Careers and Romantic Partnerships: Three Essays on Gender Differences in Role Centrality, Wage Gap, and Life Satisfaction in Dual-Career Couples

Quinn M. Coen

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Date 12/12/2019
Careers and Romantic Partnerships: Three Essays on Gender Differences in Role Centrality, Wage Gap, and Life Satisfaction in Dual-Career Couples

Quinn M. Coen

A dissertation submitted in partial fulfillment of the requirements for the degree of

Ph.D. in Business

2019

Program Authorized to Offer Degree:
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Dedication

(Not listed hierarchically)

To Grandma, for all the proofreading

Mike, for all the caloric and emotional support

Sonar, for spending 100% of the countless hours by my side

Holland, for being my best friend

The Fab Four

Cabin Crew

And last, but far from least,

to the fearless woman who’s middle name is tenacity:

you are a bright shining object,

you can do anything,

you are my hero.
Acknowledgments

The author wishes to express sincere appreciation to her dissertation committee, Bentley University, the Bentley Center for Women and Business, Patty, Jay, and Stephanie for all their support in this endeavor.
Abstract

Careers and Romantic Partnerships: Three Essays on Gender Differences in Role Centrality, Wage Gap, and Life Satisfaction in Dual-Career Couples

Quinn M. Coen

Chair of the Supervisory Committee:
Professor, Management, Susan Adams
Management Department

The purpose of this dissertation is to improve understanding of the dual-career couple phenomenon by exploring gender differences in levels of role centrality and partner support, life satisfaction, and the gender wage gap. I engage with these areas of inquiry through three research papers.

Paper 1 is motivated by the research question: Are there differences between female and male individuals in dual-career couples in levels of value placed on particular role centrality (i.e. family, career, others such as church/hobbies) or levels of perceived social support in their partnerships? This replication study investigates a series of hypotheses based on past research studies assessing these gender differences.

In Paper 2, I conduct an exploratory quantitative analysis to evaluate the research question: What variables influence overall life satisfaction for partners in dual-career couples, and how do these variables relate to one another? I utilize Classification and Regression Tree (CART) modeling, a method within machine learning, to uncover the
variables with high impact in this context from among a much larger set of variables than could be assessed with more traditional statistical methods.

In Paper 3, I pursue the following research question: What portion of the unexplained gender wage gap can role centrality levels explain? I use variance decomposition to analyze the amount of the unexplained gender wage gap that can be accounted for with the role centrality psychological construct.

This dissertation will make several contributions. Theoretically, it advances academic inquiry of theories of economics and theories of gender applied to interactions of dual-career couples. It also explores meaningful variables for those in these relationships such as life satisfaction, role centrality/role salience, and relationship specific social support. Finally, it investigates how these variables and theories relate to the gender wage gap. Empirically, this dissertation engages in replication methods to extend and refine our understanding of the structures and mechanisms at play within dual-career couples. It also advances quantitative analysis of romantic partnership dynamics for working couples by applying machine learning methodology to develop a new empirical perspective that complements existing research. Finally, I uncover a meaningful connection between level of role centrality and income. For practitioners, this dissertation contributes by seeking better understanding of the impact variables organizations or couples may be able to alter to improve their partnerships, satisfaction, and income.
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Chapter 1: Introduction

This dissertation is motivated by interest in both the gender wage gap and dual-career couple phenomenon. Specifically, I focus on considering the individual, dyadic, and societal level variables associated with career and romantic partnership outcomes for women and men. I am spurred by the findings of both Cooke (2006) and Hook (2006), that suggest societal level policies have significant lasting normative impact on relationships and careers. I am also motivated by Killewald and Gough (2010), whose findings indicate a non-linear statistical relationship between wives’ earning and housework time. I draw from this work their focus on unveiling non-linear relationships in variables relevant to individuals in dual-career couples thriving.

The overarching objective of this dissertation is to improve understanding of the dual-career couple phenomenon by exploring gender differences in levels of role centrality and partner support, life satisfaction, and the gender wage gap. I am specifically interested in individual satisfaction, social support provided in partnerships, role centrality, gender, and income as they relate to this population. The key dependent variables in this dissertation are life satisfaction, partner support, role centrality levels, and income. The key independent variables are gender, relationship satisfaction, and role centrality levels.

In my first paper, I explore several of the aforementioned variables as I examine gender role theory and gendered relationship interactions. The dual-career couple phenomenon was perceived by researchers of the 1980s to hold the promise of a tremendous step toward true gender equality, but now, over 30 years later, the distance from that objective remains (Hertz, 1986; Lachance-Grzela & Bouchard, 2010). Gender
inequality is holding the world back (Woetzel et al., 2015). Understanding the underlying structures and mechanisms perpetuating this inequality is necessary for creating successful interventions. However, there are empirical gaps in the literature. Foundational understanding of dual-career couples is based on studies and data that are now decades old, and, like much social science research, lacks replication. Replication is an important means of testing theory to acquire knowledge of underlying structures and mechanisms that “are only contingently related to observable empirical events” (Tsang & Kwan, 1999, p. 762).

In my second paper I employ machine learning to explore objective and subjective characteristics to question how these variables impact individual life satisfaction for members of dual-career couples. Life satisfaction is a very active research area but suffers from two empirical gaps that I will address here. First, the topic of life satisfaction for individuals in dual-career couples is relevant to a significant portion of the population (Barnet, 2005), but life satisfaction has infrequently been the outcome variable in research on dual-career partnerships. Second, existing research is also limited in either detail or breadth by traditional statistical methods (Galletta, 2016). Machine learning can be used to get around these limitations to compliment and extend our understanding of predictor variables (Haughton et al., 2010; Galletta, 2016; Shalizi, 2006).

In the final paper of this dissertation I further investigate two variables: role centrality and income. From the analysis in paper 1, I find gender differences in the levels of centrality of three types of roles: family, career and other. From the analysis in paper 2, I find that levels of role centralities (family and career) presented themselves as
significant predictors of overall life satisfaction for individuals in dual-career couples. Income is surprisingly not among the variables the CART algorithm selected for the tree. I explore the research question: What portion of the unexplained gender wage gap can role centrality levels explain? As the gap between male’s and female’s human capital characteristics have dramatically narrowed or reversed over time (Blau & Kahn, 2017) and progress toward closing the gender wage gap has slowed nearly to a halt (Vagins, 2018), a theoretical gap has arisen in the gender wage gap literature. As a result, a better understanding of the factors influencing the unexplained gender wage gap is critical to inform efforts to move the needle toward equality. This paper extends the potentially fruitful stream of research analyzing the ability of psychology theories and constructs to explain parts of the unexplained gap (Blau & Kahn, 2017).

These three papers connect and complement each other in several ways. These connections are displayed in Figure 5 and Table 24. First, all three papers feature role centrality and gender as key variables of interest. Beyond these, the thread that ties paper 1 to paper 2 is the partner support construct, first as a dependent variable in paper 1, and then as an independent variable in paper 2. The additional primary link between paper 2 and paper 3, income, acts in these roles in the reverse order, first as an independent variable in paper 2 and later as the dependent variable in paper 3. All papers are linked with a common dataset, ensuring that the definition and measurement of these variables match throughout this dissertation. Furthermore, examining a consistent dataset was necessary to be able to ultimately pull together conclusions from all three studies in a meaningful way. These papers complement each other by utilizing a variety of methods. Since all statistical methods offer various strengths and limitations, selecting methods
with opposing strengths and weaknesses improves understanding of the variables in this research area from a variety of statistical perspectives.

My work sits squarely in the interdisciplinary field of organizational behavior, and draws upon psychology, sociology, social psychology, family science, machine learning, and economics literature as well as management research. Within management, my research questions align with the careers, gender and diversity, and organizational behavior spheres. Investigating life satisfaction, partner support, and income for individuals in this population is rooted in the continually evolving collection of theories of economics and of gender. These include new home economics, resource bargaining, gender relations theory, and the offspring of theories and hypotheses built from this collection.

Dual-career couples are the majority family structure in the USA today (Barnett, 2005), and examinations of their experiences, particularly their successes, are broadly relevant to a wide audience. Accuracy and usefulness of this collection of hypotheses and theories are a matter of debate, and I believe further research is necessary to check the relevancy of past findings and continue to move this topic of study forward. This dissertation draws together a broad array of theories from organization studies, psychology, sociology, and economics to enhance knowledge of how members of dual-career couples are impacted by elements of money and status. These three papers most substantially add to academic discourse in the following areas: dual-career couples, life satisfaction, social support, role centrality, and the gender wage gap. The results of the studies presented in this dissertation confirm the continued relevancy of gender role
theory, challenge and extend the limited understanding of gender differences in partner social support, and extend the application of role centrality theory.
Chapter 2: Paper 1 – Role Centrality and Perceived Partner Support in Dual-Career Couples: A Replication Study

My first paper is a replication study evaluating the research question: Are there differences between female and male individuals in dual-career couples in levels of value placed on particular role centrality (i.e. family, career, others such as church/hobbies) or perceived partner support?

The dual-career couple phenomenon was perceived by researchers of the 1980s to hold the promise of a tremendous step toward true gender equality, but now, over 30 years later, the distance from that objective remains (Lachance-Grzela & Bouchard, 2010; Hertz, 1986). As the thread of logic goes, achieving gender equality in the home is a critical step to achieving gender equality in the work place and society at large because of the practical impact on females availability to concentrate on a career outside of the home, a necessary shift in work culture to accommodate shared family responsibilities for all workers, and the cultural shift from the perception of females as a subordinate sex. The dual-career couple phenomenon seemed to indicate a social shift toward the in-home equality objective.

Present disparities in gender ratios in political and business leadership positions, board of director appointments, and the gender wage gap are sufficient evidence alone to observe the persisting lack of equality between males and females in the workforce. As of Sept. 1, 2019, Women make up only 5.4% of S&P 500 CEOs, 21.2% of S&P 500 board seats (Catalyst, 2019), and as of 2016 earned on average 80% of an equivalent male’s salary (Vagins, 2018). In the U.S., the gender gaps in human capital factors observed in
the past have largely diminished to insignificance (Blau & Kahn, 2017). Progress toward equality has stagnated in recent years (Warner, 2017), and better understanding of the underlying structures and mechanisms impacting the persistence of gender inequality have been called for (Blau & Kahn, 2017; Lachance-Grzela & Bouchard, 2010).

There are many reasons workforce parity between men and women is a desirable aim, but the simplest come down to dollars and cents. In a 2015 report, it was estimated that the global economy would rise up to $28 trillion if women were to gain economic parity with men by the year 2025 (Woetzel et al., 2015). As a benchmark, this amount is equal to the annual GDPs of the U.S.A. and China combined (Woetzel et al., 2015). Cultural attitudes are one of the three elements identified in the report as requiring critical shifts in order for the women’s potential to be achieved (Woetzel et al., 2015). A better understanding of the structures and mechanisms associated with these attitudes and linked behaviors is vital for the development of effective interventions. Role centrality and social support are two of structures/mechanisms that can help us understand the hampering of the dual-career couple phenomenon in gender equality in the workforce.

Role centrality is the level of importance one ascribes to a particular life role (Bagger & Li, 2012). Levels of career centrality, family centrality, or role centrality outside of these spheres have each been linked to a variety of variables, such as family-to-work or work-to-family conflict, family and job satisfaction, marital satisfaction, and boundary management among others (Bagger & Li, 2012; Bagger, Reb, & Li, 2014; Bhowon, 2013; Capitano, DiRenzo, Aten, & Greenhaus, 2017; Carlson & Kacmar, 2000; Carr, Boyar, & Gregory, 2007; Cinamon & Rich, 2002; Kossek, Ruderman, Braddy, & Hannum, 2012; Powell & Greenhaus, 2010; Xie, Shi, & Ma, 2017). Some research
findings suggest that men rank higher than women on career centrality (Cinamon & Rich, 2002; Mauno & Kinnunen, 2000, Parusaraman, Greenhaus & Granrose, 1992), women rank higher than men on family centrality (Cinamon & Rich, 2002; Mauno & Kinnunen, 2000, Parusaraman et al., 1992), and men are more likely than women to rank highly on centrality of roles outside of these spheres (Kossek et al., 2012; Snir & Harpaz, 2002), but other studies have presented some inconsistency or pointed out significant limitations with these results (Bhowon, 2013; Pas, Eisinga, & Doorewaard, 2016; Powell & Greenhaus, 2010). Given evidence linking particular role centrality to career success and other career outcomes such as organizational identification and intention to leave (Lobel & Clair, 1992; Liu & Ngo, 2017; Mayrhofer, Meyer, Schiffinger, & Schmidt, 2007), gender differences in certain role centrality levels may indirectly impact gender differences in career success and should thus be better understood.

It is generally accepted that the interpersonal needs met by social support are required for one’s well-being (Cutrona, 1996), that close ties, such as intimate partners, are most influential on how a person thrives (Feeney & Collins, 2015), and that there is a direct correlation between the closeness of a relationship and the level and number of types of support (Gottieb & Bergen, 2010). Overall social support and social support from specific relationships, such as partner support explored in this study, have been found to be two independent constructs (Davis, Morris, & Kraus, 1998; Pierce, Sarason & Sarason, 1991). Noting this distinction is particularly relevant when considering gender differences within dual-career couples. Women have been found to perceive lower levels of support from their romantic partners (Clavé, 2017; Turner & Marino, 1994; van Daalen et al., 2005) and also experience greater levels of depression compared to men,
even though they have higher levels of perceived support overall, and are more likely than man to seek out support (Ross & Mirowsky, 1989; Thoits, 1995; Turner & Marino, 1994). However, limitations in these conclusions call for additional investigation (Clavél et al., 2017; Olson & Shultz, 1994; van Daalen et al., 2005). Given findings that partner support indirectly impacts career success (Ocampo, Restubug, Liwag, Wang, & Petelczyc, 2018), similar to role centrality, gender differences in support from a romantic partner may indirectly impede female career success and should thus be better understood.

Management and psychology literature, two umbrellas under which this research falls, both suffer from a dearth of replication studies due in part to a bias against publishing replications in journals of these disciplines (Tsang & Kwan, 1999), and research on dual-career couples is no exception to this inadequacy. This issue creates situations in which “the findings of a single uncorroborated study” are accepted and widely disseminated, but then their validity may much later be called into question (Tsang & Kwan, 1999, p. 759). “Evidence provided by a single innovative study can be rather flimsy and is subject to the idiosyncrasies of the study” (Tsang & Kwan, 1999, p. 771).

Researchers have argued the importance of replication in testing theory, as well as identified and defined several different types of replication studies (Aguinis & Solarino, 2019; Tsang & Kwan, 1999). The purpose of a conceptual replication “is to assess whether findings, in terms of constructs and relationships among constructs, can be replicated using different methodological procedures and instruments” (Aguinis & Solarino, 2019, p. 7). In this type of replication, a study examines the same population
and theory as past research (Tsang & Kwan, 1999). A generalization and extension study is another type of replication study in which the same theory or constructs are investigated, but different research procedures and a different population are employed (Tsang & Kwan, 1999). This type of study tests the external validity and generalizability of past research findings, and in fact it has been argued that “the more imprecise the replication, the greater the benefit to the external validity of the original finding, if its results support the finding” (Tsang & Kwan, 1999, p. 768).

Rather than replicating a single previous study, this paper utilizes generalization and extension replication to examine a series of stylized facts generated from separate original studies. These source studies were selected based on two overarching criteria: 1) the empirical evidence of the stylized fact is representative of the general consensus or majority of the available evidence regarding that stylized fact within the literature, and 2) the source study aligns as closely as possible to this study with regards to the research questions, constructs and variables explored, measurement tools, sample populations, and recency of the data. By design, generalization and extension studies draw strength from their variation from source studies, particularly differences in context or methods, and none of the source studies cited match this study in all respects.

