, A1819fit, C1819fit, ES2223fit, EX2223fit, O2223fit, A2223fit, C2223fit, ES2425fit, EX2425fit, O2425fit, A2425fit, and C2425fit. For each set of five scores, the input individual personality scores remained the same but

the input occupation personality scores changed (unless an individual was employed in the same occupation at two or more age variables).

To counteract the mean cancelling out effect of difference scores, each fit difference score was recoded into an absolute deviation between the individual personality value and the occupation personality value. That is, an individual ES personality value .25 SD above an occupation ES personality value is treated as the same degree of fit as an individual ES personality variable .25 SD below an occupation ES personality value. A smaller fit value signifies a better person-occupation fit.

Once Big Five fit scores were calculated for each person-occupation pairing in the dataset, mean fit for each of the Big Five variables was investigated across the Age variable (1819 thru 3435). Descriptive statistics revealed that as participants got older Openness and Conscientiousness fit got slightly better, Extraversion and Agreeableness fit got slightly worse, and Emotional Stability fit remained relatively constant (see Table 5).

The next step in creating person-occupation fit indices involved the calculation of Mahalanobis distance (Mahalanobis, 1936). Mahalanobis distance is a composite distance metric that measures fit between n individual personality variables and n occupation personality variables in n -dimensional space, taking into account the interactions among the variables. The metric also accounts for the shape, level, and dispersion of the individual and occupation personality profiles. A Big Five Mahalanobis distance fit (B5 fit) in 5-dimensional space was calculated to serve as an overall fit index between an individual's full personality profile and the full personality profile of each of their recorded occupations. In addition, based on the individual fit descriptives revealing

that Openness fit and Conscientiousness fit slightly improved with age, an Openness-Conscientiousness Mahalanobis distance fit (OC fit) was also calculated for all person-occupation pairings.

After computing all required fit variables, means, standard deviations, and intercorrelations were calculated for the individual personality variables. Next, means, standard deviations, and intercorrelations were calculated for the occupation personality variables. Big Five occupation personality means were calculated across Job Zones and simple linear regressions were run to formally test whether Big Five occupation means increase with Job Zone.

The person-occupation dataset was then converted from wide (multivariate) to long (univariate) format. The longitudinal nature of the data collection led to multiple occupations collected at various ages to be nested within individuals. Instead of having one row of data for each individual with multiple sets of fit indices at different ages (multivariate), restructuring created a data set with multiple rows of data for each individual, with a single set of fit indices for each age on each row (univariate). The new format correctly captured the nested nature of the data and allowed for hierarchical linear modeling analyses to be conducted. Upon restructuring of the dataset, means, standard deviations, and intercorrelations were computed for the person-occupation fit variables, Age, and Job Zone. Mean occupation job zone was calculated for each Age category.

To formally test whether person-occupation personality fit improves with age, longitudinal growth modeling was conducted through a series of linear mixed models in which each of the 7 fit indices were regressed onto the Age variable (coded as 0=1819, 1=2021, 2=2223, 3=2425, 4=2627, 5=2829, 6=3031, 7= 3233, 8= 3435). Next, the

relationship between occupation change and fit was investigated for individuals who had occupation data available for any two consecutive Age categories (e.g., 1819-2021). Initial fit for individuals who stayed in the same occupation across the two consecutive Age categories was compared to initial fit for individuals who changed occupations between the two consecutive Age categories to investigate whether initial fit predicted occupation change. Secondly, initial fit and post-change fit was compared for occupation changers to determine whether occupation change led to improved person-occupation fit. Two linear mixed model regressions were then run to formally test these two research questions.

To test the lateral gravitation hypothesis, the next set of analyses examined person-occupation personality fit within the context of RIASEC interest code changes. The six RIASEC codes represent varied and distinct occupational groupings. The RIASEC groupings are organized in a hexagon structure that specifies the relatedness of the types. Adjacent types are more similar than alternate types and alternate types more similar than opposite types. RIASEC codes were labeled as 1 = Realistic, 2 = Investigative, 3 = Artistic, 4 = Social, 5 = Enterprising, and 6 = Conventional. A significant career change was operationalized as an occupation change that resulted in at least a 1-code RIASEC code change (e.g., 1 → 2, 2 → 3, 3 → 4, etc.). A 2-code RIASEC code change (e.g., 1 → 3, 2 → 4, 3 → 5, etc.) was deemed to be a larger change than a 1-code change, and a 3-code change (e.g., 1 → 4, 2 → 5, 3 → 6, etc.) more significant than a 2-code change. If individuals do gravitate to occupations based on personality, then a significant career change should be accompanied by improved person-occupation fit. Initial fit and post-change fit were compared for 0-code changes, 1-code

changes, 2-code changes, and 3-code changes across all 7 fit variables to determine whether career change leads to better person-occupation fit. A formal linear mixed model was run to determine whether the degree of career change (0-, 1-, 2-, 3-code) predicted post-change fit.

The final set of analyses examined the vertical gravitation hypothesis. The vertical gravitation hypothesis proposes that individuals with the “ideal work personality” (i.e., high ES, high EX, high O, high A, and high C) will move up the occupational complexity hierarchy over time. In the current dataset, the occupational complexity hierarchy was operationalized as the Job Zone rating (1-5) for each occupation. For each participant, their initial job zone in the dataset was subtracted from their final job zone to create a job zone change variable that ranged from -2 to +3. Big Five personality means were then calculated for each of the 6 job zone change groups (-2, -1, 0, +1, +2, +3). Because initial job zone plays a large role in how much and in which direction someone can move job zones, a second set of Big Five personality means were calculated for 5 job zone change groups (-1, 0, +1, +2, +3) conditioned on individuals beginning in Job Zone 2. A third table of Big Five personality means were calculated with the final job zone for each participant serving as the grouping variable. For the last analyses, multiple regressions were ran with initial job zone, Big Five personality, and cognitive ability predicting job zone change and final job zone.

Chapter 3

Results

Table 1 presents means, standard deviations, and intercorrelations among the individual personality and cognitive ability variables. Due to the large sample size, all

correlations were significant at the $p < .05$ level, and the pattern of intercorrelations aligns with findings from previous Big Five research (Digman, 1997; Mount, Barrick, Scullen, & Rounds, 2005; Van der Linden, Nijenhuis, & Bakker, 2010). Table 2 presents means, standard deviations, and intercorrelations among the occupation personality and job zone variables. Again, due to the large sample size, all correlations were significant at the $p < .05$ level. Unlike the individual personality correlations, the SME ratings of occupation personality resulted in a significant degree of positive manifold. This result is not uncommon in ratings data, and can be compared to the general performance factor that appears in job performance ratings (Viswesvaran, Schmidt, & Ones, 2005). It appears there is a “general personality importance” factor in the occupation personality data. That is, an occupation being rated high (or low) on one Big Five factor is related to that occupation being rated high (or low) on the other four Big Five factors.

Table 3 illustrates that this “general personality importance” factor is related to occupation job zone. Occupations that are more complex and require a greater degree of education and training, as indicated by their higher standing in the job zone hierarchy, have higher personality means than less complex occupations which require lower levels of education and training. These occupation personality values could be a statistical artifact of the SME rating process, or could be an accurate representation of how personality importance relates to occupations. Even though personality values increase across job zones, there is still a good degree of within-job zone variance, as shown by the standard deviations around the Big Five means. Simple linear regression results show that the strongest relationship between personality ratings and job zone occurs for the Big

Five domains of Openness ($B = .259, R^2 = .526$) and Conscientiousness ($B = .174, R^2 = .452$).

Table 4 presents means, standard deviations, and intercorrelations among the person-occupation fit and job zone variables. Intercorrelations reveal that there are small, positive relationships between all fit variables, with some variables having stronger relationships than others. The individual Big Five fit variables have strong relationships with Big Five fit as this is a part-whole correlation. The same holds true for the relationship of Openness fit and Conscientiousness fit with Openness-Conscientiousness fit. Extraversion fit has the strongest relationship with Agreeableness fit out of any of the fit variables, and Agreeableness fit has the strongest relationship with Emotional Stability fit. Out of all the individual Big Five fit variables, Openness fit and Conscientiousness fit have the strongest relationship ($r = .35$). This is likely due to the strong correlation between Openness and Conscientiousness in both the individual personality dataset and the occupation personality dataset. Another interesting takeaway from Table 4 is the job zone intercorrelations. Openness fit and Conscientiousness fit have the strongest relationship with job zone ($r = -.23$ and $-.28$, respectively), illustrating that individuals experience better Openness fit and Conscientiousness fit at higher job zones. Table 5 provides simple descriptive statistics for the job zone variables across categories of the age variable. The table shows as the sample gets older, the mean job zone of participants' occupations increases.

Table 6 shows means and standard deviations for individual Big Five fit across age categories. The pattern of means suggests that Openness fit and Conscientiousness fit slightly decrease (improve) with age, Extraversion fit and Agreeableness fit slightly

increase (worsen) with age, and Emotional Stability fit remains relatively constant.

Tables 7-11 present linear mixed model regressions as a formal test of the relationship between age and individual Big Five fit. For each of the individual Big Five fit variable, an unconditional means model (Model 1) was fit to the data first. In an unconditional means model, no predictors are entered in the regression, and the participant ID grouping variable serves as the only random effect. The fixed effect (intercept) appearing in the output of the unconditional means model is the grand mean for the fit variable across all observations. For example, for the Emotional Stability fit model, the intercept is the mean of Emotional Stability fit, irrespective of age. A single random effect is estimated in the unconditional means model as well—the variance around the intercepts (τ_{00}). This variance captures the between-persons differences in the intercept, or simply the between-persons differences in fit, irrespective of age. The remaining residual variance in the model (σ^2) represents the within-person variance in fit, plus error. These two variance estimates are useful. The former depicts how much fit variability is due to between-person differences, and the latter represents how much participants vary from themselves. The intraclass correlation for each individual Big Five fit criteria was .57 (Emotional Stability fit), .33 (Extraversion fit), .36 (Openness fit), .44 (Agreeableness fit), and .35 (Conscientiousness fit). These ratios of between- to within-persons variance are high enough to permit the use of growth curve modeling for each individual Big Five fit variable.

A simple linear growth curve model (Model 2) was then fitted for each individual Big Five fit variable in which age was entered as a fixed effect predictor. For the model predicting ES fit (Table 7), age emerged as a small, but significant, positive predictor,

$\gamma_{01} = .005$, $SE = .002$, $p < .05$. The improved AIC value and significant log likelihood ratio ($\chi^2(1) = 4.78$, $p < .05$) illustrates that the linear growth curve model fits the data better than the fully unconditional means model. However, the addition of age as a predictor did not decrease any of the between- or within-persons variance of ES fit values ($R^2 = .00$), indicating that Emotional Stability fit does not systematically vary with age.

Table 8 presents the linear mixed model results for Extraversion fit. In Model 2, age emerged as a small, but significant, positive predictor, $\gamma_{01} = .009$, $SE = .003$, $p < .05$. The improved AIC value and significant log likelihood ratio ($\chi^2(1) = 9.88$, $p < .05$) illustrates that the linear growth curve model fits the data better than the fully unconditional means model. A small reduction in Model 1 variance ($R^2 = .001$) reveals that Extraversion fit slightly increases (worsens) with age.

Table 9 presents the linear mixed model results for Openness fit. In Model 2, age emerged as a small, but significant, negative predictor, $\gamma_{01} = -.041$, $SE = .003$, $p < .05$. The improved AIC value and significant log likelihood ratio ($\chi^2(1) = 160.32$, $p < .05$) illustrates that the linear growth curve model fits the data better than the fully unconditional means model. A small reduction in Model 1 variance ($R^2 = .01$) illustrates that Openness fit slightly decreases (improves) with age.

Table 10 presents the linear mixed model results for Agreeableness fit. In Model 2, age emerged as a small, but significant, positive predictor, $\gamma_{01} = .014$, $SE = .003$, $p < .05$. The improved AIC value and significant log likelihood ratio ($\chi^2(1) = 27.28$, $p < .05$) illustrates that the linear growth curve model fits the data better than the fully unconditional means model. A small reduction in Model 1 variance ($R^2 = .002$) shows that Agreeableness fit slightly increases (worsens) with age.

Table 11 presents the linear mixed model results for Conscientiousness fit. In Model 2, age emerged as a small, but significant, negative predictor, $\gamma_{01} = -.036$, $SE = .003$, $p < .05$. The improved AIC value and significant log likelihood ratio ($\chi^2(1) = 120.04$, $p < .05$) illustrates that the linear growth curve model fits the data better than the fully unconditional means model. A small reduction in Model 1 variance ($R^2 = .008$) indicates that Conscientiousness fit slightly decreases (improves) with age.

Table 12 presents means and standard deviations for the calculated Mahalanobis distance fit indices across age categories. Given that Openness fit and Conscientiousness fit appeared to be the only individual Big Five fit variables that improved with age, a two-dimensional Openness-Conscientiousness Mahalanobis distance fit (OC fit) was calculated in addition to the overall Big Five Mahalanobis distance fit (B5 fit). The pattern of means suggests that Openness-Conscientiousness fit and Big Five fit both slightly decrease (improve) with age.

Table 13 presents the linear mixed model results for Openness-Conscientiousness fit. In Model 2, age emerged as a small, but significant, negative predictor, $\gamma_{01} = -.023$, $SE = .003$, $p < .05$. The improved AIC value and significant log likelihood ratio ($\chi^2(1) = 55.25$, $p < .05$) illustrates that the linear growth curve model fits the data better than the fully unconditional means model. A small reduction in Model 1 variance ($R^2 = .003$) illustrates that Openness-Conscientiousness fit slightly decreases (improves) with age.

Table 14 presents the linear mixed model results for Big Five fit. In Model 2, age emerged as a small, but significant, negative predictor, $\gamma_{01} = -.015$, $SE = .003$, $p < .05$. The improved AIC value and significant log likelihood ratio ($\chi^2(1) = 367.66$, $p < .05$) illustrates that the linear growth curve model fits the data better than the fully

unconditional means model. A small reduction in Model 1 variance ($R^2 = .001$) illustrates that Big Five fit slightly decreases (improves) with age.

Tables 15-17 investigate the relationship between occupation change and all 7 fit variables. Each row of data includes individuals who had occupation data available for the two consecutive Age categories in question (e.g., 1819-2021). Independent *t*-tests were used to examine whether initial fit values significantly differed for individuals who changed occupations from Time 1 to Time 2 and individuals who stayed in the same occupation for Time 1 to Time 2. Significance results (*ns* = not significant, * = significant) for this analysis are depicted in the “____ initial fit (change)” columns in Tables 15-17. Across the 56 comparisons (7 fit variables x 8 consecutive age variables), 9 of the *t*-tests were significant. Occupation changers had worse initial Extraversion fit (higher means) than occupation stayers at the 2021-2223 change variable. Occupation changers had worse initial Openness fit than occupation stayers at the 2021-2223, 2223-2425, and 2425-2627 change variables. Occupation changers had worse initial Conscientiousness fit than occupation stayers at the 2425-2627 and 3031-3233 change variables. And finally, occupation changers had worse initial Openness-Conscientiousness fit than occupation stayers at the 2021-2223, 2223-2425, and 2425-2627 change variables. Taken as a whole, the initial fit values of occupation changers did not often differ from those of occupation stayers.

A second set of comparisons were carried out on Tables 15-17 to determine whether occupation changes resulted in improved fit (lower means) for the occupation changers. Dependent *t*-tests were used to examine whether changers initial fit values significantly differed from their post-change fit values. Significance results (*ns* = not

significant, * = significant) for this analysis are depicted in the “____ post-change fit” columns in Tables 15-17. Across the 56 comparisons (7 fit variables x 8 consecutive age variables), 12 of the *t*-tests were significant. Emotional Stability fit worsened for occupation changers at the 1819-2021 and 3233-3435 change variables. Openness fit improved for occupation changers at the 1819-2021, 2021-2223, and 2425-2627 change variables. Agreeableness fit worsened for occupation changers at the 2021-2223 change variable. Conscientiousness fit improved for occupation changers at the 1819-2021, 2021-2223, and 3031-3233 change variables. Openness-Conscientiousness fit improved for occupation changers at the 1819-2021 and 2021-2223 change variables, and Big Five fit improved for occupation changers at the 2829-3031 change variable. In all other comparisons, occupation change did not significantly improve fit.