This paper responds to the call for management research aimed at establishing empirical regularities, by investigating phenomena we observe (Helfact, 2007). This paper contributes to theory and the literature on dual-career couples, social support, and role centrality in a couple of ways. First, “replication is one important way of testing theories”, and this paper’s findings will help to support or discredit theories (Tsang & Kwan, 1999, p. 762). “The growth of knowledge is a cumulative process in which new
insights are added to the existing stock of knowledge” (Tsang & Kwan, 1999, p. 771). Second, given the fragmented nature of research in this area (Tsang & Kwan, 1999), bringing together related findings from several studies serves for replication serves to strengthen a foundation for theory development from a scattered pattern of research (Tsang & Kwan, 1999). This paper pulls together both scattered findings and disconnected but related streams of research for testing and theory development. According to Tsang and Kwan (1999):

Without bold and imaginative conjectures, no scientific theories can be generated, and no scientific breakthroughs are possible. Without attempts at refutation (i.e. critical testing of theories), we cannot separate a search for truth from wild conjectures, and no scientific progress is possible. (p. 775)

Furthermore, per gender role theory, gender differences are context dependent and subject to change (Eagly & Wood, 2011), thus continual examination is necessary for academia to maintain an accurate understanding of the practice of doing gender, such as provided in this study.

This paper sets out to assess the presence of gender differences in role centrality levels in three life spheres or in partner support (both overall and specifically in the realm of domestic chores) among individuals in dual-career relationships. See Figure 1 for visualization.

This paper will proceed as follows. First, I will review relevant literature and present hypotheses based on this literature to be retested. Next, a discussion of methods, the instruments and measurements and the statistical treatment is presented, followed by a section on the results. Then a discussion of the findings and limitations is followed by concluding remarks.
Literature

The central constructs and variables of interest to the proceeding hypotheses are role centrality, partner support, and gender. The discussion of literature proceeds as follows. First, I will offer a brief review gender role theory, the dual-career couple phenomenon, and the background theories regarding the inner workings of these relationships. Next, I touch upon theory and research findings on the construct of role centrality, its shared roots with gender role theory, and articulate a corresponding set of hypotheses to be tested in this area. Finally, I discuss the foundational theories and literature on social support generally and in romantic partnerships specifically and present the hypotheses developed from this literature.

**Gender role theory and dual-career couples.**

A dual-career couple is a committed romantic partnership of two career-orientated individuals (Rapoport & Rapoport, 1971) and presently the dominant family structure in America (Barnett, 2005). There is an important distinction made between general work or jobs and the concept of careers, “which require a high degree of commitment and which have a continuous developmental character” (Rapoport & Rapoport, 1971, p.519). In the late 1970s and 1980s the media heralded the “new” dual-career couple as the modern ideal marital relationship, while still other outlets scrutinized the dangers and challenges of this lifestyle (Gilbert, 1994, Hertz, 1986). In the academic realm, social scientists from the disciplines of psychology, sociology, anthropology, and economics have sought to analyze and explain the facets of this modern phenomenon. Today, the dual-career couple is the dominant family structure in America (Barnett, 2005), but the
true gender equality that seemed so imminent in the 1980s has yet to be achieved (Gilbert, 1994; Grunow et al., 2012).

Two types of theories have primarily been applied to understanding the division of labor and role ascription within dual-career couples: theories of economics and theories of gender. Grunow et al. (2012) concisely summarized three central theoretical mechanisms, which have been utilized iteratively in research on housework distribution:

- **Efficiency**, based on the complementary role specialization of husbands as earners and wives as homemakers (Becker, 1981); *economic dependency and resource bargaining*, where the spouse with greater earning power can refrain from doing housework (reviewed in Gupta, 2007); and *traditional gender norms and gender deviance neutralization*, according to which ‘femaleness’ is confirmed by doing housework and ‘maleness’ by avoiding it (Berk, 1985). (p. 291)

The mechanism of efficiency was derived from *new home economics* and *human capital theory*, which viewed the family as a collective unit with singular objectives (Gupta 2007). Although these theories justified the subordination of female partners as a result of fewer professional opportunities and lower wages compared to their husbands, marital arrangements in this view rely solely on relative productivity and thus these theories are fundamentally gender-neutral (Grunow et al., 2012). Resource bargaining is likewise gender-neutral, and research studies have supported this theory with findings that within couples with relatively equal incomes female partners’ housework participation decreases, while male partners’ participation increases (Carlson & Lynch, 2015).

However, other scholars have asserted that marriage is a gendered institution, and as such gender-neutral theories are ultimately inadequate (Bertrand et al., 2015). *Gender role theory* explains how society or culture socializes individuals into social roles, “prescribing different conducts, attitudes, and values for women and men” (Gustafson, 1998, p. 809; Ochsenfeld, 2014). Expectations of these roles are shared among members...
of a society and reproduced by socializing agents through rewards and sanctions (Eagly & Wood, 2011; Gustafson, 1998). Socializing agents operate all levels, such as mass media and school curriculum on the macro level, or family and peers at the micro level (Gustafson, 1998). Two key aspects of the concept of gender are that its socially constructed nature renders it subjective and dependent on time and place rather than static, and that it resides in social transactions not in the person themselves (Courtenay, 2000). However, individuals do internalize gender roles to varying extents, and thereby develop personal gender identities (Eagly & Wood, 2011).

Gender relations theory moved the analyst’s perspective past the limited view that based understanding and predictions on utilitarian assumptions and economic positions by placing “families in a social context larger than themselves” (Ferree, 2010, p. 425). In fact, it is the historical division in America between paid employment outside the home and unpaid housework from which the phrase gendered allocation of labor was derived (Lachance-Grzela & Bouchard, 2010). The gender display hypothesis presented by Brines (1994) (later clarified as compensatory gender display by Killewald and Gough (2010)) proposed that female relationship partners who contributed more than half of their family’s collective income would increase, rather than decrease, their hours of housework as a means of compensating for the gender-deviance of their economic position (Killewald & Gough, 2010). Killewald and Gough’s (2010) study findings contest the compensatory gender display hypothesis, asserting that, contrary to the theory, even wives with high-incomes relative to their husbands will decrease household work hours as income increases, though simply to a lesser degree than those starting from low-income positions. Also, they determined that “low-income wives are constrained to
perform domestic labor by their lack of financial resources, while high-income wives are constrained in spite of them” (Killewald & Gough, 2010, p20).

Per gender role theory, gender differences are context dependent and subject to change (Eagly & Wood, 2011), thus for academia to maintain an accurate understanding of the practice of gender continual examination, such as provided in this study, are necessary.

**Role centrality.**

The first set of hypotheses examine gender difference in role centralities. One’s level of role centrality is defined as the level of importance one ascribes to a particular life role (Bagger & Li, 2012). In this study I will explore three types of centralities: career (a.k.a. work), family, and other (any role outside of the career or family spheres).

“Individuals who are high on work centrality tend to believe that work plays a significant role in their life” (Bagger & Li, 2012, p. 475). This statement can also be used to define family and other centralities, such that individuals who are high on family centrality tend to believe that family plays a significant role in their life and individuals who are high on a role centrality beyond the career or family sphere tend to believe that role plays a significant role in their life.

Different researchers have linked the concept of role centrality to several constructs and theories including self-esteem, values, identity theory, role salience, and social identity theory, (Bagger & Li, 2012; Bagger, Reb & Li, 2014; Carlson & Kacmar, 2000; Carr et al., 2007; Eddleston, Veiga, & Powell, 2006; Liu & Ngo, 2017; Lobel & St. Clair, 1992; Lodahl & Kejner, 1965; Lu, Lu, Du, & Brough, 2016; Paullay, Alliger, Stone-Romero, 1994; Powell & Greenhaus, 2010; Xie, Shi, & Ma, 2017). Early research
exploring the concept of centralities focused on the work domain, with roots tracing back to Weber’s Protestant work ethic (Paullay et al., 1994). Dubin’s (1956) research showed for many that work was not a central interest in their lives and presented a study of central life interests (CLI). “Dubin’s research has demonstrated that although individuals may participate in several different social settings, only those settings where their CLI is located have significant psychological implications to them” (Bagger et al., 2014, p. 3). This development of the concept shed light on the existence of core human focus areas beyond work, however, the research setting remained the industrial workplace. In a subsequent related study, Lodahl and Kejner (1965) defined job involvement “as the degree to which a person’s work performance affects his self-esteem” (p. 25). Taking the definition of centrality of an ability as “the degree to which [an ability] affects self-esteem” (p.25), Lodahl posits that job performance will affect a worker’s self-esteem if it is central to the worker.

Identity theory (Stryker, 1987; Stryker and Serpe, 1982) considers the implications of how people identify with the many roles they occupy and recognizes that these identities will not be valued equally (Bagger et al., 2014; Powell & Greenhaus, 2010). Role centrality describes the level of value placed on different roles. Researchers that start from the concept of values, individuals’ basic convictions that are enduring and resistant to change (Rokeach, 1973), to explain role centrality describe it similarly as a means of value expression of individuals (Carlson & Kacmar, 2000; Carr, Boyar, & Gregory, 2007). In this same vein, the concept of “role salience refers to the psychological importance of a particular role in a person’s life” (Thoits, 1991, as cited in Eddleston et al., 2006, p. 438). The terms role centrality, role salience, and even role
involvement have been used fairly interchangeably within the literature (Gelb, 2014; Paullay et al., 1994). Identity salience as taken from social identity theory (Tajfel, 2010), varies only slightly from role salience, in that it “motivates attitudes and behavior in support of an identity” (Lobel & St. Clair, 1992, p. 1058). Essentially these are two facets of the same gem: Identity salience gets at the activation to engage and perform a role, whereas role centrality describes one’s psychological hierarchy of roles.

Family was the second role centrality to be considered in the literature. Work and family centrality have almost exclusively been assessed as two ends of the same spectrum, and analysis have been based on the assumption that these centralities are reciprocally tied. From this perspective, a high interest in one has been deemed sufficient information to interpret a low interest in the other (Carlson & Kacmar, 2000; Carr, Boyar, & Gregory, 2008; Lobel & St. Clair, 1992). However, Bagger and Li (2012) identify this assumption as a significant limitation to research in this area and point out theoretical and empirical findings that suggest these centralities are not mutually exclusive. Presumably as a result of Bagger & Li’s findings, more recent research has asserted that career and family centrality constructs “are considered as independent dimensions rather than as polar opposites, and people can assign equal or unequal importance to” these roles (Liu & Ngo, 2016, p. 113). Bhowon (2013) found that role salience levels were significantly positively correlated such that the higher the level of one role salience the more likely an individual also exhibits higher levels of the other role salience. Kossek et al. (2012) present the term dual-centricity to denote individuals with equally high levels of work and family centrality, while also acknowledging that other individuals may rate low on both work and family centrality and hold a primary identity outside of these two realms,
such as “hobbyists, athletes, or church or community volunteers” (p. 114), referred to in this paper as other centrality or a centrality beyond the career or family spheres.

With regard to the effects of role centrality levels, it is assumed based on theory that “individuals gain more meaning, purpose, and behavioral guidance as a result of enacting a role that is more central to their self-concept and that such gains contribute to greater psychological adjustment and less stress” (Martire, Stephens, & Townsend, 2000, p. 148). In a study examining this assumption by analyzing women’s’ levels of centrality of four roles (provider, mother, wife, and employee), Martire et al. (2000) found that centrality of all four roles positively related to greater life satisfaction, thus expanding on earlier research findings of the positive effects of greater career-centrality on well-being for both genders.

Based on traditional gender roles, males will exhibit higher career centrality than females because work is more central to the male identity (Bhowon, 2013; Eagly & Wood, 2011). Empirical findings have most often supported this understanding (Mauno & Kinnunen, 2000). Researchers also recently confirmed the connection of gender role orientation and role centrality in a Chinese sample of full-time employees, such that masculinity is positively related to career centrality (Liu & Ngo, 2017). A relationship between masculinity and career salience was found for both males and females, though the relationship was significantly stronger for men (Liu & Ngo, 2017). The strictness with which individuals are expected to adhere to traditional gender roles is thought to be on the decline (Eagly & Wood, 2011), and Eddleston et al.’s (2006) findings suggest that female managers have become freer to adopt traditionally male self-schemas (characterized by high career centrality and masculine characteristics), which aligns with
the social shift of the increase in female paid workforce participation. In one recent study of dual-career couples’ work and family role salience, no gender differences were found in either level of work role salience or family role salience (Bhowon, 2013).

The series of hypotheses presented assumes no change from past empirical findings. A rejection of these hypotheses would indicate potential shift in gender role practice within this population. (Source studies for hypotheses listed in Table 1.) Taken altogether, it seems as if the gender role association with regard to career centrality is shifting, but it appears likely that males continue to exhibit higher career centrality than females.

\[ HY1_0: \text{There is no statistically significant difference in career centrality scores between males and females} \]

\[ HY1_1: \text{There is a statistically significant difference in career centrality scores between males and females such that males will be higher on career centrality compared to females} \]

Traditional gender roles also suggest that females will exhibit higher levels of family centrality than males because family is more central to women’s identity (Bhowon, 2013; Eagly & Wood, 2011). Again, empirical findings have supported this understanding (Cinamon & Rich, 2002; Mauno & Kinnunen, 2000), and femininity was recently found to be positively related to family centrality (Liu & Ngo, 2017). Research has found male managers are more constrained than women to adopt gender schemas of the opposing gender (female self-schemas being high family centrality and feminine characteristics) (Eddleston et al., 2006). However, Powell and Greenhaus (2010) offer potentially contrasting findings to Eddleston et al. (2006) and Liu & Ngo (2017). They
found men and women in their sample of managerial professionals did not experience differing levels of work-family conflict, but individuals higher in family role salience did experience lower conflict (Powell & Greenhaus, 2010). Only weak linkage between sex and family role salience were found in this sample (Powell & Greenhaus, 2010), which could suggest that there may be populations in which one’s likelihood of presenting high levels of family centrality does not vary between males and females. Because this study only looked at family role salience and did not evaluate career role salience, a direct comparison of these results with the aforementioned studies that suggest comparatively less sex difference in career centrality relative to family centrality cannot be made. Again, there is inconsistency within the empirical evidence. Gender roles associated with family centrality could be shifting, but there is less evidence to suggest compared to career centrality. It seems most likely that females are still likely to exhibit higher family centrality than males.

\textit{HY2}_0: \textit{There is no statistically significant difference in family centrality scores between males and females}

\textit{HY2}_1: \textit{There is a statistically significant difference in family centrality scores between males and females such that females will be higher on family centrality compared to males}

Relative to the work centrality and family centrality literature, there is a dearth of empirical studies that measure role centrality beyond work and family spheres (Capitano et al., 2017; Kossek et al., 2012; Wilson, 2013). This significant gap in the literature is surprising given that one of the earliest centrality studies’ key finding was that 75% of industrial workers’ central life interests existed outside of work (no distinction between
family and non family interests outside of the workplace was made) (Dubin, 1956). Theoretically we know that “to become a salient part of individuals' overall self-concepts, these third(extra) roles must a) be integral to how individuals define themselves, b) create social ties with others within the role/domain, and c) specify a set of role-related activities, tasks, and/or duties” (Capitano et al., 2017, p. 102). Common non-career and non-family spheres in which one may hold a central identity are community volunteering, secondary employment, church, athletics, or hobbies (Capitano et al., 2017; Kossek et al., 2012).

The breadth of the individual/communal spectrum on which this varied collection of activities fall render it difficult to predict based on gender role theory alone whether one gender is more likely than the other to exhibit higher centrality of these non-career/non-family roles. Femininity is associated with attention to the needs of others (Liu & Ngo, 2017). The social service sector has, from its inception, been fueled by female unpaid labor (Outon, 2015), and in traditional western society charity work was seen as one of the limited acceptable activities ladies could engage in outside of the home (Prochaska, 1980). Based on these traditionally established norms, one might anticipate females to be more likely than males to exhibit high other centrality. However, hobbies and athletic pursuits are engaged upon generally for the benefit of the individual rather than a community, and thus align more closely with traditionally male gender role orientation characterized by independence (Liu & Ngo, 2017). Consistent with this communal vs. individual line of reasoning, medical research has found that elderly women derive the greatest decreases in mortality risk from social activities, whereas men benefit from solitary activities (Agahi & Parker, 2008).
One study to report gender data for a group with other centrality in their dataset (termed in the study nonwork-eclectics) found this cluster to be 61% male (Kossek et al., 2012). However, other centricity was not measured with its own instrument. Observations where categorized as matching the other-centric profile if both their work and family centrality scores were at least one standard deviation below the mean (Kossek et al., 2012). In a study comparing only work centrality and leisure centrality, across two samples 63% of leisure oriented individuals were male (Snir & Harpaz, 2002). There are some limitations in our ability to draw conclusions from this study for our purposes here. First, although Snir and Harpaz (2002) measured leisure orientation more directly than Kossek et al. (2012), the instrument they utilized required a delegation of 100 points across five life areas (leisure, community, work, religion, and family). Meaning that, just as Bagger and Li (2012) pointed out, role centralities are conceptualized in a zero sum fashion. Points allocated to one role deplete the points available to other roles. Furthermore, since this measure assessed three areas of other centrality separately (leisure, community, and religion), these results can’t directly compare to the construct under investigation here. However, of the five areas their instrument measures, leisure was ranked most important after family and work (Snir & Harpaz, 2002). In another study by the same authors, using the same instrument, leisure was rated on average in the range of 15.4 to 18.4 points higher than community or religion (Snir & Harpaz, 2005), which suggests that leisure dominates the other sphere with regards to role centrality. Despite the limitations in the available data, evidence points towards the potential existence of gender differences in other centrality scores, such that men appear more likely to exhibit higher level of centrality outside of work or the home.
HY3a: There is no statistically significant difference in other role centrality scores between males and females.

HY3b: There is a statistically significant difference in other role centrality scores between males and females such that males will be higher on other centrality compared to females.

**Partner support.**

Partner support as a concept falls under a larger umbrella concept known as social support. Social support has been a concept examined primarily within psychology and applied psychology research for several decades, with frequently cited foundational theorizing on human social needs and support systems developed in the 1970s (Caplan, 1974; Weiss, 1974). Most frequently, social support has been examined regarding its impact on health and wellness outcomes (Broadhead et al., 1983; Callaghan & Morrissey, 1993; Clavél, 2017; Coker, Watkins, Smith, & Brandt, 2003; Coyne & Downey, 1991; Cutrona, 1989; Cutrona & Russell, 1987; Feeney & Collins, 2015; Gottlieb & Bergen, 2010; Graham & Barnow, 2013; House, Landis, & Umberson, 1998; Leavy, 1983; Sarason et al., 1983; Schwarzer & Leppin, 1992; Uchino, 2004), and occasionally on the functioning of romantic relationships and perceptions of relationship quality (Barbee, 1990; Dehle et al., 2001; Perrone & Worthington, 2001).

Though scholars have debated if social support is something perceived or rather received and whether it comes into play day to day or rather only in times of stress, Cutrona (1996) established a definition that encompasses the spectrum of these discussions. She conceptualizes social support “as responsiveness to another’s needs and, more specifically, acts that communicate caring; that validate the other’s worth, feelings,
or actions; or facilitate adaptive coping with problems through the provision of information, assistance, or tangible resources” (p. 10). Present definitions, including this one, conceptualize social support through its functions, such as “emotional sustenance, self-esteem building, provision of information and feedback, and tangible assistance” (Cutrona & Russell, 1987, p. 37). In laymen’s terms, social support can be thought of as the output of our personal support systems.

The elements of social support have been broken down in several different ways within various literature. Weiss (1974) presented a six-part model of provisions of social relationships including: “reliable alliance (practical help), guidance (informational support), attachment (emotional support), social integration (belonging to a group of similar peers), reassurance of worth (esteem support), and opportunity to provide nurturance (providing support)” (Gottlieb & Bergen, 2010, p. 515). However, when drawing upon this model, later studies have not included the last provision, the opportunity to provide nurturance, in measurement instruments based on the justification the giving support is not a dimension of the support available to be received (Clavél, Cutrona, & Russell, 2017; Graham & Barnow, 2013).

Within the applied psychology literature, social support has been broken down into two components: emotional support (such as listening or providing empathy) and instrumental support (tangible assistance to address a problem) (Adams, King, & King, 1996; Kaufmann & Beehr, 1986). This breakdown aligns easily with Cutrona’s (1996) definition above. Acts “that validate the other’s worth, feelings, or actions” (Cutrona, 1996, p.10) would be categorized as emotional support, and acts that “facilitate adaptive coping with problems through the provision of information, assistance, or tangible
resources” (Cutrona, 1996, p.10) would logically be considered instrumental support. Four of Weiss’ (1974) six social provisions appear to be easily able to be categorized based on the emotional and instrumental dimensions, with attachment (emotional support) and reassurance of worth (esteem support) clearly aligning with emotional support, while reliable alliance (practical help) and guidance (informational support) matching the instrumental support concept.

Regarding the scholarly debate as to whether social support is something perceived or rather received, the distinction between measures of perceived versus measures of received support is of critical importance because research has only shown a moderate correlation between the results of these measures (Melrose, Brown, & Wood, 2015). Thus measures of perceived social support and measures of received social support do not assess identical constructs. Furthermore, “measures of received support correlate less strongly with physical and mental health outcomes than do measures of perceived social support” (Cutrona, 1996, p. 8). Melrose et al. (2015) found that the correlation between perceived and received measures was significantly strengthened when measures of received support incorporated assessment of how often the received support was needed.

It is generally accepted that the interpersonal needs met by social support are fundamental, or required for one’s well-being (Cutrona, 1996), which aligns with the copious research findings that suggest its significant impact on mental and physiological health. This paper draws upon this Cutrona’s (1996) comprehensive definition of social support (cited earlier in this section) in its discussion of support within dual-career partnerships.
While the foundations to this body of literature consider social support broadly across a spectrum of relationships, including professional relationships and communities, the branch of this research that looks specifically at support within romantic relationships is most relevant to this paper. Feeney and Collins (2015) theorized based on extant literature that “the presence or absence of support from close social ties (e.g. friends, family, intimate partners), and within relationships that are highly interdependent, is likely to be more influential than support from peripheral social ties” on how well a person thrives (p. 132). Similarly, in a series of studies, Cutrona and Russell (1987), found that dependent on context, the source of certain types of support significantly affected how beneficial that support was, meaning that some types of support needs cannot be sufficiently met by someone other than an intimate partner or vice versa. They found that the need for attachment, (“emotional closeness from which one derives a sense of security,” (p.40) deficits of which lead to emotional loneliness), was significantly linked to romantic partnerships, and not other types of relationships (Cutrona & Russell, 1987). Gottieb and Bergen (2010) asserted that despite the interrelationships between support types and sources, there is a direct correlation between the closeness of a relationship and the level and number of types of support.

According to Dehle et al. (2001) “not only is spousal support qualitatively different and sometimes superior to other types of support, but when crises occur the spouse is often the first person sought for support” (p. 308). Furthermore, “according to Berscheid [1994], a crucial dimension of how people evaluate their relationship with their intimate partner is whether or not that person will provide support when needed” (as cited in Cutrona, 1996). Finally, Pierce et al.’s (1991) empirical study also supports the need to
distinguish the relationship context of social support, because they found that “people’s beliefs concerning the availability for support within specific relationships are distinct from their general perceptions of available support” (p. 1037), and the conclusion that these are independent constructs was subsequently supported in later research (Davis, Morris, & Kraus, 1998).

Historical research has presented conflicting information regarding social support within marital relationships. In many studies from the 1970s and 1980s married men and women reported higher levels of support than other groups, but other studies found no such differences (Turner & Marino, 1994). House (1981) noted that having one or more stable relationships with others is a minimum condition for experiencing social support, and “being married usually defines the existence of one such relationship” (as cited in Turner & Marino, 1994, p. 196). Research on married couples have found that although higher ratings of perceived marital support adequacy do not correlate significantly with positive marital quality, perceptions of inadequate marital support do indicate negative quality of the relationship (Dehle et al. 2001).

Evidence of gender differences in perceived social support in general and within marital relationships specifically presents a complex picture. In general, research has shown that women are more likely than men to seek out social support to manage stress and report higher or equal levels of perceived social support compared to men (Ross & Mirowsky, 1989; Thoits, 1995; Turner & Marino, 1994). Although Turner & Marino’s (1994) findings align with this overall, they found that in the case of spouse/partner support men reported slightly higher levels of perceived support than women, although the difference was not statistically significant. Consistent with these findings, van Daalen
et al. (2005), in a study of dual-earner Dutch families, also found that men received greater social support from their spouses and women received greater support from colleagues, relatives, and friends. Further studies suggest that women tend to be better support providers than men, and men seek support primarily from their partner and derive greater health benefits from partnership than women (Taylor, 2011). According to Clavél (2017) within the heterosexual romantic couples in his study women were on average less satisfied with the support they received from their romantic partners. Although this finding was derived from a small sample of 55 couples from a student population and therefore might not generalize to workforce aged dual-career marital or cohabitating partnerships, this evidence is both recent and consistent with other research. Based on these data, the first hypotheses in this set test the following null and alternative hypotheses:

HY$_{40}$: There is no statistically significant difference in perceived levels of overall partner support between males and females

HY$_{41}$: There is a statistically significant difference in perceived levels of overall partner support between males and females such that males will be higher on overall partner support compared to females.

As mentioned previously, there a several types of support (i.e. emotional, informational, tangible assistance (Cutrona & Russell, 1987)). Specifically considering tangible support and incorporating the research indicating that despite equal participation in full-time employment, women continue to shoulder the majority of household responsibilities and caregiving duties (Eagly & Wood, 2011; Lachance-Grzela &
Bouchard, 2010), I would expect that domestic chore support would also exhibit gender differences.

HY50: There is no statistically significant difference in perceived levels of domestic chore partner support between males and females.

HY51: There is a statistically significant difference in perceived levels of domestic chore partner support between males and females such that males will be higher on domestic chore partner support compared to females.

Method

Sample.

A proprietary dataset is employed to test these hypotheses. The dataset was produced from a survey focused on couples that was collected by a Center at the author's institution. A professional services company was employed to administer the survey and collect responses from a random sample of 500 men and 500 women from across the United States. All survey participants were in or had been in committed long-term relationships (specified in the survey as marriage or any domestic partnership with a shared household) and held a minimum of an associate degree. These survey results do not present paired data, that is, the 500 men and 500 women were not in relationships with corresponding survey respondents. Only one member of each couple was surveyed.

During the initial data cleaning and coding process, 74 observations were removed from the original sample based on responses that indicated these survey

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1 This survey was funded by Bentley University’s Center for Women and Business. It was written by Dr. Susan Adams and conducted by Qualtrics in 2014.
participants were not in relationships meeting the specifications of a dual-career couple as a committed romantic partnership of two career-oriented individuals (Rapoport & Rapoport, 1971). Observations were eliminated if the available data indicated: one partner identified as a homemaker, or if the respondent indicated he or she was not currently employed and had no former job title. An additional 100 survey responses from individuals age 60+ and retired were eliminated for this analysis to keep the focus on the generations currently in the workforce. After making these modifications, 826 observations remained for analysis. Sex representation was almost perfectly equal, with 407 female survey respondents (49.2%). The majority of sample respondents (71.9%) have at least one child.

**Dependent variables and instruments.**

Table 3 contains the means, standard deviations, reliability coefficients, and item information for the dependent variables.

**Career Centrality.**

Career centrality was assessed using a scale adapted from Eddleston et al. (2006). Their instrument is an adaptation of “Lodahl and Kejner’s (1965) job involvement scale with the word career substituted for job” (Eddleston et al., 2006, p. 439) and the addition of one item based on Lobel and St. Clair’s (1992) Career identity salience scale. On a 7-point Likert scale respondents indicate their level of agreement with three statements (“A major source of satisfaction in my life has been my career,” “Most of the important things that have happened to me have involved my career,” “Most of my interests have been centered around my career,” 1 = strongly disagree, 7 = strongly agree). These responses
are averaged to establish the career centrality score (Eddleston et al., 2006). High scores indicate higher levels of career centrality.

Eddleston et al. (2006) and Lodahl and Kejner’s (1965) scales included an additional item (“I am very much involved personally in my career”), but the item was deemed unnecessary based on results of pilot studies\(^1\) that were conducted of the survey utilized here. The reliability of the three-item scale is strong (\(\alpha = .82\)), and closely compares to Eddleston et al.’s four-item scale (\(\alpha = .84\)).

Though titled differently as job involvement scale, the items in this measurement tool were also used in Mauno and Kinnunen’s (2000) study, whose findings provide empirical support for HY1.

**Family Centrality.**

Family centrality was assessed with the same three-item scale as Career centrality, with the word family taking the place of career. On a 7-point Likert scale respondents indicate their level of agreement with three statements (“A major source of satisfaction in my life has been my family,” “Most of the important things that have happened to me have involved my family,” “Most of my interests have been centered around my family,” 1 = strongly disagree, 7 = strongly agree). The Cronbach alpha for this instrument in the sample is .89. High scores indicate higher levels of family centrality.

These items were also included in Mauno and Kinnunen’s (2000) family involvement scale.

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\(^1\) This pilot survey was distributed to members of the International Association of Exhibitions and Events (IAEE) in October of 2013 and garnered 135 analyzable observations from voluntary respondents.
**Other Centrality.**

In order to take into consideration the possibility of centralities beyond career or family, other centrality was assessed with a single item measured. On a 7-point Likert scale respondents indicate their level of agreement with the statement: “A major source of satisfaction in my life has come from activities related to personal interests beyond work and family such as hobbies, reading, pets, exercise/personal care, time with friends, volunteer work, etc.,” (1 = strongly disagree, 7 = strongly agree). High scores indicate higher levels of role centrality beyond career or family.

**Partner Support.**

**Overall.**

Overall perceived partner support (labeled Partner Support-Overall in figures and tables) was measured with a three-item tool based on Heikkinen’s (2014) study results of the spousal roles of employed partners of highly successful managers. Each item examines a particular support action or area (“My current (or most recent) partner has shown support for my career by "being" supportive (e.g., as a discussion partner, expressing acceptance of new career opportunities for me, participating in my business-related social activities, helping presentation practices),” “My current (or most recent) partner has shown support for my career by helping me maintain a life beyond work (e.g., considering the impact of work assignments and promotions on family life before accepting them – both of us make decisions as a couple),” “My current (or most recent) partner has supported my life-related desires (e.g., personal time, time with friends, hobbies),”). On a 5-point Likert scale, respondents indicate the frequency at which they receive each type support (1 = never; 5 = All of the time) (α = .86).
Although many instruments have been used in research to assess the construct of social support, such as the Social Support Questionnaire (SSQ) (Sarason et al., 1983), the Social Provisions Scale (SPS) (Cutrona & Russell, 1987), and the ENRICHd Social Support Instrument (ESSI) (Mitchell et al., 2003), the instrument used here offers three particular benefits to this study. First, it is developed to be specifically contextually relevant to dual-career couples. Second, this tool enjoys the benefits of brevity, a quality of self-report scales strongly advocated for by Burisch (1984) for sake of discriminant validity and preventing boredom. Third, it addresses the perceived versus received social support measurement debate (Cutrona, 1996; Gottlieb & Bergen, 2010). As a self-report measure, the answers are a matter of the respondents’ perceptions, but items are answered with regard to frequency, which considers measurement of received support.

*Domestic chores.*

In addition to assessing overall partner support, a single-time instrument is used to measure tangible partner support in the form of domestic chore responsibility: “My current (or most recent) partner has shown support for my career by managing or taking care of most of the domestic chores (children, extended family, housekeeping.)” As articulated above, respondents indicated the frequency at which they receive support from their partner in the form of domestic chores on a 5-point Likert scale, (1 = never; 5 = All of the time). This variable is labeled *Partner Support-Domestic* in tables and figures.