To formally test 1) whether initial fit predicts occupation change and 2) whether occupation change leads to improved fit, two linear mixed model regressions were run on data collapsed across age categories. Table 18 shows the logistic regression results for initial individual Big Five fit (Time 1 fit) predicting occupation change (0 = stay, 1 = change). The individual Big Five fit predictors were standardized. Coefficient estimates give the change in the log odds of the outcome for a one unit increase in the predictor variable. For example, controlling for the effects of the other four individual Big Five fit predictors, for every 1 SD increase in Openness fit (worse fit), the log odds of occupation change (versus stay) increases by .123. Extraversion fit ($\gamma_{01} = -.048, SE = .025$), Openness fit ($\gamma_{03} = .123, SE = .026$), Agreeableness fit ($\gamma_{04} = -.079, SE = .024$), and Conscientiousness fit ($\gamma_{05} = .101, SE = .026$) were significant predictors of occupation change, and the significant log likelihood ratio ($\chi^2(5) = 71.21, p < .05$) reveals the model

as a whole fits significantly better than an empty model (i.e., a model with no predictors). Coefficient estimates were also transformed into odds ratios by exponentiating the coefficient for each predictor. The result is the odds ratio for when the predictor is $x+1$, compared to when the predictor is x . For example, the Openness fit odds ratio of 1.13 shows that for every 1 SD increase in Openness fit (worse fit), the probability of changing occupations increase by about 13%. Also of note from Table 18 is that the coefficients for Emotional Stability and Agreeableness fit are negative, while the coefficients for Openness and Conscientiousness fit are positive. This signals that an increase in Openness and Conscientiousness fit (worse fit) increases the likelihood of changing occupations, whereas an increase in Emotional Stability and Agreeableness fit (worse fit) decreases the likelihood of changing occupations.

Table 19 shows the logistic regression results for initial Openness-Conscientiousness fit (Time 1 fit) predicting occupation change (0 = stay, 1 = change). The Openness-Conscientiousness fit predictor was standardized. Openness-Conscientiousness fit ($\gamma_{01} = .146$, $SE = .024$) was a significant predictor of occupation change, and the significant log likelihood ratio ($\chi^2(1) = 37.53$, $p < .05$) illustrates the model is significant. For every 1 SD increase in Openness-Conscientiousness fit (worse fit), the probability of changing occupations increase by about 16%.

Table 20 presents the same analysis for Big Five fit. Again, the Big Five fit predictor was standardized. Big Five fit ($\gamma_{01} = .090$, $SE = .024$) was a significant predictor of occupation change, and the significant log likelihood ratio ($\chi^2(1) = 14.14$, $p < .05$) shows the model fits the data significantly better than an empty model. For every 1 SD

increase in Big Five fit (worse fit), the probability of changing occupations increase by about 9%.

Table 21 presents linear mixed model regressions in which occupation change (0 = stay, 1 = change) predicts Time 2 fit improvement. Time 2 fit improvement is equal to Time 1 fit minus Time 2 fit. A positive improvement value indicates that fit improved (decreased) with change. The intercept for each model is .000 because when occupation change = 0, the participant remained in the same occupation from Time 1 to Time 2, so there is no fit change and thus no fit improvement. The occupation change coefficient shows that occupation change positively predicts Openness ($\gamma_{01} = .066$, $SE = .016$), Conscientiousness ($\gamma_{01} = .058$, $SE = .017$), and Openness-Conscientiousness ($\gamma_{01} = .040$, $SE = .016$) fit improvement.

Tables 22 and 23 present the results from the lateral gravitation analyses. Occupation changes were classified into 0-code changes, 1-code changes, 2-code changes, and 3-code changes. A career change was operationalized as an occupation change that resulted in at least a 1-code RIASEC code change (e.g., 1 → 2, 2 → 3, 3 → 4, etc.) with higher code changes deemed to be larger and more significant career changes. First, dependent *t*-tests were conducted to determine whether fit improves for 0-code, 1-code, 2-code, and 3-code occupation changes. Significance results (*ns* = not significant, * = significant) for this analysis are depicted in the “_____ post-change fit” columns in Tables 22 and 23. Results show that 0-code occupation changes resulted in better Conscientiousness fit. 1-code occupation changes resulted in better Openness, Conscientiousness, Openness-Conscientiousness, and Big Five fit. 2-code occupation changes resulted in better Openness, Conscientiousness, and Openness-

Conscientiousness fit but worse Extraversion and Agreeableness fit. 3-code occupation changes resulted in better Openness and Conscientiousness fit but worse Emotional Stability and Agreeableness fit. Second, linear mixed model regressions were ran to investigate whether degree of occupation change (0-code to 3-code) predicted post-change fit. Table 24 presents these results. Degree of occupation change only significantly predicted Extraversion ($\gamma_{01} = .036$, $SE = .009$), Agreeableness ($\gamma_{01} = .039$, $SE = .008$), and Big Five ($\gamma_{01} = .044$, $SE = .010$) post-change fit. For all 3 outcomes, a larger and more significant career change predicted worse Extraversion, Agreeableness, and Big Five post-change fit.

Tables 25-28 present the results from the vertical gravitation analyses. Table 25 shows Big Five personality and cognitive ability means for participants categorized based on unconditional job zone movement. That is, for each participant, their initial job zone in the dataset was subtracted from their final job zone to create a job zone change variable that ranged from -2 to +3. Big Five personality and cognitive ability means were then calculated for each of the 6 job zone change groups (-2, -1, 0, +1, +2, +3). No mean differences are seen in the Big Five or cognitive ability across the job zone change groupings.

Table 26 reports Big Five personality and cognitive ability means for participants based on conditional job zone movement. Because initial job zone plays a large role in how much and in which direction someone can move job zones, a second set of Big Five personality means were calculated for job zone change groups (-1, 0, +1, +2, +3), but only individuals who began in Job Zone 2 (the most populous job zone) were included in

the analyses. Table 27 presents Big Five personality and cognitive ability means, but participants are grouped by their final job zone.

Linear multiple regression analyses were carried out to statistically test whether Big Five personality and cognitive ability predict job zone change and final job zone. Table 28 reports the results of these regressions. In predicting job zone change, initial job zone was entered as a control variable in Block 1. Big Five personality variables and cognitive ability were entered in Block 2. Personality and cognitive ability variables were standardized and unstandardized coefficients are reported. Results revealed Extraversion ($B = .043, SE = .014$), Conscientiousness ($B = .064, SE = .015$), and cognitive ability ($B = .231, SE = .014$) positively predicted job zone change. Openness ($B = -.029, SE = .015$) emerged as a significant, negative predictor. Agreeableness negatively predicted job zone change ($B = -.027, SE = .014$), but just failed to reach significance, $p = .059$. In predicting final job zone, a similar pattern of results were found. Extraversion ($B = .047, SE = .015$), Conscientiousness ($B = .061, SE = .016$), and cognitive ability ($B = .296, SE = .015$) emerged as significant, positive predictors of final job zone. Openness ($B = -.028, SE = .016$) trended in the negative direction, but did not reach significance.

In regards to the personality and job zone movement, the nature of the data did not allow for the author to control for a job zone change resulting from completion of an academic degree. However, if all job zone movement was driven by cognitive ability and degree completion, then results should show no personality mean differences across job zones. This is not the case, so personality must play a role in job zone movement.