As previously mentioned, social support has been broken down within the applied psychology literature into two components: emotional support (such as listening or providing empathy) and instrumental support (tangible assistance to address a problem) (Adams, King, & King, 1996; Kaufmann & Beehr, 1986). Although this item does
exhibit significant correlation to the measure of overall partner support (.739 coefficient) it is considered conceptually distinct in the literature. Confirmatory factor analysis of another instrument used to measure social support, the Social Provisions Scale (Cutrona & Russell, 1987), indicated the presence of distinct factors within the scale despite high correlations among these, meaning that the first-order subscales are distinct from the second-order overall combined scale measure (Gottlieb & Bergen, 2010). Analysis of the correlation matrix for the domestic chore measure and the three individual items within the partner support overall scale reveals the difference in the strength of the correlations among the three scale items and between those items and the domestic chore measure (Table 2).

**Independent variable.**

**Gender**.

Survey respondents were asked to select their gender from two options. The traditional binary designations of female or male were the only options presented, and the question was mandatory to proceed with the survey, so 100% of the sample declared one of these genders.

**Covariates.**

**Age.**

Respondent ages range from 21 to 75. The median age is 40 and an average age of 41.6, with a large standard deviation of 13.15 years. Age data within the sample does not

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1 Engaging in the extensive conversation surrounding the distinctions between biological sex and socially constructed gender is outside the scope of this project, but it is recognized that there is much to be said on this topic. In this dissertation self-reported sex is used as a proxy for gender, as is common practice in the role centrality/salience research area. See Liu and Ngo (2017) for an example.
adhere to a normal distribution and are significantly positively skewed (see histogram in Figure 2).

**Education.**

The survey targeted college educated individuals, thus “Do you have a college degree?” was an initial screening question, and “Associate degree” was the lowest level of education available for respondents to select. Respondents were asked to indicate their highest level of education (Associate degree = 2; Bachelor degree = 3; Master degree (including MBA) = 4; Professional doctorate (e.g. MD, DDS, EdD, Law, Engineering) = 5; Academic doctorate (PhD) = 6). In the cleaning and coding process, all terminal degrees (professional doctorate and academic doctorate) were combined to one category (=5) so that the variable is truly ordinal by education level.

**Partner education.**

When indicating the highest education level of their partners, respondents selected one of six options (High school or some college with no degree = 1; Associate degree = 2; Bachelor degree = 3; Master degree (including MBA) = 4; Professional doctorate (e.g. MD, DDS, EdD, Law, Engineering) = 5; Academic doctorate (PhD) = 6). Just as was done for the respondent education variable, all terminal degrees (professional doctorate and academic doctorate) were combined to one category (=5).

**Life Satisfaction.**

Life satisfaction was assessed with a single item measured on a 7-point Likert scale as supported in the literature (Cheung & Lucas, 2014; Cummins, 2005). Respondents rated their level satisfaction based on the following statement: ‘All things
considered, how satisfied are you with life as a whole?’ (very dissatisfied = 1; very satisfied = 7).

**Good Relationship.**

Respondents were asked about the quality of their relationship from their perspective. On a 5-point Likert scale, respondents ranked their agreement with the statements “My current (or most recent) partner and I have had a good relationship” (strongly disagree = 1 to strongly agree =5).

**Relationship history and parental status.**

Respondents in the dataset can be assumed to be fairly homogenous with regard to marital/partnership status because a qualifying question for participation was “are you or have you been in a committed relationship (i.e. marriage of any domestic partnership with a shared household),” thus the dataset excludes individuals who are single, not-cohabitating, never married. A variable to report the number of committed relationships, as defined above, respondents have been in is included. This variable is capped such that respondents selected from four options (1, 2, 3, 4 or more).

Respondents were also asked about their number of children including adoptions. The number of children variable is capped continuous (selections available: 0, 1, 2, 3, 4, 5 or more). The majority of sample respondents (71.9%) have at least one child, with an average of 1.46 children per household. A total of 210 individuals report having one child (25.42% of the sample), 240 have two children (29.06% of the sample), and 143 reported 3, 4, 5 or more children, collectively.
Employment status.

Respondents selected among five options to indicate current status of employment (Employed full-time, not including self-employment=1; Employed part-time, not including self-employment=2; Self-employed=3; Not employed=4; Retired=5).

Log of annual salary.

Consistent with the prior literature, the natural log of wages is taken as the dependent variable, as the “log transformation is used to address the high degree of skew present in individual earnings data” (Tharp et al., 2019, p. 8).

Within the survey data, annual gross salary is reported in categories and category mid-points are used to define a continuous variable, as done in past studies with categorical wage data (Chevalier, 2007). Respondents are asked to report the highest level of income they sustained for at least three consecutive years. Multiple choice options required respondents to select one for five annual salary ranges (Less than $100,000/year; $100,000-$250,000; $251,000-$500,000; $501,000-$1 million/year; or More than $1 million/year). Because of the small number of observations in the top category (N=4) these were combined with the category below it. Mid-points were assigned for the first four categories ($50k, $175K, $340k, and $750k).

Statistical treatment.

The data were analyzed using STATA/SE 13.0, SPSS Statistics 25, and Intellectus Statistics online statistical software. A multivariate analysis of covariance (MANCOVA) was conducted to assess if there were significant differences in the linear combination of the five dependent variables (Career Centrality, Family Centrality, Other Centrality, Partner Support-Overall, and Partner Support-Domestic Chores) and the levels of gender.
after controlling for seven covariates (Age, Education, Employment Status, # of Relationships, # of Children, Life Satisfaction, and the log of Annual Salary).

MANCOVA was selected as an appropriate statistical method to test these five hypotheses because of its ability to assess the differences in two or more scale dependent variables, as presented here, by a nominal independent variable with at least two levels, such as gender, while controlling for the effect of covariates (Intellectus statistics, 2019). A primary benefit of this method of analysis is that it “addresses the problem of inflating the Type I error rate that arises when making a series of t-tests of group means on several dependent measures” (Hair, Black, Babin, & Anderson, 2010, p. 671). Furthermore, the inclusion of covariates in the model can both help eliminate possible confounds in the analysis as well as reduce the error variability, which increases the ability to identify differences between groups (Intellectus statistics, 2019).

Assumptions.

Multivariate normality.

To assess the assumption of multivariate normality, the squared Mahalanobis distances were calculated for the model residuals and plotted against the quantiles of a Chi-square distribution (DeCarlo, 1997; Field, 2013). In the scatterplot, the solid line represents the theoretical quantiles of a normal distribution. Multivariate normality can be assumed if the points form a relatively straight line. The scatterplot for normality is presented in Figure 1. From observing this plot, I conclude that there is some level of violation of the assumption of normality due to left-skewedness. However, “violations of this assumption have little impact with larger sample sizes, [and] with moderate sample sizes, modest violations can be accommodated as long as the differences are due to
skewness and not outliers” (Hair et al., 2010, p. 686). Given the more than adequate sample size available here it is reasonable to proceed with the analysis despite this deviation from normality.

*Homogeneity of covariance matrices.*

To examine the assumption of homogeneity of covariance matrices, Box's M test was conducted. The results were significant based on an alpha of 0.01, $\chi^2(15) = 33.56, p = .004$, indicating that the covariance matrices for each group of gender were significantly different from one another. However, this test is known for its increased sensitivity to finding differences as the number of dependent variables or number of groups increases, thus increasingly conservative significance thresholds should be used to identify violation from this assumption (Hair et al., 2010). Given the moderate number of dependent variables used here and the insignificance of this p-value if a more conservative 0.1% is used as the threshold, as well as the fact that “in most situations the presence of relatively equal sample sizes among groups [i.e. larger group N / smaller group N <1.5] mitigates any violations in this assumption” Hair et al., 2010, p. 686), again it is reasonable to proceed with the analysis despite this deviation from multivariate homogeneity. (Group size difference here is 419/407=1.029.)

*Multivariate Outliers.*

To identify influential points in the model residuals, the mcd command in STATA/SE 13.0 was used to calculate the minimum covariance determinant estimator, a robust statistics version of Mahalanobis distances (Verardi & Dehon, 2010). These robust Mahalanobis distances were then compared to a $\chi^2$ distribution (Newton & Rudestam, 2012). An outlier was defined as any Mahalanobis distance that exceeds 20.52, the 0.999
quantile of a $\chi^2$ distribution with 5 degrees of freedom (Kline, 2015). There were zero observations detected as outliers.

**Absence of multicollinearity.**

A correlation matrix was calculated to examine multicollinearity between the dependent variables. All variable combinations had correlations less than 0.9 in absolute value, indicating the results are unlikely to be significantly influenced by multicollinearity, thus this assumption is met. The correlation matrix is presented in Table 4.

**Homogeneity of regression slopes.**

The assumption for homogeneity of regression slopes was assessed by rerunning the mixed model ANCOVA including interaction terms between each independent variable and covariate (Field, 2013; Stevens, 2009). If there are no significant interactions between an independent variable and a covariate, homogeneity of regression slopes is met. Every interaction between each independent variable and covariate was not significant based on an alpha of 0.05 and the assumption was met.

**Results**

The main effect for gender was significant, $F(5, 813) = 3.58, p = .003, \eta_p^2 = 0.02$, suggesting the linear combination of Career Centrality, Family Centrality, Other Centrality, Partner Support-Overall, and Partner Support-Domestic Chores was significantly different between the levels of gender after controlling for Age, Education, Employment Status, # of Relationships, # of Children, Life Satisfaction, and the log of Annual Salary.
All covariates except for age were significantly related to the five dependent variables (Career Centrality, Family Centrality, Other Centrality, Partner Support-Overall, and Partner Support-Domestic Chores) at the $p < .05$ level. Age was found to be significant at the $p < .10$ level ($p = .090$). Table 5 shows the results of the MANCOVA.

Post-hoc.

To further examine the effects of gender on Career Centrality, Family Centrality, Other Centrality, Partner Support-Overall, and Partner Support-Domestic Chores controlling for the covariates, an analysis of covariance (ANCOVA) was conducted for each dependent variable (Results in Table 6, Table 7, Table 8, Table 9, and Table 10). The first three ANCOVA analyses tested HY1, HY2, and HY3, respectively to determine whether there were significant differences in Career Centrality, Family Centrality, or Other Centrality by gender while controlling for Age, Education, Employment Status, # of Relationships, # of Children, Life Satisfaction, and the log of Annual Salary. Each of these were significant at the $p < .001$ level. The eta squared for each round to 0.01, indicating gender explains approximately 1% of the variance in Career Centrality, Family Centrality, or Other Centrality.

Marginal means for all five ANCOVAs are reported in Table 11. Examining the marginal means by gender for Career Centrality, we see that males in our sample do exhibit higher levels of career centrality relative to females, thus the null hypothesis for HY1 is rejected and the hypothesized direction is also supported. Repeating this process for Family centrality, females in our sample do exhibit higher levels of family centrality relative to males, so HY2 and the hypothesized direction is also supported. Moving to the data for Other Centrality, although the significance of the analysis indicated a rejection of
the null for HY3, females in our sample actually exhibit higher levels of other centrality relative to males, thus the direction of the third hypothesis is not supported.

The final two ANCOVAs for Partner Support, both overall and domestic chores, are not significant, \( p = .684 \) and \( p = .396 \), respectively, indicating that the differences between males and females was not significant for these variables controlling for Age, Education, Employment Status, # of Relationships, # of Children, Life Satisfaction, and the log of Annual Salary.

**Discussion and Limitations**

The results of the multivariate analyses presented here suggest the continued presence of gender differences in levels of career centrality (HY1), family centrality (HY2), and level of centrality for life roles beyond these realms (other centrality) (HY3). Consistent with Mauno and Kinnunen’s (2000) findings, males in this sample exhibited higher average levels of career centrality compared to females, and consistent with Cinamon and Rich’s (2002) findings, females in this sample exhibited higher average levels of family centrality compared with males. Theoretically, these findings align with gender role theory and suggest that societal gender norms have not yet shifted to a great enough degree to eliminate these differences.

In the case of other centrality (HY3), females were found to exhibit on average higher levels of centrality beyond the work or home life spheres relative to males. The ANCOVA model for other centrality as a whole explained substantially less than the ANCOVA models for career and family centrality (partial eta squared of .06 versus .2 and .17, respectively), and the direction of this difference was not as one would have anticipated based on Kossek et al. (2012) and Snir and Harpaz’s (2002) findings.
However, the empirical findings available in the research regarding centrality levels of roles outside of work/home is extremely limited and less clear cut compared to findings about career or family centrality. Therefore, this extends our understanding of how gender role theory plays out in this area of role centrality. Theoretically, the results suggest that the societal gender norms by which female engagement in non-paid activities (such as community involvement or charity work) is sanctioned, expected, or encouraged may still maintain an influence on centrality levels in the modern area.

In the cases of overall support received from one’s romantic partner and tangible domestic chores and childrearing support, the null hypotheses that no significant gender differences exist could not be rejected (HY4 and HY5). The failure to replicate findings supporting these stylized facts is arguably as important, if not more important than the findings that achieved replication, because the inability to find gender differences where researchers have in the past could be the result of any number of factors. The well-known publication bias for positive results, limits our understanding of phenomenon by over reporting significant findings and underreporting insignificant findings (Tsang & Kwan, 1999). While the two insignificant results for HY4 and HY5 do not assist in the establishment of empirical regularities (Helfact, 2007), they do contribute to the accumulation of knowledge in the social support research area.

Digging further into the details of these results, as reported earlier, even after controlling for a number of covariates, I find that roughly 1% of the variation in each of these three levels of centrality can be explained by differences between genders. Taking that information one step further, this also means that 99% of the variation in the levels of centrality for these roles cannot be explained by differences between genders. Thus, only
a very small portion of the variation in these levels is due to gender, with the other 99% of the variation due to the effects of other variables. Furthermore, in the case of overall and domestic chore partner support, gender cannot explain any significant amount of the variation. According to Barnett and Rivers (2004), there is much more variation within genders (so among women and among men – in particular those wielding varying degrees of power) than between women and men.

While replication is important to strengthen our understanding of a phenomenon, without thorough evaluative discussion, results such as these run the risk of perpetuating the between gender difference perspective. The findings presented here are insufficient to conclude that there are natural or base level differences between men and women in levels of centrality but do point to the presences of gender differences in centrality levels due to undefined driving forces. Per gender role theory, these differences are present due to gender socialization, but these genders roles can shift and vary across both time and societies. While these results align with that theory, it is nonetheless possible that there are theories of alternative or additional driving forces at play, such as evolutionary or biological justifications or economic rationalization.

Given the fact that gender explains relatively little of the variation in these three centrality levels, further discussion of the explanatory power of the controlled covariates is appropriate. Examining the impact of the covariates within the three significant post-hoc ANOVA models (for career centrality, family centrality, and other centrality), there are several relationships worth mentioning. In the career centrality model, all seven covariates are significantly related to level of career centrality. Number of relationships, education, employment status, life satisfaction, and log annual salary are significant at the
1% level \( p < .01 \), while age is significant at the 5% level \( p = .025 \), and number of children is significant at the 10% level \( p = .051 \). Life satisfaction, log annual salary, and education all have stronger explanatory power than gender, at 4.9%, 3.8% and 1.1%, respectively.

In the family centrality model fewer covariates are significant. Only number of relationships, number of children, and life satisfaction are significant to family centrality level, all at the 1% level \( p < .01 \). Life satisfaction again has the highest explanatory power, with 12.2% of the variation in family centrality level being accounted for by this variable. Number of children explains an additional 5.8%, while number of relationships explains just slightly more than gender at 1.09%. For other centrality, only number of children and life satisfaction are significant predictors, explaining 1.9% and 3.6% of the variation, respectively.

The fact that life satisfaction emerged as the variable with the highest explanatory power for each of the types of centrality lends support for the generalizability of Martire et al.’s (2000) findings of the positive relationship between levels of four different role centralities (provider, mother, wife, and employee) and life satisfaction. These findings suggest that people with higher life satisfaction also exhibit higher levels of role centralities in general. Because these sorts of data cannot be used for causal inferences, this relationship could exist in either direction, or be self-reinforcing such that higher life satisfaction leads people to be more into the things that they are into, which in turn contributes to higher life satisfaction.