Based on the emerging pattern of results, a final set of linear mixed model regressions were run to test whether occupation job zone predicts person-occupation fit. Table 29 presents the results from these regressions. Occupation job zone significantly predicted all 7 fit indices. Occupation job zone positively predicted Emotional Stability fit ($\gamma_{01} = .015$, $SE = .007$), Extraversion fit ($\gamma_{01} = .074$, $SE = .007$), and Agreeableness ($\gamma_{01} = .062$, $SE = .007$) fit. That is, as occupation job zone increased, Emotional Stability, Extraversion, and Agreeableness fit worsened. Alternatively, occupation job zone negatively predicted Openness fit ($\gamma_{01} = -.176$, $SE = .008$), Conscientiousness fit ($\gamma_{01} = -.221$, $SE = .008$), Openness-Conscientiousness fit ($\gamma_{01} = -.182$, $SE = .008$), and Big Five fit ($\gamma_{01} = -.078$, $SE = .008$), which means as job zone increased, Openness, Conscientiousness, Openness-Conscientiousness, and Big Five fit improved.

Chapter 4

Discussion

Taken as a whole, the current dissertation's findings revealed nuanced and previously unreported relationships between personality and occupation gravitation. For the main research question which asked whether individuals gravitate to occupations providing better personality fit over time, results indicated that Openness, Conscientiousness, Openness-Conscientiousness, and Big Five fit improved with age. On the other hand, and somewhat surprisingly, results also revealed that Extraversion and Agreeableness fit worsened with age. No significant age effect was found for Emotional Stability fit. Although findings were significant, it is important to note that the effect sizes were not large. For example, of all the 7 fit variables, age most strongly predicted Openness fit. However, the coefficient estimate was only $-.041$, indicating that a 1-unit

increase in age predicted a $-.041$ decrease (improvement) in Openness fit. Across the eight age time points in the dataset, Openness fit would only be predicted to improve by $.328$ from age 1819 to age 3435. This is a $.38$ *SD* improvement.

Given that some evidence was found for the improvement of person-occupation personality fit over time, the main objective was then to try and decipher the underlying mechanism that is causing this to occur. As a first step, paired groups of occupation changers and occupation stayers at different ages were analyzed. In general, there were very little differences in terms of initial fit on all seven fit indices between occupation changers and stayers. When occupation switches or non-switches were collapsed across ages, logistic regression results revealed that worse Openness and Conscientiousness fit, predicted a higher probability of switching careers, whereas worse Extraversion and Agreeableness fit predicted a lower probability of switching careers. Again, like the effect of age on all fit indices, these effects were small and could have been driven by the fact that the worst Openness and Conscientiousness fit occurs at early ages when individuals are most likely to making occupation changes.

When analyzing the paired groups of occupation changers at different ages for post-change fit improvement, again little effect was found. For most fit indices across most changes, no significant differences in initial fit and post-change fit were found. However, when collapsing across ages, results did show that on average an occupation change leads to improved Openness, Conscientiousness, and Openness-Conscientiousness fit. This is likely driven by occupation changes that include job zone changes.

To further investigate whether the improvement of person-occupation personality fit is caused by lateral gravitation, the next set of analyses focused on occupation changes that could only be considered as significant career changes. Occupation changes were classified into 0-code changes, 1-code changes, 2-code changes, and 3-code changes. A career change was operationalized as an occupation change that resulted in at least a 1-code RIASEC code change (e.g., 1 → 2, 2 → 3, 3 → 4, etc.) with higher code changes deemed to be larger and more significant career changes. Findings indicated that more significant career changes did not predict improved fit. In fact, 3-code occupation changes lead to worse Extraversion and Agreeableness fit. Of the 594 3-code occupation changes, further investigation found that 463 (or 78%) of those changes occurred between Realistic and Social RIASEC groups. These large changes leading to worse fit suggest that individuals do not have enough knowledge to gravitate to occupations with good personality fit, or it could also mean that people make career decisions on factors other than personality. Instead of personality driving occupation choice and subsequent gravitation, factors like money, location, promotions, and work-life balance may drive labor force movement instead.

Since little evidence was found for lateral gravitation leading to improved fit over time, analyses then turned to the vertical gravitation hypothesis. That is, do individuals with the “ideal work personality” (high Emotional Stability, Extraversion, Openness, Agreeableness, and Conscientiousness) move upward in the occupational complexity hierarchy over time (i.e., move up job zones). Regression results revealed that Extraversion, Conscientiousness, and cognitive ability positively predicted upward job zone movement, while Openness negatively predicted the same outcome. Agreeableness

just failed to reach significance as a negative predictor. These findings indicate that the phenomenon of vertical gravitation occurs over time. These results led to the final question of whether vertical gravitation predicts improved fit over time.

To investigate this final question, a series of linear mixed model regressions were run to see if occupation job zone predicts Emotional Stability, Extraversion, Openness, Agreeableness, Conscientiousness, Openness-Conscientiousness, and Big Five fit. Results overwhelming showed that Openness, Conscientiousness, Openness-Conscientiousness, and Big Five fit are better at higher job zones, whereas Extraversion and Agreeableness fit become worse as job zone increases. Putting this together with the vertical gravitation findings, we can see how the overall pattern of results occurred.

The main finding was that as individuals got older, they found better Openness, Conscientiousness, Openness-Conscientiousness, and Big Five fit, and worse Extraversion and Agreeableness fit. We also know that Extraversion (+), Conscientiousness (+), Openness (-), and Agreeableness (-) predict upward job zone movement over time. Additionally, occupation personality ratings for all Big Five dimensions steadily increase at higher job zones. The relationship between individual personality scores and occupation personality ratings then dictates that Conscientiousness fit will be better at higher job zones and Agreeableness fit will be worse at higher job zones. If people higher in Conscientiousness move up job zones to more Conscientious occupations, Conscientiousness fit should improve. Similarly, if people lower in Agreeableness move up job zones to more Agreeable occupations, Agreeableness fit should worsen. It is unclear why Openness fit improves and Extraversion fit worsens at higher job zones, because based on the individual personality scores and occupation

personality ratings, the opposite would be predicted. Finally, since average job zone increases with age, we are left with age predicting better or worse fit. Essentially, job zone mediates the relationship between age and fit.

Overall, findings illustrate that personality's relationship with occupational gravitation functions more like cognitive ability's relationship with occupational gravitation than vocational interest's relationship with occupational gravitation. It does not appear that personality predicts dramatic career switching, nor improved fit when it does occur. Personality does predict upward or downward job zone movement and this in turn predicts better or worse fit on the various Big Five dimensions and composite fit indices (Openness-Conscientiousness and Big Five). The overall effect sizes for improved or worsened fit over time were not large.

The most significant limitation of the current dissertation is the small age range (i.e., 19-35 y/o) for which individuals' occupations were tracked. Unfortunately, almost all participants in the dataset had only reached their late 20s or early 30s by the final data collection. If participants were tracked for the entirety of their working careers (from early 20s to early 60s), this would have allowed time for more job zone movement and stronger effects may have appeared.

A second limitation of the current study is the nature of the O*NET occupation personality ratings. O*NET personality ratings are sometimes provided by occupation incumbents, but oftentimes the ratings are provided by industrial-organizational psychologist subject matter experts (SMEs) who have never worked in the occupation they are rating. Providing an occupation personality rating based solely on a description of the occupation's tasks and responsibilities may be less valid than providing an

occupation personality rating based on first-hand knowledge of working in the occupation. Further, defining the “personality” of an occupation by its tasks and responsibilities may not be the best approach— Holland (1997) defined vocational interest environments of occupations as the mean score of individuals working in that occupation. Similarly, defining the personality of an occupation as the mean personality score of individuals working in that occupation may be a better approach than relying on personality ratings based on tasks and responsibilities.

A third limitation of the current dissertation is the personality inventory used to assess individuals’ personalities— the Ten Item Personality Inventory (TIPI). The TIPI is a 10-item personality measure that uses two items to assess each of the Big Five dimensions. Although the TIPI has been shown to have adequate reliability given the scale length (Gosling, Rentfrow, & Swann, 2003), it would have been ideal to use a longer measure to more comprehensively measure the full construct space of individuals’ personalities. However, because the National Longitudinal Survey of Youth was an already existing dataset, the author had no control over which personality measure was used and had to make the best of what was available.

In conclusion, the current dissertation investigated the role of personality in occupational gravitation. Two different directions of occupational gravitation were proposed and tested— lateral and vertical gravitation. Results revealed that individuals found improved person-occupation personality fit over time as measured by the indices of Openness, Conscientiousness, Openness-Conscientiousness, and Big Five fit. Analyses further showed that improved fit over time was driven by vertical gravitation and not lateral gravitation. Extraversion (+), Openness (-), Agreeableness (-), and

Conscientiousness (+) predicted upward job zone movement, and this job zone movement resulted in improved fit. That is, job zone mediated the relationship between age and person-occupation personality fit.

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Appendix

Table 1
Means, SDs, and Correlations Among Individual Personality and Cognitive Ability Variables

	ES	EX	O	A	C	Mean	SD
Emotional Stability						5.01	1.33
Extraversion	.09					4.70	1.37
Openness	.16	.21				5.48	1.17
Agreeableness	.24	.04	.17			5.01	1.78
Conscientiousness	.26	.08	.21	.17		5.68	1.19
Cognitive Ability	.06	.12	.07	.05	-.06	99.04	12.52

Note. $N = 5,727$. Ten Item Personality Inventory (TIPI) range: 1-7. Due to the large sample size, all correlations are significant at the $*p < .05$ level.

Table 2
Means, SDs, and Correlations Among Occupation Personality and Job Zone Variables

	ES	EX	O	A	C	Mean	SD
Emotional Stability						4.01	.40
Extraversion	.75					3.51	.49
Openness	.45	.54				3.74	.42
Agreeableness	.77	.81	.37			3.96	.41
Conscientiousness	.55	.57	.83	.44		4.09	.30
Job Zone	.27	.40	.73	.25	.67	3.06	1.17

Note. $N = 772$. O*NET Personality (Work Styles) range: 1-5. O*NET Job Zone range: 1-5. Due to the large sample size, all correlations are significant at the $*p < .05$ level.

Table 3
Occupation Personality Means and SDs across Job Zones

	ES mean	EX mean	O mean	A mean	C mean
Job Zone 1	3.64 (.37)	3.13 (.41)	3.10 (.33)	3.72 (.33)	3.60 (.26)
Job Zone 2	3.90 (.37)	3.34 (.41)	3.43 (.32)	3.86 (.34)	3.87 (.25)
Job Zone 3	4.08 (.37)	3.51 (.45)	3.81 (.26)	4.00 (.41)	4.15 (.21)
Job Zone 4	4.08 (.40)	3.67 (.50)	4.03 (.25)	3.97 (.40)	4.27 (.17)
Job Zone 5	4.14 (.42)	3.83 (.45)	4.15 (.22)	4.15 (.48)	4.35 (.18)
Regression					
Job Zone	B = .094*	B = .166*	B = .259*	B = .086*	B = .174*
	R ² = .073	R ² = .159	R ² = .526	R ² = .061	R ² = .452

Note. Mean (SD). O*NET Personality (Work Styles) range: 1-5. O*NET Job Zone range: 1-5. * $p < .05$.

Table 4
Means, SDs, and Correlations Among Person-Occupation Personality Fit and Job Zone Variables

	ES	EX	O	A	C	OC	B5	Age	Mean	SD
ES fit									1.07	.80
EX fit	.12*								1.03	.77
O fit	.09*	.14*							1.20	.87
A fit	.22*	.12*	.09*						1.04	.78
C fit	.13*	.07*	.35*	.06*					1.19	.87
OC fit	.14*	.13*	.69*	.10*	.69*				1.80	.93
B5 fit	.47*	.40*	.44*	.42*	.45*	.66*			2.99	1.04
Age	.01	.03*	-.10*	.05*	-.08*	-.06*	-.03*		2.97	1.94
Job Zone	-.00	.08*	-.23*	.08*	-.28*	-.23*	-.13*	.26*	2.31	.98

Note. $N = 18,544$. OC fit = Openness-Conscientiousness Mahalanobis Distance fit. B5 fit = Big Five Mahalanobis Distance fit. Age coded as 1819=0, 2021=1, 2223=2, 2425=3, 2627=4, 2829=5, 3031=6, 3233=7, 3435=8. O*NET Job Zone range: 1-5. Lower fit value = better fit. * $p < .05$.

Table 5
Job Zone Means and SDs across Age Categories

Age	Job Zone Mean	Job Zone SD
1819	1.78	.77
2021	1.99	.83
2223	2.21	.90
2425	2.43	.99
2627	2.57	1.03
2829	2.59	1.03
3031	2.60	1.02
3233	2.64	.99
3435	2.60	1.00

Note. O*NET Job Zone range: 1-5.

Table 6
Individual Big Five Fit across Age Categories

Age	ES fit	EX fit	O fit	A fit	C fit
1819	1.06 (.80)	1.00 (.75)	1.41 (.93)	.97 (.74)	1.35 (.90)
2021	1.07 (.79)	1.01 (.74)	1.31 (.91)	1.00 (.77)	1.29 (.90)
2223	1.05 (.79)	1.02 (.74)	1.21 (.87)	1.01 (.78)	1.20 (.87)
2425	1.06 (.79)	1.04 (.77)	1.17 (.86)	1.05 (.78)	1.15 (.84)
2627	1.07 (.81)	1.06 (.79)	1.13 (.85)	1.06 (.77)	1.12 (.84)
2829	1.06 (.80)	1.05 (.78)	1.12 (.84)	1.08 (.80)	1.14 (.86)
3031	1.10 (.81)	1.05 (.81)	1.10 (.84)	1.09 (.80)	1.13 (.88)
3233	1.10 (.80)	1.06 (.83)	1.10 (.84)	1.11 (.83)	1.03 (.81)
3435	1.09 (.78)	1.11 (.83)	1.10 (.86)	1.08 (.79)	1.08 (.87)

Note. Mean (SD). Lower fit value = better fit.

Table 7
Linear Mixed Model Regressions: Age Predicting Emotional Stability Fit

Fixed Effects		Model 1	Model 2
Intercept	₀₀	1.062* (.009)	1.047* (.011)
Age	₀₁		.005* (.002)
Random Effects		Model 1	Model 2
Intercept	₀₀	.356	.356
Residual	₂	.272	.272
Model Fit Statistics			
	AIC	37404.51	37401.73
	Log Likelihood Ratio ² (1)		4.78*
	R ²		.00

Note. Estimate (SE). ICC=.57. Age coded as 1819=0, 2021=1, 2223=2, 2425=3, 2627=4, 2829=5, 3031=6, 3233=7, 3435=8. Lower fit value = better fit. * $p < .05$.

Table 8
Linear Mixed Model Regressions: Age Predicting Extraversion Fit

Fixed Effects		Model 1	Model 2
Intercept	₀₀	1.036* (.008)	1.010* (.012)
Age	₀₁		.009* (.003)
Random Effects		Model 1	Model 2
Intercept	₀₀	.198	.198
Residual	₂	.394	.393
Model Fit Statistics			
	AIC	38005.30	37997.42
	Log Likelihood Ratio ² (1)		9.88*
	R ²		.001

Note. Estimate (SE). ICC=.33. Age coded as 1819=0, 2021=1, 2223=2, 2425=3, 2627=4, 2829=5, 3031=6, 3233=7, 3435=8. Lower fit value = better fit. * $p < .05$.

Table 9
Linear Mixed Model Regressions: Age Predicting Openness Fit

Fixed Effects		Model 1	Model 2
Intercept	₀₀	1.216* (.010)	1.332* (.013)
Age	₀₁		-.041* (.003)
Random Effects		Model 1	Model 2
Intercept	₀₀	.274	.277
Residual	₂	.496	.486
Model Fit Statistics			
	AIC	42792.22	42633.90
	Log Likelihood Ratio ² (1)		160.32*
	R ²		.01

Note. Estimate (SE). ICC=.36. Age coded as 1819=0, 2021=1, 2223=2, 2425=3, 2627=4, 2829=5, 3031=6, 3233=7, 3435=8. Lower fit value = better fit. * $p < .05$.