However, it is also interesting to note that life satisfaction doesn’t explain the same degree of variation in centrality level for each type of role centrality. It seems likely
that this relates to past theorizing that only outcomes within the spheres that a person has relatively higher role centrality have significant psychological implications (Dubin, 1956; Bagger et al., 2014). It is possible that because this survey that produced the dataset used here focused heavily on life within romantic relationships, respondents were primed with the family sphere of life at the forefront of their minds when reporting overall life satisfaction. If that was the case, then it would make sense that the life satisfaction measure would be more strongly influenced by satisfaction in one’s home life, which would explain the stronger connection between this measure and family role centrality relative to the other types of centrality.

Like all studies of this type, the chance of omitted variable bias is one limitation of the analysis presented here. Causal relationships cannot be identified, and caution should be taken in making inferences based on these results. The data for this study was originally collected for a larger research project, and thus there are limitations with regard to the variables available for inclusion in this model. Further research with more detailed or extensive survey items, or longitudinal panel data would be able to overcome some of these limitations.

Another potential limitation is that there is not a definitive way to distinguish between individuals that are currently versus previously in relationship within the dataset. It could be argued that people reporting retrospectively on a relationship that has ended may provide different responses than people presently in a partnership. However, roughly half of our sample (49.94%) report they’ve never had a marriage or cohabitating relationship end. When analysis are rerun for only this portion of the sample, which we
can be fairly certain are presently in a relationship, the results are identical with regard to which variables are and are not significant, and the direction of statistical relationships.

The generalization and extension replication used in for this study present both strengths and limitations to the findings presented. Investigating these five stylized facts with a modern dataset provides a much needed check in on the empirical regularities within romantic couples. Where these findings are consistent with past literature (HY1 and HY2), they serve to enhance the confidence in these findings (Tsang & Kwan, 1999). Utilizing measurement tools with the same items, such as is done here with Mauno and Kinnunen’s (2000) study, supports the “internal consistency of the first study, as well as the validity and reliability of the measurement instrument” (Tsang & Kwan, 1999, p. 768). Whereas the generalization and extension piece of this study serves to benefit the external validity of past findings to a greater and greater degree as tools, procedures, and sample populations are more and more varied. One need only look at the stylized fact source table (Table 1) to understand the significant degree to which this study deviates from these sources in the aforementioned ways. Thus, the findings here support the external and internal (in one case) validity of past research findings of males’ higher average career centrality levels, and females’ higher family centrality levels.

However, the deviations from source study measurement tools, procedures, and sample populations present unfortunate limitations for the findings that are inconsistent with past research (HY3, HY4, HY5). As Tsang and Kwan (1999) have pointed out, as greater differences in these areas are introduced it becomes more and more difficult to pinpoint reasons that lie behind disconfirmation. The disconformity results presented in this study could be an outcome of societal changes or, in the case of support, the evolving
nature of romantic relationships, but these findings could also be a product of the differences in sampling and measurement tools. Further still, there is always at least some risk of type II errors in which results fail to reject the null hypothesis when in fact it is false. Therefore, further research is needed to investigate gender differences in other centrality, overall partner support and tangible support with household duties, ideally with the aim to identify within gender differentials and their sources. Research designs and analysis with the power to identify causal relationships, as well as moderation and mediation such as structural equation modelling would be an excellent next step to this academic conversation.

**Conclusion**

This replication and extension study aimed at exploring the stylized facts regarding gender differences in levels of role centralities and perceived partner support uncovered findings both consistent and inconsistent with these facts as they have been presented in past literature. The motivation for this inquiry lies in the need for better understanding of the structures and mechanisms that impact gender inequality. Variable relationships established in the literature suggest the constructs of role centrality and partner support are potential mechanisms that may be of particular assistance in understanding why the phenomenon of the dual-career couple has thus far failed to fulfill its prophecy as a driving force for gender equality in the workforce.

The findings presented in this study point to some degree of continued relevance of traditional gender roles impact on individual life role hierarchy with males’ stronger career identity and females’ stronger family identity present even within dual-career couples in the modern era. As generalization and extension replication results, these
findings serve to improve confidence in the continued relevance and validity of these stylized facts. Furthermore, logical inferences can be made regarding the question of the efficacy of dual-career phenomenon in bringing about social change. If these couples don’t exhibit substantive progress in the shedding of prescriptive gender role identities, insofar as those gender roles are a driving force to the perpetuation on gender inequality, then it is unsurprising that the mere existence of the dual-career phenomenon did little to move society toward that goal. However, further research comparing these between gender differences to the levels of variation within genders is needed to better interpret the relative significance of these findings.

On the other hand, the results of testing the three gender difference hypotheses found to be inconsistent with past literature (HY3, HY4, HY5) move academic understanding forward in different ways. While there was a small amount empirical evidence to suggest the presence of gender differences in levels of role centrality residing outside of the work or family life spheres (other centrality), such that men would be more likely to have higher centrality than women in this area, these conclusions were not the primary focus of past research, and the ways with which other centrality levels were assessed substantially different than the tool used here. It is possible that measuring this type of centrality directly and independently reveals different information from respondents than if it is gauged based on the low centrality in other life areas, or when respondents must indicate level of importance in different life areas in a zero sum fashion. It is also possible that the sample here, adult individuals in dual-career couples in the U.S., is different in this regard compared to the samples in past research (the Israeli
labor force that is probably quite different culturally, or U.S. based managers exclusively that might not be representative of population trends across more varied occupations).

However, the finding that females exhibit significantly higher levels of other role centrality relative to males can also be interpreted as further support for the relevance of traditional gender roles in this sample, based on the traditional links between charity and attention to the needs of community and femininity in western society. Although the ability to make inferences based on these findings is limited, they nonetheless contribute to the accumulation of knowledge and serve to pull together literature from a scattered pattern of research.

The interpretation of the partner support hypotheses findings (HY4, HY5) is likewise limited to similar speculation. For both overall partner support and tangible partner support with domestic labor there is insignificant evidence to reject the null hypotheses that these variables do not vary between genders. Taking into account the presence of inconsistent findings across various past studies, these findings point to a lack of empirical regularities regarding presence or direction of gender difference in partner support. As discussed above though, the reasons for these inconsistencies (difference in sampling, measurement, or other study parameters) cannot be pinpointed. To the extent that these findings may reflect true trends within the population, they could be helpful in ruling out gender differences in partner support as an explanation for the persistence of gendered professional outcomes. However, much further research in the spirit of the study presented here would certainly be necessary to verify or discredit such a conclusion.
As Tsang and Kwan asserted “without attempts at refutation […] we cannot separate a search for truth from wild conjectures” (p. 775). This study serves as one such attempt at refutation, and the findings presented strengthen some stylized facts while bringing others into question for further scrutiny. Equally beneficial to the creation of knowledge, this study pulled together findings from related but highly scattered research on role centralities, partner support, and dual-career couples. The nature of gender roles as ever evolving and changing call for regular investigation of both between genders and within gender differences across time and societal contexts as an up to date understanding of gender roles is critical to the utility of gender role theory to help explain phenomena.
Chapter 3: Paper 2 – Happily Ever After: Maximizing Life Satisfaction in Dual-Career Relationships

My second paper presents an exploratory quantitative analysis to evaluate the research question: What variables influence overall life satisfaction for partners in dual-career couples, and how do these variables relate to one another?

Happiness and life satisfaction are often used synonymously (Ackerman, 2018). If I say ‘I am happy’ that could mean a number of things. It could mean that I feel happy in that moment, that I’m pleased with an object or event I’m experiencing, or that I am experiencing contentment overall. Common English language is imprecise. Within academic literature types of happiness have been broken down into separate constructs. “Life-satisfaction is the degree to which a person positively evaluates the overall quality of his/her life as-a-whole. In other words, how much the person likes the life he/she leads” (Veenhoven, 1996, section 2.1). Life satisfaction is a key indicator of subjective well-being, “a broad construct that reflects a global evaluation of the quality of a person’s life as a whole” (Erdogan, Bauer, Truxillo, & Mansfield, 2012; Wortman & Lucas, 2016, p. 625).

Life satisfaction has often been used in studies as the operationalized measurement of happiness (Erdogan, Bauer, Truxillo, & Mansfield, 2012; Vanassche, Swicegood, & Matthijs, 2013), but has also been defined academically as a fleeting emotion, experienced in a moment or context and is considered comparatively narrower in scope (Ackerman, 2018). Life satisfaction, the “cognitive assessment of satisfaction with life circumstances” (Erdogan et al., 2012, p. 1039), rather than happiness in this narrower academic definition or the broader construct of subjective well-being, is what is
explored in this study, though all of these constructs are encompassed within the
dictionary definition of happiness.

In the management literature life satisfaction is most often employed as an
independent variable. In a business context, recent studies verify and reiterate the
intuitive conclusions and copious findings that link happiness and satisfaction to work
productivity (Oswald, Proto, & Sgroi, 2015; Halkos & Bousinakis, 2010), as well as link
life satisfaction to a variety of other outcomes such as employee turnover intentions or
mortality (Erdogan et al., 2012).

In the psychology and economic literatures life satisfaction is frequently
investigated as a dependent variable. For example, some studies have found there to be
no significant effect of weather on life satisfaction (a particular type of happiness) (Lucas
& Lawless, 2013), and that economic growth does not raise life satisfaction (Easterlin,
McVey, Switek, Sawangfa, & Zwieg, 2010), though joblessness, not income, does play a
significant role (Oswald, 1997). However, other studies present counter or inconclusive
evidence (Frijters, Haisken-DeNew, & Shields, 2004; Tsutsui, 2013).

Though many studies have looked at life satisfaction broadly across populations,
past research findings suggest the importance of context in studying life satisfaction
(Borooah, 2006; Vanassehe, Swicegood, & Matthijs, 2013). Marital status has been
shown to significantly influence life satisfaction, such that married individuals report
higher levels of life satisfaction than other groups (Galletta, 2016; Gustavson, Røysamb,
Borren, Torvik, & Karevold, 2016; Vanassehe et al., 2013) Indeed, literature
investigating life satisfaction in romantic partnerships have identified particular variables
of importance to this demographic, such as relationship quality (Diener & Diener
McGavran, 2008; Diener, Suh, Lucas, & Smith, 1999; Gere & Schimmack, 2013; Heller, Watson, & Ilies, 2004), which are not applicable to uncoupled portions of the population. Thus, examining the coupled population specifically enables the evaluation of variables with greater context relevance than studies of wider populations.

Dual-career couples are currently the dominant family structure in America (Barnett, 2005) and face challenges unique to this demographic (Bunker, Zubek, Vanderslice, & Rice, 1992; Sekaran, 1983). Therefore, focusing on this population allows for potentially more meaningful and specific findings relative national or global studies, which are still of interest to a large portion of the general population.

Aside from conflicting empirical results previously mentioned, there are a couple of tensions in the literature this paper seeks to address. First, despite the shared attention to life satisfaction as a variable of interest, the management and life satisfaction literatures have largely ignored each other, leaving a critical research gap (Erdogan et al., 2012). There is still avid inquiry to better understand the links between antecedents and individual satisfaction (Galletta, 2016). Next, as Galletta points out, the majority of studies identify correlations “based on estimations of standard parametric approaches such as OLS and ordered linear probit or logit regressions,” however, “these models have a limited power to uncover multiple structures in those data which would suggest heterogeneity in the reported happiness within certain groups of individuals” and are inappropriate to manage “nonlinear relations between regressors and the dependent variable” (p. 121).
This paper contributes to the lively area of research on life satisfaction by zooming in on the subset of the U.S. adult population in dual-career relationships and utilizing machine learning to conduct an exploratory analysis of the variables contributing to their life satisfaction. The use of statistical methodology beyond the common parametric techniques provides an alternative perspective to complement existing research (Galletta, 2016). In this analysis, demographic variables commonly reported to predict life satisfaction, aside from age, are not selected as relevant by the machine learning algorithm. Indicating that, when meaningful subjective measures are included in the analysis, demographic information such as income, education level, employment status, industry, gender, etc., do not surface as significant predictors of life satisfaction.

This paper contributes to both life satisfaction and dual-career couple research theoretically by inductively gathering information to be used to build better theories. The iterative process of data-driven science, as pursued here, pairs inductive method with deductive approaches to inform future hypothesis generation and theory creation (Tonidandel, King, & Cortina, 2018). Furthermore, it contributes by retesting with a new method previously identified variables to offer support or counter extant knowledge limited by publication bias. It contributes methodologically by being one of the first studies in this area to utilize machine learning to circumvent several major limitations of the traditional methods used in past studies, such as variable limitations and ease of identifying non-linear relationships. Finally, the disconnection of life satisfaction literature and management literature presents fertile but under cultivated ground, calling for research attention (Erdogan et al., 2012). This study contributes in practice to by
exploring the structures and mechanisms associated with life satisfaction for individuals in dual-career couples, a significant proportion of the working population. Given the links between life satisfaction and work outcome variables, such as job performance, organizational commitment and withdrawal (Erdogan et al., 2012), a better understanding of these mechanisms will assist employers in creation and prioritization of policies or programs to increase quality of performance and stave off negative outcomes.

This paper will proceed as follows. First, in the literature section I will start with a brief overview of the life satisfaction construct and the limited use of tree methods in this area. I then review relevant literature on life satisfaction in dual-career couples, synthesize these sections and articulate the case for using machine learning in this area. I then proceed to the methods section of this paper to describe the sample, instruments and variables, and statistical treatment. Finally, I present the model results, discussion and limitations, and conclusion sections.

**Literature**

The popular and academic interest in studying human life satisfaction and/or happiness is so vast that it is practically impossible to consider the full spectrum of published information in this area or accurately cite the origin of public interest. Despite the fact that available literature in this area would comprise countless volumes if compiled (Google scholar searches for “life satisfaction” and “happiness” identify nearly 3 million results collectively), interest persists unabated evidenced by over 16,600 academic publications on these topics in the first two months of 2019 alone. Although an exhaustive review of the literature on life satisfaction and happiness is beyond the scope of this project, I will first touch upon some key points of the extant literature in this area
that are relevant to the inquiry presented here and how decision trees, the machine learning technique selected for this exploratory study, have been used in this research area. Next, I will define the population of interest in a brief review of dual career couples, and touch upon some factors connected to their satisfaction that research has considered. The final area of the literature section presents a summary of the proceeding sections.

**Life satisfaction.**

Research findings suggest that there are two classes of variables that influence life satisfaction, stable internal characteristics and external factors, though there is much debate as to which of these classes takes priority, there is empirical evidence to support that both can be significant (Wortman & Lucas, 2016). According to Ackerman (2018), academic inquiry of how the mechanism with which one evaluates their level of life satisfaction is of greater interest than the previous debate. For example, Suikkanen (2011) posits a new Whole Life Satisfaction theory that states: “An agent is happy when a more informed and rational hypothetical version of her would judge that the agent’s actual life matches the best life-plan for her” (p. 149). Life satisfaction is subjective, determined by factors that are personally meaningful to the individual, and can only be accurately measured by subjective measurement tool, such as surveys (Ackerman, 2018). Borooah (2006) found that subjective measures supplemented significant objective factors when included in the model. The dataset explored in this study contains both objective and subjective variables, as well as instruments to assess the level of personal focus on key dimensions of life, including career, family, and beyond.

To my knowledge there have been few studies that have utilized tree methods to study research questions related to well-being or happiness. Diez-Pinol, Dolan, Sierra,
and Cannings (2007), used the CART algorithm to examine the organizational variables impacting well-being in the workplace. Hannak et al. (2012) used bagged decision trees, a multi-tree aggregate method, to explore the predictive capability of Twitter data to anticipate societal level sentiment patterns. Bogomolov, Lepri, and Pianesi (2013) created a random forest model to predict individual-level daily happiness from smartphone data, weather conditions, and personality traits. Galletta (2016) conducted a study most similar to the one presented here, in which he utilized the CART algorithm to explore the variables influencing life satisfaction for a sample of Italian citizens. Income level, employment status, and industry of employment were among variables Galletta found to be significant and are included in the study presented here. As mentioned previously and consistent with past research, Galletta also found marital status to play a positive central role in predicting a person’s happiness. The study presented here furthers this line of research by focusing in on this partnered population that has been shown to have higher than average likelihood of happiness, and explores whether intangible variables, such as partner support or relationship satisfaction, are significant to explaining variation in life satisfaction within this group.