Table 10
Linear Mixed Model Regressions: Age Predicting Agreeableness Fit

Fixed Effects		Model 1	Model 2
Intercept	₀₀	1.028* (.009)	.988* (.012)
Age	₀₁		.014* (.003)
Random Effects		Model 1	Model 2
Intercept	₀₀	.267	.265
Residual	₂	.336	.336
Model Fit Statistics			
AIC		37088.88	37063.60
Log Likelihood Ratio	₂₍₁₎		27.28*
R ²			.002

Note. Estimate (SE). ICC=.44. Age coded as 1819=0, 2021=1, 2223=2, 2425=3, 2627=4, 2829=5, 3031=6, 3233=7, 3435=8. Lower fit value = better fit. * $p < .05$.

Table 11
Linear Mixed Model Regressions: Age Predicting Conscientiousness Fit

Fixed Effects		Model 1	Model 2
Intercept	₀₀	1.195* (.009)	1.295* (.013)
Age	₀₁		-.036* (.003)
Random Effects		Model 1	Model 2
Intercept	₀₀	.266	.270
Residual	₂	.492	.483
Model Fit Statistics			
	AIC	42758.09	42640.04
	Log Likelihood Ratio ² (1)		120.04*
	R ²		.008

Note. Estimate (SE). ICC=.35. Age coded as 1819=0, 2021=1, 2223=2, 2425=3, 2627=4, 2829=5, 3031=6, 3233=7, 3435=8. Lower fit value = better fit. * $p < .05$.

Table 12
Openness-Conscientiousness Mahalanobis Distance Fit and Big Five Mahalanobis Distance Fit across Age Variables

Age	OC Fit	B5 Fit
1819	1.93 (.91)	3.06 (1.04)
2021	1.88 (.92)	3.04 (1.03)
2223	1.80 (.93)	2.98 (1.04)
2425	1.79 (.93)	2.98 (1.04)
2627	1.75 (.93)	2.97 (1.04)
2829	1.75 (.95)	2.96 (1.05)
3031	1.74 (.94)	2.96 (1.04)
3233	1.74 (.95)	2.96 (1.06)
3435	1.73 (.97)	2.96 (1.07)

Note. Mean (SD). OC Fit = Openness-Conscientiousness Mahalanobis Distance. B5 = Big Five Mahalanobis Distance. Lower fit value = better fit.

Table 13

Linear Mixed Model Regressions: Age Predicting Openness-Conscientiousness Mahalanobis Distance Fit

Fixed Effects		Model 1	Model 2
Intercept	₀₀	1.814* (.011)	1.877* (.014)
Age	₀₁		-.023* (.003)
Random Effects		Model 1	Model 2
Intercept	₀₀	.457	.458
Residual	₂	.415	.411
Model Fit Statistics			
	AIC	42349.62	42296.38
	Log Likelihood Ratio ² (1)		55.25*
	R ²		.003

Note. Estimate (SE). ICC=.52. Age coded as 1819=0, 2021=1, 2223=2, 2425=3, 2627=4, 2829=5, 3031=6, 3233=7, 3435=8. OC fit = Openness-Conscientiousness Mahalanobis Distance. Lower fit value = better fit. * $p < .05$.

Table 14
Linear Mixed Model Regressions: Age Predicting Big Five Mahalanobis Distance Fit

Fixed Effects		Model 1	Model 2
Intercept	₀₀	3.001* (.013)	3.041* (.015)
Age	₀₁		-.015* (.003)
Random Effects		Model 1	Model 2
Intercept	₀₀	.784	.738
Residual	₂	.305	.350
Model Fit Statistics			
	AIC	42706.84	42343.18
	Log Likelihood Ratio ² (1)		367.66*
	R ²		.001

Note. Estimate (SE). ICC=.72. Age coded as 1819=0, 2021=1, 2223=2, 2425=3, 2627=4, 2829=5, 3031=6, 3233=7, 3435=8. B5 fit = Big Five Mahalanobis Distance. Lower fit value= better fit. * $p < .05$.

Table 15
Emotional Stability, Extraversion,, and Openness Initial Fit compared to Post-Change Fit across Consecutive Age Variables

Consecutive Age Variables	ES initial fit (stay)	ES initial fit (change)	ES post-change fit	EX initial fit (stay)	EX initial fit (change)	EX post-change fit	O initial fit (stay)	O initial fit (change)	O post-change fit
1819-2021 change	1.09 (.84)	1.07 (.81) ^{ns}	1.12 (.81)*	1.01 (.73)	.99 (.76) ^{ns}	1.01 (.73) ^{ns}	1.34 (.92)	1.44 (.94) ^{ns}	1.30 (.92)*
2021-2223 change	1.13 (.83)	1.05 (.78) ^{ns}	1.06 (.80) ^{ns}	.93 (.68)	1.01 (.73)*	1.05 (.76) ^{ns}	1.21 (.85)	1.32 (.91)*	1.23 (.88)*
2223-2425 change	1.08 (.82)	1.04 (.79) ^{ns}	1.05 (.79) ^{ns}	1.00 (.75)	1.03 (.73) ^{ns}	1.02 (.76) ^{ns}	1.11 (.84)	1.24 (.86)*	1.20 (.85) ^{ns}
2425-2627 change	1.07 (.83)	1.05 (.78) ^{ns}	1.08 (.81) ^{ns}	1.02 (.76)	1.05 (.78) ^{ns}	1.07 (.79) ^{ns}	1.10 (.82)	1.17 (.86)*	1.11 (.83)*
2627-2829 change	1.06 (.80)	1.04 (.81) ^{ns}	1.04 (.78) ^{ns}	1.06 (.78)	1.06 (.79) ^{ns}	1.04 (.79) ^{ns}	1.13 (.85)	1.12 (.82) ^{ns}	1.10 (.83) ^{ns}
2829-3031 change	1.08 (.78)	1.10 (.80) ^{ns}	1.07 (.79) ^{ns}	1.04 (.79)	1.07 (.81) ^{ns}	1.05 (.81) ^{ns}	1.05 (.82)	1.10 (.85) ^{ns}	1.10 (.79) ^{ns}
3031-3233 change	1.14 (.84)	1.12 (.83) ^{ns}	1.07 (.73) ^{ns}	1.05 (.81)	1.13 (.85) ^{ns}	1.18 (.92) ^{ns}	1.07 (.79)	1.16 (.87) ^{ns}	1.12 (.89) ^{ns}

3233-3435 change	1.12 (.73)	1.21 (.96) ^{ns}	.95 (.83)*	1.17 (.86)	1.09 (.84) ^{ns}	1.21 (.88) ^{ns}	1.01 (.84)	1.14 (.86) ^{ns}	1.06 (.84) ^{ns}
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Note. Mean (SD). Lower fit value = better fit. * $p < .05$, ns = non-significant.

Table 16
Agreeableness and Conscientiousness Initial Fit compared to Post-Change Fit across Consecutive Age Variables

Consecutive Age Variables	A initial fit (stay)	A initial fit (change)	A post-change fit	C initial fit (stay)	C initial fit (change)	C post-change fit
1819-2021 change	1.02 (.70)	.96 (.75) ^{ns}	1.00 (.77) ^{ns}	1.43 (.94)	1.37 (.92) ^{ns}	1.27 (.88)*
2021-2223 change	.97 (.81)	.99 (.75) ^{ns}	1.04 (.78)*	1.24 (.87)	1.31 (.98) ^{ns}	1.21 (.88)*
2223-2425 change	1.07 (.81)	1.02 (.78) ^{ns}	1.04 (.77) ^{ns}	1.16 (.84)	1.21 (.88) ^{ns}	1.17 (.86) ^{ns}
2425-2627 change	1.08 (.78)	1.05 (.78) ^{ns}	1.04 (.75) ^{ns}	1.08 (.81)	1.17 (.86)*	1.13 (.84) ^{ns}
2627-2829 change	1.07 (.80)	1.05 (.78) ^{ns}	1.07 (.79) ^{ns}	1.07 (.83)	1.12 (.82) ^{ns}	1.14 (.87) ^{ns}
2829-3031 change	1.13 (.80)	1.09 (.80) ^{ns}	1.06 (.79) ^{ns}	1.08 (.85)	1.18 (.92) ^{ns}	1.13 (.89) ^{ns}
3031-3233 change	1.16 (.83)	1.09 (.75) ^{ns}	1.10 (.78) ^{ns}	.95 (.81)	1.27 (.91)*	1.00 (.87)*

3233-3435 change	1.13 (.75)	1.12 (.88) ^{ns}	1.11 (.88) ^{ns}	.94 (.89)	1.02 (.76) ^{ns}	1.14 (.88) ^{ns}
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Note. Mean (SD). Lower fit value = better fit. * $p < .05$, ns = non-significant.

Table 17
Openness-Conscientiousness and Big Five Initial Fit compared to Post-Change Fit across Consecutive Age Variables

Consecutive Age Variables	OC initial fit (stay)	OC initial fit (change)	OC post-change fit	B5 initial fit (stay)	B5 initial fit (change)	B5 post-change fit
1819-2021 change	1.92 (.87)	1.95 (.90) ^{ns}	1.86 (.94)*	3.06 (1.03)	3.07 (1.02) ^{ns}	3.04 (1.04) ^{ns}
2021-2223 change	1.76 (.87)	1.89 (.94)*	1.84 (.95)*	2.97 (1.02)	3.03 (1.04) ^{ns}	3.03 (1.04) ^{ns}
2223-2425 change	1.73 (.92)	1.84 (.92)*	1.81 (.93) ^{ns}	2.96 (1.09)	2.99 (1.02) ^{ns}	2.98 (1.01) ^{ns}
2425-2627 change	1.71 (.91)	1.79 (.92)*	1.75 (.92) ^{ns}	2.91 (1.05)	3.00 (1.04) ^{ns}	2.97 (1.04) ^{ns}
2627-2829 change	1.70 (.93)	1.75 (.91) ^{ns}	1.75 (.94) ^{ns}	2.89 (1.04)	2.98 (1.04) ^{ns}	2.97 (1.02) ^{ns}
2829-3031 change	1.66 (.92)	1.76 (.97) ^{ns}	1.74 (.90) ^{ns}	2.93 (.99)	2.99 (1.01) ^{ns}	2.91 (1.02)*
3031-3233 change	1.62 (.86)	1.82 (.98) ^{ns}	1.72 (1.02) ^{ns}	2.87 (.96)	3.09 (1.14) ^{ns}	3.05 (1.12) ^{ns}

3233-3435 change	1.57 (.98)	1.74 (.97) ^{ns}	1.71 (1.00) ^{ns}	2.85 (.99)	2.98 (1.18) ^{ns}	2.97 (1.21) ^{ns}
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Note. Mean (SD). OC fit = Openness-Conscientiousness Mahalanobis Distance. B5 fit = Big Five Mahalanobis Distance. Lower fit value = better fit. * $p < .05$, ns = non-significant.

Table 18

Linear Mixed Model Logistic Regressions: Individual Big Five Time 1 fit Predicting Occupation Change (0, 1)

Fixed Effects		Model 1	Model 2	Odds Ratio
Intercept	00	.696* (.026)	.700* (.026)	
ES fit	01		-.048* (.025)	.95
EX fit	02		.013 (.024)	1.01
O fit	03		.123* (.026)	1.13
A fit	04		-.079* (.024)	.92
C fit	05		.101* (.026)	1.11
Random Effects		Model 1	Model 2	
Intercept	00	.480	.481	
Model Fit Statistics				
	AIC	13588.53	13527.32	
	Log Likelihood Ratio $\chi^2(5)$		71.21*	

Note. Estimate (SE). Fit variables were standardized. Residual variance fixed to $\frac{2}{3}$ in logistic regression. Occupation change coded as 0 = stay (no change), 1 = change. Lower fit value = better fit. * $p < .05$.

Table 19
Linear Mixed Model Logistic Regressions: Openness-Conscientiousness Time 1 fit Predicting Occupation Change

Fixed Effects		Model 1	Model 2	Odds Ratio
Intercept	.00	.696* (.026)	.698* (.026)	
OC fit	.01		.146* (.024)	1.16
Random Effects		Model 1	Model 2	
Intercept	.00	.480	.479	
Model Fit Statistics				
AIC		13588.50	13553.00	
Log Likelihood Ratio	$\chi^2(1)$		37.53*	

Note. Estimate (SE). OC fit = Openness-Conscientiousness Mahalanobis Distance. OC fit variable was standardized. Residual variance fixed to $\frac{2}{3}$ in logistic regression. Occupation change coded as 0 = stay (no change), 1 = change. Lower fit value = better fit. * $p < .05$.

Table 20
Linear Mixed Model Logistic Regressions: Big Five Time 1 fit Predicting Occupation Change

Fixed Effects		Model 1	Model 2	Odds Ratio
Intercept	₀₀	.696* (.026)	.697* (.026)	
B5 fit	₀₁		.090* (.024)	1.09
Random Effects		Model 1	Model 2	
Intercept	₀₀	.480	.480	
Model Fit Statistics				
AIC		13588.50	13576.40	
Log Likelihood Ratio	$\chi^2(1)$		14.14*	

Note. Estimate (SE). B5 fit = Big Five Mahalanobis Distance. B5 fit variable was standardized. Residual variance fixed to $2/3$ in logistic regression. Occupation change coded as 0 = stay (no change), 1 = change. Lower fit value = better fit. * $p < .05$.

Table 21
Linear Mixed Model Regressions: Occupation Change Predicting Time 2 Fit Improvement

Fixed Effects	ES fit improvement	EX fit improvement	O fit improvement	A fit improvement	C fit improvement	OC fit improvement	B5 fit improvement
Intercept ₀₀	.000 (.011)	.000 (.012)	.000 (.013)	.000 (.011)	.000 (.013)	.000 (.013)	.000 (.012)
Occupation Change (0,1) ₀₁	-.011 (.014)	-.007 (.014)	.066* (.016)	-.021 (.014)	.058* (.017)	.040* (.016)	.022 (.015)
Model Fit Statistics							
Log Likelihood Ratio ² (1)	.70	.27	16.08*	2.35	12.14*	6.77*	2.21

Note. Estimate (SE). OC fit = Openness-Conscientiousness Mahalanobis Distance. B5 fit = Big Five Mahalanobis Distance. Occupation change coded as 0 = stay (no change), 1 = change. Time 2 fit improvement = Time 1 fit – Time 2 fit. Higher fit improvement value = improved fit. * $p < .05$.

Table 22
Lateral Gravitation— Individual Big Five Initial Fit compared to Post-Change Fit across RIASEC Change Variables

RIASEC Change Variables	ES initial fit	ES post- change fit	EX initial fit	EX post- change fit	O initial fit	O post- change fit	A initial fit	A post- change fit	C initial fit	C post- change fi
0 code change	1.09 (.80)	1.08 (.79) ^{ns}	1.02 (.75)	1.03 (.77) ^{ns}	1.23 (.88)	1.20 (.87) ^{ns}	1.04 (.79)	1.04 (.77) ^{ns}	1.22 (.85)	1.18 (.85)
1 code change	1.04 (.79)	1.04 (.80) ^{ns}	.99 (.74)	1.01 (.76) ^{ns}	1.27 (.88)	1.16 (.84)*	.99 (.73)	1.01 (.76) ^{ns}	1.28 (.91)	1.17 (.88)
2 code change	1.02 (.79)	1.06 (.81) ^{ns}	1.06 (.77)	1.11 (.80)*	1.24 (.89)	1.13 (.86)*	1.01 (.75)	1.07 (.80)*	1.20 (.88)	1.13 (.89)
3 code change	1.03 (.79)	1.14 (.83)*	1.14 (.84)	1.17 (.83) ^{ns}	1.36 (.96)	1.22 (.94)*	1.11 (.87)	1.25 (.89)*	1.33 (.95)	1.21 (.93)

Note. Mean (SD). * $p < .05$, ns = non-significant.