**Dual-career couples.**

As previously defined in paper 1, Rapoport and Rapoport (1971) coined the phrase “dual career family” in 1969 and define the term as a family in which both partners pursue individual careers whilst maintaining a family life together. The distinction made between general *work or jobs* and the concept of *careers*, “which require a high degree of commitment and which have a continuous developmental character,” is important to this concept (Rapoport & Rapoport, 1971, p.519). A dual-career couple is a
committed romantic partnership of two career-orientated individuals that work outside of the home.

Early literature on dual-career families suggested 10 variables expected to impact life satisfaction for the individuals in these relationships, some directly and others indirectly: multiple role stresses (stress brought by managing potentially conflicting roles (i.e. CEO, soccer mom, and spouse)), enabling processes (within couple practices of equitably sharing responsibilities and support), integration (ability to control the level of segregation or integration of the work and family systems), hired help, self-esteem, career salience (how integral to one’s life they consider their career), job involvement, discretionary time spent on job-related matters, work context specific self-esteem, and income (Sekaran, 1983). These variables were analyzed as two sets of five variables (work and non-work variables) rather than reported on individually but most have been explored and developed further within subsequent studies, either in the dual-career couple literature or beyond.

For example, results of a later meta-analysis support the significance of work-family conflict (multiple role stress) on life satisfaction (Kossek & Ozeki, 1998). Although the level of significance varied widely depending on the selected measurement instrument and sample, a consistently negative relationship was found across studies, meaning that higher conflict relates to lower life satisfaction (Kossek & Ozeki, 1998). It has been said that the career and home spheres are “inextricably intertwined, especially for dual-earner employees” (Schooreel, Shockley, & Verbruggen, 2016, p. 124).

Social support, a construct within which enabling processes could be categorized, has also been linked to life satisfaction in a sample of Dutch dual-earner couples (van
Daalen, Sanders, & Willemsen, 2005). The study found that most sources of social support from one’s spouse were significantly positively predictive of life satisfaction in this sample, and women reported higher life satisfaction than men (van Daalen et al., 2005). In one modern study, career salience (a.k.a. work salience) and a corresponding role variable, family salience, were both found by Bhowon (2013) to be positively correlated to work satisfaction but not family satisfaction, though within regression analysis family salience was found to have a significant main effect on both work and family satisfaction. Overall life satisfaction was not assessed.

A limited amount of research has also homed in on variation within the dual-career relationship exhibiting specific life structures. For example, Bunker et al. (1992) compared satisfaction, stress, and quality of life between dual-career couples living in a single-residence and those living and working geographically separate from one another who commute to spend time with their partner (commuters). They found the perks of the commuting lifestyle to be greater satisfaction with work and available personal time relative to cohabitating dual-career couples, but drawbacks included less satisfaction with their relationship and family life, and lower life satisfaction overall (Bunker et al., 1992). Couples in both habitational structures exhibited equal levels of stress, and cohabitating couples experienced greater levels of overload (Bunker et al., 1992). These results suggest that relationship and family life satisfaction strongly influence global measures of life satisfaction. A recent article uncovered contrasting results with regard to commuting and relationship satisfaction. Chrishianie, Ginanjar, and Primasari (2018) found commuter dual-career couples to have significantly higher marital satisfaction then single-residence dual-career couples, however they did not assess life satisfaction overall.
or other variables explored by Bunker et al. (1992), which inhibits our ability to compare the results of these studies directly. A potential differentiating factor between the results of these two studies could be the use of control variables. Whereas Bunker et al. clearly report controlling for several variables in an ANCOVA analysis, such as demographic differences among the single-residence and commuter groups, Chrishianie et al. only report on conducting factorial ANOVA analyses, which does not account for control variables in the model.

**Literature Summary.**

Internal characteristics and external factors, as well as subjective and objective factors, can all be significant variables associated with life satisfaction (Borooah, 2006; Wortman & Lucas, 2016). Tree methods have rarely been used in this research area, but the one relevant study found income level, employment status, industry of employment, and marital status to be significant predictors of overall life happiness (Galletta, 2016). Ten variables identified in early research have been found to be directly or indirectly linked life satisfaction for those in dual-career couples (Bhowon, 2013; Kossek & Ozeki, 1998; Sekaran, 1983; van Daalen et al., 2005). Relationship and family life satisfaction strongly influence overall life satisfaction (Bunker et al., 1992). Other variables, such as residence structure have also been identified, though contrasting results leave it unclear whether marital satisfaction is improved or impaired by multi-residence commuting couples (Bunker et al., 1992; Chrishianie et al., 2018).

This study compliments and extends the extant literature by overcoming several limitations of past research. First, studies have either lacked detail or lacked breadth. Methodologically, existing studies suffer from the limitations inherent in traditional
statistical methods such as limitations on the number of variables which can be included in a model. For example, Sekaran’s (1983) study identified 10 variables, but then compressed those variables into two variable groupings, thereby hiding details of relationships at the individual construct level. Subsequent studies generally home in on one or two key independent variables per study, gaining detail, but increasing the likelihood of omitted variable bias. These limitations also leave the nature of the relationships between variables from separate studies unknown. Exploratory analysis techniques that are far less constrained by the number of variables that can be examined move toward addressing this gap. CART reveals the nature of even non-linear relationships between variables and is less likely to suffer from variable selection bias because so many more variables can be included (Haughton et al., 2010; Galletta, 2016; Shalizi, 2006).

Furthermore, existing research suffers from a new results publication bias that discourages replication efforts (Martin & Clarke, 2017), leaving much of the knowledge regarding each of these variable relationships established by a handful or less of studies with varying levels of generalizability. Measures of satisfaction (global or specific) are regularly found as control, mediating, or moderating variables in statistical models in the dual-career couple space (i.e. Byrne & Barling, 2017; Perrone & Worthington, 2001), but studies specifically examining satisfaction as the outcome variable of interest within this population context are comparatively more limited. The analysis presented in this study may not only reveal previously unidentified variables of importance, but also extend the understanding of variables previously identified by both revealing non-linear relationships and supporting or contrasting extant knowledge limited by publication bias.
All of Sekaran’s (1983) variables, closely related constructs, and other available measures within the proprietary dataset were included in the analysis presented in this study.

To my knowledge this study is the first to explore this particular research agenda in the dual-career context through machine learning.

**Method**

**Sample.**

To conduct exploratory analysis this paper will analyze the same dataset described in paper 1 of this dissertation proposal. Utilizing the same dataset across multiple studies provides the empirical stability to ultimately draw together conclusions regarding several facets of life for this population, ensuring the consistency of measurement of variables and sample characteristics. I repeat the description of this sample here for the convenience of the reader. These data come from a proprietary dataset from a survey focused on couples that was conducted by a Center\(^1\) at the author's institution. A professional services company was employed to administer the survey and collect responses from a random sample of 500 men and 500 women from across the United States. All survey participants were in or had been in committed long-term relationships (specified in the survey as marriage or any domestic partnership with a shared household) and held a minimum of an associate degree. These survey results do not present paired data, that is, the 500 men and 500 women were not in relationships.

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\(^1\) This survey was funded by Bentley University’s Center for Women and Business. It was written by Dr. Susan Adams and conducted by Qualtrics in 2014.
with corresponding survey respondents. Only one member of each couple was surveyed.

Figure 2

Sex representation was almost perfectly equal, with 409 female survey respondents (49.4%). The majority of sample respondents (71.9%) have at least one child.

**Instruments.**

Drawing upon the same dataset as used in paper 1, several of the variables and measurement instruments are also identical. In this section, each of the scaled instruments included in this analysis are defined. Where measures are identical between the two studies, the definitions presented in paper 1 are repeated for the reader’s convenience.

**Life Satisfaction.**

Life satisfaction was assessed with a single item measured on a 7-point Likert scale. Respondents rated their level satisfaction based on the following statement: ‘All things considered, how satisfied are you with life as a whole?’ (1 = very dissatisfied; 7 = very satisfied).

Although single-item measures sometimes draw questions as to their validity and reliability in accurately assessing a construct, past research comparing single-item measures of life satisfaction with a popularly used multi-item measures have found these measures performed similarly and concluded results of either measure are virtually identical (Cheung & Lucas, 2014; Cummins, 2005). Thus, there is empirical evidence to support the researcher’s choice of a single-item measure for this variable.
Career Centrality.

Career and family centralities are defined as the importance one ascribes to the work/family roles (Bagger & Li, 2012). “Individuals who are high on work centrality [labeled here as career centrality] tend to believe that work plays a significant role in their life” (Bagger & Li, 2012, p. 475).

Career centrality was assessed using a scale adapted from Eddleston, Veiga, and Powell (2006). Their instrument is an adaptation of “Lodahl and Kejner’s (1965) job involvement scale with the word career substituted for job” (Eddleston et al., 2006, p. 439) and the addition of one item based on Lobel and St. Clair’s (1992) Career identity salience scale. On a 7-point Likert scale respondents indicate their level of agreement with three statements (“A major source of satisfaction in my life has been my career,” “Most of the important things that have happened to me have involved my career,” “Most of my interests have been centered around my career,” 1 = strongly disagree, 7 = strongly agree). These responses are averaged to establish the career centrality score (Eddleston et al., 2006). High scores indicate higher levels of career centrality.

Eddleston et al. (2006) and Lodahl and Kejner’s (1965) scales included an additional item (“I am very much involved personally in my career”), but the item was deemed unnecessary based on results of a pilot study\(^1\) that were conducted of the survey utilized here. The reliability of the three-item scale is strong (\(\alpha = .82\)), and closely compares to Eddleston et al.’s four-item scale (\(\alpha = .84\)).

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\(^1\) This pilot survey was distributed to members of the International Association of Exhibitions and Events (IAEE) in October of 2013 and garnered 135 analyzable observations from voluntary respondents.
Family Centrality.

Family centrality was assessed with the same three-item scale as Career centrality, with the word family taking the place of career. On a 7-point Likert scale respondents indicate their level of agreement with three statements (“A major source of satisfaction in my life has been my family,” “Most of the important things that have happened to me have involved my family,” “Most of my interests have been centered around my family,” 1 = strongly disagree, 7 = strongly agree). The Cronbach alpha for this instrument in the sample is .89. High scores indicate higher levels of family centrality.

Other Centrality.

Literature has acknowledged that multiple roles people hold vary in salience (Liu & Ngo, 2017), and some individuals may rate low on both work and family centrality and hold a primary identity outside of these two realms, such as “hobbyists, athletes, or church or community volunteers” (Kossek et al., 2012, p. 114). In order to take into consideration the possibility of centralities beyond career or family, other centrality was assessed with a single item measured. On a 7-point Likert scale respondents indicate their level of agreement with the statement: “A major source of satisfaction in my life has come from activities related to personal interests beyond work and family such as hobbies, reading, pets, exercise/personal care, time with friends, volunteer work, etc,” (1 = strongly disagree, 7 = strongly agree). High scores indicate higher levels of role centrality beyond career or family.

Overall Partner Support.

Overall perceived partner support was measured with a four-item instrument based on Heikkinen’s (2014) study results of the spousal roles of employed partners of
highly successful managers. Each item examines a particular support action or area ("My current (or most recent) partner has shown support for my career by "being" supportive (e.g., as a discussion partner, expressing acceptance of new career opportunities for me, participating in my business-related social activities, helping presentation practices),” “My current (or most recent) partner has shown support for my career by helping me maintain a life beyond work (e.g., considering the impact of work assignments and promotions on family life before accepting them – both of us make decisions as a couple),” “My current (or most recent) partner has supported my life-related desires (e.g., personal time, time with friends, hobbies),” “My current (or most recent) partner has shown support for my career by managing or taking care of most of the domestic chores (children, extended family, housekeeping)”). On a 5-point Likert scale, respondents indicate the frequency at which they receive each type support (1 = never; 5 = All of the time) ($\alpha = .86$).

**Relationship Satisfaction.**

Relationship satisfaction was assessed with a version of Norton (1983) Quality Marriage Index (QMI) modified to be inclusive of non-married partnerships, such as used by Denes, Dhillon, and Speer (2017), Merolla (2012), and Patrick, Knee, Canvello, and Lonsbary (2007) and Porter et al. (2009). The scale is abbreviated here to include two of its most frequently utilized six items ("My current or most recent partner and I have a good relationship"); ("I really felt like part of a team with my current or most recent partner"). Items are assessed on the 5-point Likert scale (1 = Strongly Disagree; 5 = Strongly agree) and an average of these items’ responses taken as the score ($\alpha = .90$).
Education Equality.

Respondents were asked in two separate items to indicate their highest level of education and the highest level of education of their current (or most recent) partner. Since the survey was targeting college educated individuals, “Do you have a college degree?” was an initial screening question, and “Associate degree” was the lowest level of education available for respondents to select. When indicating the highest education level of their partners, respondents selected one of six options (1 = High school or some college with no degree; 2 = Associate degree; 3 = Bachelor degree; 4 = Master degree (including MBA); 5 = Professional doctorate (e.g. MD, DDS, EdD, Law, Engineering); 6 = Academic doctorate (PhD)).

A binary dummy variable was created to indicate education equality within partnership (1 = equal; 0 = unequal). Equality was determined based on school level (undergraduate, graduate, and terminal) rather than specific degree type. Associate and Bachelor degrees were considered equal as both reside at the undergraduate level, and Professional doctorate and Academic doctorate were also equal as both types fall into the terminal degree level.

Other variables.

Table 13 lists the 60 independent variables, including the measures listed above, that were entered into the decision tree model, how each was measured and coded, and references to prior literature. These variables were selected based on extant literature. Relative to other studies of life satisfaction, this is a high number of variables, and it is the capability of the chosen analysis method to process large sets of possibly correlated variables that afford this study the advantage to include a wider breadth of information.
(Gallette, 2016). Furthermore, aggregate measures can be included along with their component parts to better identify the variables of the greatest explanatory values (Galletta, 2016). For example, in this analysis the overall partner support score measure was included along with its component parts in case a particular type of support emerged as having greater impact on life satisfaction.

**Statistical treatment.**

In this section I will describe the selected treatment method and methodological procedure and settings utilized in this analysis.

Decision trees are a class of predictive techniques within machine learning/data mining, in which “a target variable is singled out and the hope is to build a model with suitable predictors that explains or predicts the target variable well” (Haughton, Nguyen, & Senne, 2010, p. 90). The CART decision tree method selected and employed in this analysis has been chosen for its ability to offer a novel informative perspective on this research area, as decision trees are seldom seen in organizational behavior journals.

Tree-generating techniques are comparatively better than a number of other methods (logistic regression, discriminant analysis, and log-linear modeling) at identifying important predictors and significant interactions when analyses contain a myriad of variables (Haughton & Oulabi, 1997). As previously mentioned, CART is capable of accommodating a high number of variables without the statistical risks of traditional methods such as overfitting, which presents the added benefit of decreasing the likelihood variable selection bias (Haughton et al., 2010; Galletta, 2016; Shalizi, 2006). Classification trees, and the CART method specifically, offer several advantages compared to other predictive analysis methods. Since they are nonparametric, distribution
assumptions of predictor variables are not necessary (Gordon, 2013; Haughton et al., 2010). Furthermore, these methods are non-linear (Gordon, 2013) and can handle data that are multi-faceted with complicated interactions (Haughton & Haughton, 2011, p. 84; Shalizi, 2006; Shalizi, 2009). Unlike some other non-linear methods, decision trees maintain high interpretability, producing outputs that are easy to interpret and present intuitive insights (Eliashberg et al., 2007; Gordon, 2013; Loh, 2014).

The CART algorithm can be used with all manner of variables (both categorical and/or continuous) (Bagdatli Kalkan & Bahar Yucel, 2017; Haughton & Oulabi, 1997). This method has fast computation speed (Loh, 2014; Shalizi, 2006), good prediction accuracy (Loh, 2014; Giudici, 2005a; Salford Systems, 2013), and it engages easily in model training through fast and reliable learning algorithms (Hannak et al., 2012; Shalizi, 2006). Finally, the CART method is reportedly well equipped to be applied to a dataset even when there are missing values and is “robust to the effects of outliers” (Haughton & Haughton, 2011, p. 84; Shalizi, 2006; Shalizi, 2009). A thorough discussion of background literature, researcher considerations, and technical processes of this method is presented in the Appendix of this dissertation.

The statistical software package SPSS Statistics 25 was employed for this study. Following the decision tree process discussed above, the data was first split into a training dataset (80%, N=662) and a testing dataset (20%, N=166) to test the model. Many of the survey responses within this dataset are 5 or 7-point Likert scale responses, including the dependent variable, life satisfaction, and thus the dependent and large portion of the independent variables are ordinal scale variables. The CART method was selected for its ability to accommodate ordinal categorical target variables using the
ordered-twoing impurity measure. With the CART tree algorithm specified, minimal restrictions to the growth were selected. A maximum depth of 100, and minimum parent and child node sizes of 20 observations were selected to avoid arbitrarily restricting the tree’s growth. It is recommended that the minimum number of observations per node be set between 0.25 and 1% of the full training dataset to avoid overfitting or underfitting (Song & Lu, 2015). Roughly seven observations per node would be 1% of the training dataset, so setting a minimum of 20 observations is an extra conservative amount by this guideline. The option to prune the tree to avoid overfitting was selected, and the maximum acceptable difference in risk set to a value of 1 (in standard errors). The ordered-twoing impurity measure was set with a minimum change in improvement of 0.0001 for splitting. Missing values were excluded from the tree-growing process and later classified using surrogates. The resulting tree contains a total of 15 nodes, of which 8 are terminal nodes, and has a depth of 5 layers.

**Results**

Figure 4 shows the best classification tree specified by the CART algorithm. We see that of the 60 explanatory variables entered into the model, the algorithm selected five: relationship satisfaction, family centrality, career centrality, current age, and age at the time of your first committed relationship. The figure displays the percent and count of training dataset observations that fall into each of the seven response levels for life satisfaction (1 = very dissatisfied; 7 = very satisfied; 1,2,3 = levels of dissatisfaction; 4 = neutral; 5,6,7 = levels of satisfaction). For each independent variable included in the model the figure shows the level of improvement in node purity gained by splitting based on that variable. As mentioned above, ordered-twoing was the measure of impurity
utilized for this model and a minimum of 0.0001 improvement was required for a variable to be included in the tree.

Figure 4 also specifics the splitting point for each included variable. For example, the dataset is first split on the variable *Relationship Satisfaction*, and the greatest gain in node purity was derived from splitting the sample at or below 3.5 and above 3.5. We know that a response of 3 indicates a neutral level of satisfaction, so we see there is a significant difference between people that agree or strongly agree that they have a good relationship (values of 4 and 5), and those that are neutral or dissatisfied with their relationships. The average relationship satisfaction score is 4.11, so we also see that the observations to the left all fall below average for this sample. This split suggests that people whose relationship satisfaction score is above 3.5, nearing or above average, are just over 36% more likely to report being somewhat or more satisfied with life overall (54.7% vs. 91%) and roughly 46% more likely to report being satisfied or very satisfied (27.7% vs. 73.5%).

If the branches are followed down to the far left of the tree, that terminal node (Node 7) contains observations of individuals least likely to be satisfied with their lives overall. We see that 58.4% of individuals that score at or below 3.5 for relationship satisfaction, have a moderate of low level of family centrality (<=5, average value is 5.9), and do not consider their career to be a central focus of their life (<=3.3, average value 4.3), are somewhat unsatisfied or less with their lives, compared to 9.2% of the training dataset that report any of the three levels of dissatisfaction. This node contains 3.6% of the total observations in the training dataset. Since 61 individuals in this training dataset
reported any of the three levels of dissatisfaction, we see that this node contains 23% all individuals in the dataset reporting dissatisfaction with their life.

Following the branches to the far right of the tree leads to the terminal node (Node 14) with observations most likely to be highly satisfied with their lives overall. A total of 85.9% of individuals that have above average satisfaction with their relationships (>4.5, average 4.11), score higher than average on family centrality (>6.3, average is 5.9), are over 34.5 years of age, and had their first committed relationship after the age of 19.5 are satisfied or very satisfied with their lives, compared to 64.1% of the entire sample. Similar to our analysis of the far-left node, we know that of the 414 observations in the training dataset reporting being satisfied or very satisfied with their live, this node contains about 13% of these individuals. Thus, it appears that for this sample the three variables leading to the least satisfied node have greater explanatory capability than the three variables leading to the most satisfied node (23% vs. 13%).

Within the complete sample (training and testing sets combined) 64.1% of respondents reported being satisfied or very satisfied with life overall (Likert scores of 6 or 7 for this measure). Since the average life satisfaction score for the sample is 5.58, this 64.1% present above average satisfaction levels. By comparing the percentage of satisfied and very satisfied individuals in each node to the percentage overall one sees that all the nodes to the right of the first split contain a greater percentage of individuals with these highest levels of satisfaction (Node 2 = 73.5%, Node 5 = 65.7%, Node 6 = 84.3%, Node 9 = 76.4 %, Node 10 = 88.5%, Node 11 = 92.1, Node 12 = 86.3, Node 13 = 87.5, Node 14 = 85.9%). In contrast, all the nodes to the left of the first spilt have a lower percentage of these higher than average satisfaction individuals (Node 1 = 27.7%, Node 3
= 13.9%, Node 4 = 39%, Node 7 = 12.5%, Node 8 = 14.5%). Of the eight terminal nodes, Node 5, 9, 11, 13 and 14 exhibit higher than sample average levels of satisfaction.

**Discussion and Limitations**

The CART algorithm can consider practically countless variables without risking over specification and identifies non-linear relationships (such as interactions like moderation, or curvilinear relationships) (Haughton et al., 2010; Galletta, 2016; Shalizi, 2006). Given the rarity of linear relationships in the real world, it was expected that the algorithm would reveal meaningful variables that have been identified in the past actually relate in a non-linear fashion. It was also anticipated that the algorithm would select one or more variable that had not been identified as significant in the past, because the tree builds a model of conditional prediction. This means that something that isn’t directly very meaningful, can still become meaningfully predictive when certain conditions are met.

In this analysis, demographic variables commonly reported to predict life satisfaction, aside from age, were not selected as relevant by the CART algorithm. When meaningful subjective measures are included in the analysis, demographic information such as income, education level, employment status, industry, gender, etc., do not surface as significant predictors of life satisfaction. Past research has found an empirical regularity that high income improves life satisfaction up to a dollar amount where scarcity of money is no longer a stressor (Clingingsmith, 2016; Jebb, Tay, Diener, & Oishi; Kahneman & Deaton, 2010). However, the variables for reporting income level are not significantly correlated with any of the predictor variables in the tree model except for career centrality, meaning it does not appear to be masked by a highly similar
variable. Further evidence for this conclusion is in the Independent Variable Importance table (Table 14) within the tree’s statistical software output. The variable for reporting income level for oneself has a normalized importance level of 6.4% and is 8th on the list, and the variable for reporting the income level of one’s partner has a normalized importance level of 5.8% and is 11th on the list.

Theoretically, it is possible that jointly most dual-career couples earn near or above their personal dollar amount where scarcity of money is no longer a stressor, since naturally this threshold could vary to an extent for different individuals. If this is the case, it would explain the prioritization of other predictors in the model. Alternatively, it is possible that the added sense of financial security dual-career couples experience based on the teamwork approach to breadwinning and the potential psychological benefits of that dynamic could supersede or raise the actual earnings scarcity stressor threshold.

The results also suggest that life satisfaction depends positively on relationship satisfaction because the likelihood of reporting higher life satisfaction than the sample as a whole is greater for higher values of this variable. Family centrality exhibits similar features to relationship satisfaction as every time it appears in the tree the sample is split such that higher values of this variable improve the likelihood of greater life satisfaction regardless of the group being considered. Career centrality, current age, and age at first relationship are also positively related to life satisfaction, but their level of relevance varies depending on the group considered. “Although the tree does not allow to produce any clear hypothesis testing because there are no results in terms of inference, these findings give a descriptive insight coherent with previous research” (Gallette, 2016, p, 124).
The CART methodology can help identify interactions and complex variable relationships (Haughton et al., 2010), and as anticipated the model uncovered one such non-linear relationship. In the model presented *Family Centrality* is the second split for each of the two initial branches, but the splitting value is different. The effect of family centrality of life satisfaction depends on whether that individual reports relationship satisfaction scores at or below 3.5, or above 3.5 (which falls between the scores for somewhat satisfied (value = 5) and satisfied (value = 6)). This indicates an interaction between these two predictors, relationship satisfaction and family centrality, which, to my knowledge, has not been articulated in previous research. Similarly, we see that the relationship satisfaction variable appears more than once in the tree, splitting at different values at each point. This means that there is a complex, non-linear, relationship between one’s level of relationship satisfaction and their overall life satisfaction that was not identified in past studies that report correlation of these variables (Bunker et al., 1992). This provides meaningful information to support the argument that overall life satisfaction is not simply an average of domain satisfactions as it has been operationalized and measured in some past studies (Erdogan et al., 2012).

Comparing the tree results with Sekaran’s (1983) list of variables there are a couple of related constructs that emerged in the analysis. Sekaran’s study used the *career salience* variable, which has been used interchangeably in the literature with *career centrality*. Also, the family centrality variable that presented itself significantly in our model could logically be a component of *multiple role stresses*, another of Sekaran’s variables. In contrast with Sekaran, as well as van Daalen et al. (2005) *partner support* did not present itself in our tree, however neither of the aforementioned studies included
a direct measure of *relationship satisfaction*. Given that the level of one’s *partner support* is significantly related to one’s *satisfaction with the dual-career lifestyle* (Perrone & Worthington, 2001), a construct that naturally overlaps with relationship satisfaction and life satisfaction, it is not surprising that did not get selected by the CART algorithm.

The lack of confirmatory ability is among the method’s most significant limitations. Further analysis is required for us to be able to enable more meaningful conclusions. Additionally, because individual trees are so sensitive to minor changes in the data, this study would benefit further analysis though ensemble tree or forest methods, even though the ease of interpretability is then lost (Loh, 2014).

Finally, tree models cannot be used to address all types of research questions. Further research with different statistical methods is necessary to move beyond the variable identification question explored here and onto questions regarding the degrees to which these statistical relationships exist. For example, an inquiry into how important work and career centrality are in predicting life satisfaction would be a natural follow on question to this study that could be explore through path analysis or other statistical means.

**Conclusion**

This exploratory study is beneficial in that “it reveals how variables interact with each other without imposing any model specification” (Gallette, 2016, p. 125). It identified non-linear relationships between the DV (life satisfaction) and both relationship satisfaction and family centrality. This adds depth to the study of life satisfaction for dual-career couples, that future research should take into account. Although classification trees cannot be used to test hypotheses, they are powerful
preliminary tools that help us better understand the data, thereby enabling superior development of confirmatory research projects.

These findings add to the conceptualization of life satisfaction within dual-career couples in three key ways. First, the fact that none of the income variables were selected for the model is surprising. Several past research studies have shown that income positively impacts life satisfaction but only up to a dollar amount where scarcity of money is no longer a stressor (Clingingsmith, 2016; Jebb, Tay, Diener, & Oishi; Kahneman & Deaton, 2010). It is possible that jointly most dual-career couples earn near or above this threshold, which would explain the prioritization of other predictors in the model. Second, identifying the non-linear relationship between relationship satisfaction and overall life satisfaction provides meaningful information to support the argument that overall life satisfaction is not simply an average of domain satisfactions as it has been operationalized and measured in some past studies (Erdogan et al., 2012). Finally, the interaction identified between relationship satisfaction and family centrality could be a result of a moderating or mediation relationship, which should be explored further to allow for proper controlling of this variable in future quantitative dual-career couple research.

Further research is also called for to look into the relationship between life satisfaction for these individuals and income to uncover why it appears to be a less meaningful predictor for this population. Are the drivers practical, such as actual higher family income, or psychological, such as reduced perception of money as a stressor resulting from two incomes? More generally, further research to clarify the nature of the
relationships found here with alternative methods is needed to replicate these findings and draw more meaningful conclusions.

This descriptive analysis contributes to our knowledge life satisfaction for dual-career couples, updating and extending this line of inquiry with modern data. Not only does this study provide methodological novelty to this research area, but also aims to establish an inroads for the utilization of other data mining techniques to be used in this research. These methods can both avoid some of the shortcomings of traditional methods, as well as a richer understanding of phenomenon but approaching data from an alternative perspective.
Chapter 4: Paper 3 – *Role Centrality and the Gender Wage Gap*

In this final paper, I pursue the following research question: What portion of the unexplained gender wage gap can role centrality levels explain? I use variance decomposition to analyze the amount of the unexplained gender wage gap that can be accounted for with the role centrality psychological construct.

Decades of studies have presented theories and identified variables to explain a significant portion of the gender wage gap, but it is the general consensus in the literature that an unexplained gap (residual) still remains (Blau & Kahn, 2017; Chevalier, 2007; England, 1992; Manning & Swaffield, 2008; Weichselbaumer & Winter-Ebmer, 2005). It was hypothesized several decades ago that gender differences in values, particularly how much personal value women vs. men place on earnings might be a meaningful factor to address the unexplained gap, but empirical findings have been mixed, with some evidence suggesting that women value earnings as much or more than men (England, 1992).

Economic theories have explored the role of factors such as education, work experience, region, race, unionization, industry, and occupation in explaining the gender wage gap and as of 2010, in the U.S., these factors were found to account for only 62% of the variance in wages between genders (Blau & Kahn, 2017). Unable to make sense of 100% of the wage gap by controlling for classic economic variables some research has recently explored constructs and theories from psychology such as norms, psychological attributes (i.e. risk taking, self-esteem), or noncognitive skills, to continue to seek greater understanding of this phenomenon (Blau & Kahn, 2017; Manning & Swaffield, 2008). These studies have found these factors to account for a small to moderate portion of the
wage gap, 2.5 to 27.6% depending on the traits examined and the study (Blau & Kahn, 2017). Accounting for economic variables and the psychological constructs examined thus far, an unexplained gap still exists. Given the vast ocean of psychological constructs and the many ways they can be conceptualized and measured, the mere handful of theories that have been explored in only a small number of studies suggests a need to more thoroughly examine the explanatory power of psychology constructs within this context.

With this theoretical gap in the gender income gap literature in mind, it seems potentially fruitful to return to the earlier theorizing on the impact of individual values. Empirical work has had mixed results regarding the existence of gender differences in the value placed on earning (Crosby, 1982; Golding, Resnick, & Crosby, 1983; Harris & Earle, 1986), but perhaps earnings are not the most meaningful value to measure. As discussed in the literature section of my first paper, the concept of values is one of the main theoretical underpinnings of the role centrality construct. Role centrality is a mechanism through which we can observe and measure the value an individual places on each of the various roles in life that she occupies (Carlson & Kacmar, 2000; Carr, Boyar, & Gregory, 2007). Given that career/work centrality, as well as family centrality, have often been identified as significant variables impacting outcomes in both the work and personal settings (Bagger & Li, 2012; Carlson et al., 2000; Chrouser & Ryff, 2006; Cinamon & Rich, 2002; Dubin, 1956; Liu & Ngo, 2017; Xie, Shi, & Ma, 2017), it is logical to suspect there could be some type of relationship between levels of role centralities and wages. This same path of logical reasoning has served as the basis for past studies such as Mueller and Plug’s (2006) examination of the impact of personality
on the gender wage gap, in which they found adding psychological factors to their model explained 16 percent of the gender wage gap.