Table 23

Lateral Gravitation— Openness-Conscientiousness and Big Five Initial Fit compared to Post-Change Fit across RIASEC Change Variables

Paired RIASEC Change Variables	OC initial fit	OC post-change fit	B5 initial fit	B5 post-change fit
0 code change	1.82 (.91)	1.81 (.93) ^{ns}	2.99 (1.03)	2.96 (1.03) ^{ns}
1 code change	1.87 (.94)	1.80 (.95)*	3.05 (1.04)	3.00 (1.04)*
2 code change	1.82 (.93)	1.75 (.96)*	3.00 (1.04)	3.02 (1.06) ^{ns}
3 code change	1.94 (.98)	1.87 (1.03) ^{ns}	3.20 (1.09)	3.21 (1.10) ^{ns}

Note. Mean (SD). * $p < .05$, ns = non-significant.

Table 24
Linear Mixed Model Regressions: Interest Code Change Predicting Post-Change Fit

Fixed Effects	ES post-change fit	EX post-change fit	O post-change fit	A post-change fit	C post-change fit	OC post-change fit	B5 post-change fit
Intercept ⁰⁰	1.069* (.013)	1.015* (.013)	1.181* (.014)	1.015* (.013)	1.168* (.014)	1.788* (.016)	2.95* (.017)
Interest Code Change (0-3) ⁰¹	.006 (.008)	.036* (.009)	-.011 (.009)	.039* (.008)	-.002 (.010)	-.002 (.010)	.044* (.010)
Model Fit Statistics							
Log Likelihood Ratio ²⁽¹⁾	.45	17.19*	1.50	21.97*	.06	.03	21.16*

Note. Estimate (SE). OC fit = Openness-Conscientiousness Mahalanobis Distance. B5 fit = Big Five Mahalanobis Distance. Interest code change coded as 0 = 0-code change, 1 = 1-code change, 2 = 2-code change, and 3 = 3-code change. * $p < .05$.

Table 25
Vertical Gravitation— Individual Big Five and Cognitive Ability Means by Job Zone Change

Job Zone Change	Emotional Stability mean	Extraversion mean	Openness mean	Agreeableness mean	Conscientiousness mean	Cognitive Ability mean
-2	5.08 (1.32)	4.79 (1.46)	5.75 (1.04)	5.25 (1.16)	5.75 (1.16)	99.63 (12.16)
-1	5.03 (1.36)	4.74 (1.37)	5.51 (1.18)	5.07 (1.19)	5.67 (1.23)	97.80 (12.05)
0	4.99 (1.32)	4.68 (1.36)	5.45 (1.17)	4.98 (1.17)	5.68 (1.21)	97.76 (12.67)
+1	4.99 (1.38)	4.71 (1.32)	5.49 (1.18)	4.98 (1.17)	5.74 (1.22)	98.51 (11.54)
+2	5.04 (1.28)	4.87 (1.42)	5.53 (1.14)	4.97 (1.16)	5.80 (1.09)	101.88 (11.27)
+3	4.97 (1.16)	4.92 (1.33)	5.42 (1.21)	4.95 (1.19)	5.72 (1.09)	103.30 (12.56)
F(5, 4516)	.31	2.56*	1.85	1.71	1.12	16.39*

Note. Mean(SD). Ten Item Personality Inventory (TIPI) range: 1-7. * $p < .05$.

Table 26

Vertical Gravitation— Individual Big Five and Cognitive Ability Means by Job Zone Change for participants with Initial Job Zone 2

Job Zone Change	Emotional Stability mean	Extraversion mean	Openness mean	Agreeableness mean	Conscientiousness mean	Cognitive Ability mean
-1	5.03 (1.43)	4.57 (1.41)	5.57 (1.21)	5.08 (1.20)	5.65 (1.30)	95.01 (12.03)
0	4.98 (1.33)	4.66 (1.35)	5.47 (1.18)	4.94 (1.16)	5.66 (1.20)	96.31 (12.28)
+1	5.05 (1.38)	4.76 (1.37)	5.52 (1.16)	5.00 (1.17)	5.84 (1.14)	99.46 (11.09)
+2	5.07 (1.24)	4.98 (1.40)	5.61 (1.08)	4.94 (1.13)	5.82 (1.07)	103.55 (10.55)
+3	5.19 (1.14)	4.74 (1.49)	5.48 (1.29)	5.08 (1.25)	5.75 (1.20)	103.41 (12.15)
F(4, 2265)	.71	4.27*	1.00	1.02	2.61*	31.46*

Note. Mean(SD). Ten Item Personality Inventory (TIPI) range: 1-7. * $p < .05$.

Table 27
Vertical Gravitation— Individual Big Five and Cognitive Ability Means by Final Job Zone

Final Job Zone	Emotional Stability mean	Extraversion mean	Openness mean	Agreeableness mean	Conscientiousness mean	Cognitive Ability mean
1	4.98 (1.41)	4.59 (1.43)	5.48 (1.21)	5.07 (1.21)	5.66 (1.29)	94.84 (12.64)
2	4.97 (1.35)	4.67 (1.34)	5.47 (1.18)	4.95 (1.17)	5.67 (1.21)	96.55 (11.87)
3	5.01 (1.34)	4.79 (1.36)	5.47 (1.16)	5.02 (1.18)	5.77 (1.16)	100.39 (11.09)
4	5.09 (1.23)	4.97 (1.32)	5.53 (1.12)	5.03 (1.13)	5.81 (1.10)	104.84 (11.28)
5	5.07 (1.20)	4.69 (1.37)	5.48 (1.16)	5.01 (1.19)	5.67 (1.19)	105.48 (12.00)
F(4, 4575)	1.20	9.21*	.32	1.74	2.67*	101.15*

Note. Mean(SD). Ten Item Personality Inventory (TIPI) range: 1-7. * $p < .05$.

Table 28

Vertical Gravitation—Regressions of Individual Big Five, Cognitive Ability, and Initial Job Zone Predicting Job Zone Change and Final Job Zone

Predictors	Regression 1: Job Zone	Predictors	Regression 2: Final Job Zone
<i>Block 1</i>		<i>Block 1</i>	
Initial Job Zone	-.581* (.016)	Emotional Stability	.008 (.016)
<i>Block 2</i>		Extraversion	.047* (.015)
Initial Job Zone	-.632* (.016)	Openness	-.028 (.016)
Emotional Stability	.002 (.015)	Agreeableness	-.021 (.016)
Extraversion	.043* (.014)	Conscientiousness	.061* (.016)
Openness	-.029* (.015)	Cognitive Ability	.296* (.015)
Agreeableness	-.027 (.014)	R ²	.09*
Conscientiousness	.064* (.015)		
Cognitive Ability	.231* (.014)		
R ²	.28*		

Note. Estimate (SE). Big Five and cognitive ability variables were standardized. Unstandardized coefficients are reported for all regressions. Job Zone range = -2 to +3. Initial Job Zone range = 1 to 5. Final Job Zone range = 1 to 5. * $p < .05$.

Table 29

Linear Mixed Model Regressions: Occupation Job Zone Predicting Person-Occupation Personality Fit

	ES fit	EX fit	O fit	A fit	C fit	OC fit	B5 fit
Fixed Effects							
Intercept ₀₀	1.046* (.015)	.929* (.015)	1.415* (.016)	.955* (.015)	1.478* (.016)	2.037* (.017)	3.083* (.019)
Occupation Job Zone ₀₁	.015* (.007)	.074* (.007)	-.176* (.008)	.062* (.007)	-.221* (.008)	-.182* (.008)	-.078* (.008)
Model Fit Statistics							
Log Likelihood Ratio ² (1)	4.31*	97.58*	461.05*	72.58*	726.64*	485.73*	91.57*

Note. Estimate (SE). OC fit = Openness-Conscientiousness Mahalanobis Distance. B5 fit = Big Five Mahalanobis Distance. Occupation Job Zone range 1-5 was recoded to 0-4 so the intercept values represent mean fit in Job Zone 1. * $p < .05$.