Bringing together these two disparate streams of research (the economic analyses of the gender wage gap and the social psychology research on role centrality) stands to contribute to both literatures by breaking down disciplinary silos, integrating and furthering our understanding of the role centrality construct and explaining some portion of the outstanding unexplained gender income gap. Furthermore, the present context of a sustained period in which there has been disproportionate narrowing of gender differences in human capital but very little movement in the gender wage gap demands a more thorough understanding of the factors and mechanisms at play (Blau & Kahn, 2017).

This paper proceeds as follows. The first section will cover a review of selected literature on the gender wage gap phenomenon concentrated on research investigating theories and constructs from psychology. This section will also review role centrality research, summarizing what variable relationships have been identified in past research and what similar constructs have been used in wage gap literature. The second and third sections will report on the methodology and results of the quantitative analysis, employing the same dataset from the previous papers. Finally, I will present a discussion of the findings and their implications, limitations of this research study, and conclusion.

Literature

How wide is the gap?

The literature on the wage gap is both vast and conflicting, making it difficult to present any sort of academic synthesis that is not a gross oversimplification (Tharp et al.,
2019), however, I will attempt to briefly share a few facts that outline the phenomenon and theorizing in this area at a high level. Based on data from the United Nation’s International Labor Organization (ILO), in the global population, women earn less than men in an absolute sense. If the adult population is looked at as a whole, including both working and non-working individuals, women earn less than men in every country (Ortiz-Ospina & Roser, 2019). Part of this is due to gender differences in labor participation, meaning that the percentage of females in the workforce relative to the number of females in the population is less than the percentage of males in the workforce relative to the number of males in the population. This ratio has changed dramatically over the last century, though progress toward convergence has slowed in the last couple of decades (Blau & Kahn, 2017). In 2013, 57.3% of adult females in the U.S. were part of the workforce, compared to roughly 69% of males (Blau & Kahn, 2017).

The estimated size of the gender wage gap varies widely based on how it is calculated, who is included in the sample, what reference value is being utilized, and what factors are being taken into account. Based on data from the Michigan Panel Study of Income Dynamics, among full-time workers in the U.S. in “2014, women full-time workers earned about 79 percent of what men did on an annual basis and about 83 percent on a weekly basis” (Blau & Kahn, 2017, p. 792). However, ILO data indicates that looking at gross hourly earnings of both full-time and part-time workers, unadjusted for worker characteristics, there are a handful of countries where women currently earn more than men, such as Thailand (21.57% more than men), Belize (20.03%), Honduras (15.05%), El Salvador (5.26%), Argentina (3.62%), Ecuador (2.8%), Malaysia (2.25%), Paraguay (1.77%), Turkey (2.16%) (Ortiz-Ospina & Roser, 2019). It should be noted
though that this does not indicate differences in the number of hours people are working, thus it is possible that women in these countries could still be bringing in less than men on a weekly/monthly/annual basis.

As pointed out in my first paper, in a 2015 report, it was estimated that the global economy could rise by an estimated $28 trillion if women were to gain economic parity with men by the year 2025 (an amount equal to the annual GDPs of the U.S.A. and China combined), and increase the world’s labor force by 240 million workers (Woetzel et al., 2015). These projections envision a scenario that goes beyond the concept of equal pay for equal work to a reality in which women and men are actually equal players in the labor market (Woetzel et al., 2015).

**What drives the gap?**

The clear take away from these facts and figures is that, on a global population scale, there are disparities in economic production between males and females, a wage gap of some magnitude that is disadvantageous to females can be observed nearly everywhere, and there is strong economic motivation to do something about this issue. Quite naturally, economists and other researchers have sought to explain the sources of these disparities for decades. However, the phenomenon seems to be a moving target with outcomes heavily context dependent and constantly evolving over time, providing effectively infinite fertile ground for new streams of innovative and relevant research (Blau & Kahn, 2017).

Although a detailed discussion of the extant literature on this topic is outside of the scope of this study, I attempt to outline the key concepts this area. The wage gap has classically and most frequently been attributed to differences between males and females
in human capital, selection bias, compensating wage differentials, discrimination, and the
gender division of labor within the family (Blau & Kahn, 2017). I will touch upon each of
these briefly to orient this study within this broad area of research.

**Human Capital Theory.**

Based on *human capital theory*, systematic wage differentials are thought to be a
consequence of differences in individual productive skills, which can be innate or
developed over time, with the level of return of particular skills varying by occupation
and job requirements (Mueller & Plug, 2006). Based on this theory, if a man and a
woman offer equal human capital to an employer, they will be paid the same for the same
job, but the person possessing less valuable human capital will be paid less. Empirical
evidence has confirmed the extent to which this theory is accurate in reality, though it
cannot fully explain the gender wage gap phenomenon. Education and labor-market
experience, two areas of human capital often measured within research to explain the
gap, “taken together explain little of the gender wage gap” in 2010 (Blau & Kahn, 2017).
In fact, women are now more educated than men and have nearly eliminated the gap in
years of full-time labor experience, which accounts for the decrease in the U.S. wage gap
over the last several decades, but the portion of the wage gap that is left unexplained after
accounting for these and other classically observed variables has remained stable during
the period of 1980 to 2010 (Blau & Kahn, 2017).

**Compensating Wage Differentials.**

The insufficiency in human capital theory in explaining more than a small part of
the wage gap led researchers to explore the application of equalizing or compensating
wage differentials (Jacobs & Steinberg, 1990), which has been cited as “the fundamental
(long-run) market equilibrium construct in labor economics” (Rosen, 1986, p. 641).
Essentially, according to the compensating wage differentials construct, wages are
dictated by the market based on the attributes of the particular job. “Activities that offer
favorable working conditions attract labor at lower than average wages, whereas jobs
offering unfavorable working conditions must pay premiums as offsetting compensation
in order to attract workers” (Rosen, 1986, p. 641). The equilibrium achieved in this
construct results from a matching or sorting function by which the best workers for the
task and firm are matched with that job and firm (Rosen, 1986). This provides the
theoretical foundation for occupational sorting or occupational segregation also
frequently referenced in the wage gap literature.

Whereas many people would say female gendered work is undervalued in our
society, compensating wage differentials were brought into the conversation about the
wage gap to argue that female work is perhaps not undervalued, but rather it is more
attractive work and thus simply commands lower wages (Jacobs & Steinberg, 1990). Like
human capital theory, this construct is effectively gender neutral, and implies that any
difference in wages “that flows from [occupational] sex segregation is the legitimate
result of job differences” (Jacobs & Steinberg, 1990, p. 440). Although the results of
Jacobs and Steinberg’s (1990) empirical investigation were in direct contrast to this
theory (“both male- and female-dominated jobs are disadvantaged on a similar number of
working-conditions indicators [and...] neither men nor women received wage premiums
for working in unfavorable conditions once other compensable characteristics are taken
into account” (p. 439)), other work has found support for this theory in specific contexts,
particularly when considering the micro level (Blau and Kahn, 2017).
Goldin (2014) presents the argument that within-occupation gender wage differences (as opposed to differences between occupations) are the key to understanding the persistence of the unexplained wage gap, and presents a compensating wage differential framework based on job flexibility and the linearity vs. non-linearity of the hours worked to wages earned relationship in different occupations. Goldin analyzes the differences between occupations in which the hours one works and the compensation they receive present a linear relationship, such as pharmacists, and occupations where the relationship between hours and wages is convex (i.e. an occupation where working 70 hours a week garners wages substantially more than double working 35 hours), like law or banking. She finds “the wage penalty for flexibility is likely to be high in jobs that require meeting deadlines (time pressure), being in contact with others to perform the job, maintaining and establishing interpersonal relationships, adhering to preset schedules, and doing work for which other workers are not close substitutes,” and that the gender wage gaps in these occupations are much higher than those where employers can offer flexibility with lower costs to the firm (Blau & Kahn, 2017, p. 818). Therefore, per the compensating differential construct, temporal flexibility holds differential values to the individual workers, as well as to the firm. There is a wage premium paid to workers that can conform to the inflexibility in occupations where offering flexibility would be costly, but there is an absence of a non-linear wage premium (penalty) for working more (less) hours weekly in occupations where flexibility is less costly (Goldin, 2014). Given that females are roughly twice as likely as males to work part-time, as well as the fact that 78% of part-time workers choose part-time work for noneconomic reasons, this
framework has substantial power to explain occupation specific wage gaps, particularly in positions with low flexibility (Blau & Kahn, 2017).

Selection.

The discussion of selection bias as it pertains to research on the wage gap does not provide a theory of explanation of the wage gap, but rather draws into question the accuracy of what we think we know about the size, direction, trends, and existence of the gap. Selection issues are a concern with all wage studies because we cannot observe wage offers for people who choose not to be employed, meaning that the sample consists of only those people who have selected into the workforce (Blau & Kahn, 2017), and thus not a representative sample of the population as a whole. Since a greater percentage of the male population participate in the workforce relative to the percentage of the female population that participates, the effect of selection bias on estimating average male wages is less of a concern than the impact on calculation of female wages averages because the closer the sample is to 100% of the population “the smaller the selection bias” (Blau & Kahn, 2017, p. 809). Blau and Kahn (2017) explain “if inclusion in the wage sample is selective of those with higher (lower) wage offers, the mean of observed wages will be higher (lower) than the mean of wage offers” (pp. 809-810). Research aimed at assessing the magnitude of selection bias effects on wage gap estimates present mixed evidence on both how to manage this bias and if it is a sizable concern, so at this time there is no fool proof best method to combat this issue but logically it would seem that analyses skewed by this issue are more likely to understate than overstate the gaps (Blau & Kahn, 2017).
Discrimination.

The d-word (discrimination) is a complicated element of the gender wage gap discussion. It may seem that the motivation of economists in applying human capital theory, compensating wage differentials, selection issues, or other constructs is to explain away the wage gap. The potential underlying assumption being that if the wage gap can be attributed to measurable factors, then it is not a result of gender discrimination, and if it is not a result of gender discrimination that there is nothing inherently wrong because it is acceptable for the market forces to act as they will. The opposing perspective would be then that if some portion of the wage gap cannot be explained, then that portion of the wage gap is attributable to gender discrimination. However, both of these perspectives would be flawed.

Drawing accurate conclusions regarding the presence or absence of discrimination as a determinant of wage differentials is problematic. The unexplained portion of the wage gap, the residual, has often been termed “wage discrimination,” but this is misleading (Blau & Kahn, 2017; Ortiz-Ospina & Roser, 2019). As Tharp, Lurtz, Mielitz, and Kitces (2019) have skillfully articulated, studies that illustrate the existence of an unexplained gender wage gap cannot assume this gap is a product of discrimination because of the risk of omitted variable bias. At the same time, a model that accounts for 100% of gap cannot conclude that gender differences in measurable variables aren’t being driven by discrimination, such as the quality of work being assigned to male vs. female laborers. For example, in assessing stockbroker compensation, controlling wage equality for the management of equal quality accounts masks the situation where female stockbrokers are being assigned inferior accounts (Tharp et al., 2019).
The motivation of this paper is not to draw inferences or make any statement regarding the presence, absence, or severity level of discrimination, but rather to simply contribute to our understanding of the relationship between the role centrality construct and wage outcomes.

The Gender Division of Labor.

The phrase *gendered allocation of labor* or *gender division of labor* was derived from the historical division in America between paid employment outside the home and unpaid housework (Lachance-Grzela & Bouchard, 2010). *Gender role theory* explains how society and culture socializes individuals into social roles, “prescribing different conducts, attitudes, and values for women and men” (Gustafson, 1998, p. 809; Ochsenfeld, 2014). Expectations of these roles are shared among members of a society and reproduced by socializing agents through rewards and sanctions (Eagly & Wood, 2011; Gustafson, 1998). An important element of this theory is that gender differences are context dependent and subject to change (Eagly & Wood, 2011).

Like human capital theory, and the compensating wage differentials construct, literature on the wage gap has often turned to gender role theory, and the impact of traditional gender roles, to explain females’ disadvantaged labor market outcomes (Blau & Kahn, 2017). There a number of factors by which gender roles have been connected to this issue, such as the gender differences in participating in nonpaid work, as well as mechanisms through which these factors impact the wage gap (Blau & Kahn, 2017).

Expected gender differences in labor-force attachment has been key among these, for example, “under a traditional division of labor by gender in the family, women will anticipate shorter and more discontinuous work lives as a consequence of their family
responsibilities; they will thus have lower incentives to invest in on-the-job training than men” (Blau & Kahn, 2017, p. 817). This example, in which women are deemed to be less incentivized to develop their human capital, circles back to human capital theory, whereas an alternative interpretation that as a result of the gender division of labor in the family women put a higher value on temporal flexibility than men, brings us back to the compensating differentials model. Negative outcomes stemming from this example could also be a result of employers discriminating “against the ‘type’ of worker who puts a high premium on temporal flexibility” (Blau & Kahn, 2017, p. 818). Yet another theoretical mechanism that has been discussed is resource allocation. Becker (1985) theorized that greater domestic commitment of women leads them to put less energy into work, due to allocation of energy, a finite resource, across different activities, which translates to lower earnings.

Within the applied psychology research space, a converse concept, work-family enrichment has been theorized and explored, by which positive spillover (“transfer of positive affect, values, skills, and behaviors from one domain to another”) might be expected (Powell & Greenhaus, 2010, p. 513). However, unlike the wage gap research, empirical evidence of sex differences in either positive or negative interdependencies has been mixed (Powell & Greenhaus, 2010).

One empirical finding in this area worth noting is the wage penalty for motherhood; that is, the negative difference in wages between mothers and nonmothers, which empirical evidence suggests is (at least partially) a causal relationship (Blau & Kahn, 2017). Fathers on the other hand do not exhibit the same penalties relative to non-fathers (Blau & Kahn, 2017; Ortiz-Ospina & Roser, 2019), in fact wage premiums
enjoyed by men for both marriage and fatherhood are sometimes observed in the
literature, though these findings are mixed and appear to be dependent on a number of
contingent factors (Killewald, 2013).

**Applied psychology and the gender wage gap.**

As mentioned previously, the insufficiency of these classic explanations discussed
above to fully account for the gender wage gap has motivated researchers to employ a
more interdisciplinary approach. A relatively small but growing body of research¹ has
explored the direct and indirect relationships of psychology constructs (such as the *five-
factor model of personality structure*, a.k.a. the *big five* (Mueller & Plug, 2006; Flinn,
Todd, & Zhang, 2018; Fletcher 2013), *locus of control* (Babcock & Laschever, 2003;
Semykina & Linz, 2007; Fortín, 2008; Manning & Swaffield, 2008; Nyhus & Pons,
2012), *self-esteem* (Babcock & Laschever, 2003; Fortin, 2008; Manning & Swaffield,
2008), *risk aversion* (Croson & Gneezy, 2009; Manning & Swaffield, 2008), *taste for
competition* (Reuben, Sapienza & Zingale, 2015), *ambition* (Babcock & Laschever, 2003;
Chevalier, 2007), *social skills* (Fisher, 1999), *career orientation* (Manning & Swaffield,
2008), *values* (Chevalier, 2007), etc.) to labor market outcomes and the gender wage gap
(Blau & Kahn, 2017; Fortin, 2008; Manning & Swaffield, 2008). Fortin (2008) posits that
analyzing noncognitive factors is becoming increasingly critical to understanding
enduring gender wage differences in light of the closure of gender gaps in factors such as
educational attainment. According to Chevalier (2008), “most studies are likely to

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¹ For a recent detailed review see Blau and Kahn (2017).
overestimate the unexplained component of the gender wage gap” due to the omission of attitudinal variables (p. 819).

Mueller and Plug (2006) provide one of the most thorough discussions regarding the potential links between these psychology constructs, specifically the personality traits, and wage outcomes, namely differences in skills, differences in preferences, and labor market discrimination. Based on human capital theory, systematic wage differentials are thought to be a consequence of differences in individual productive skills, which can be innate or developed over time, with the level of return of particular skills varying by occupation and job requirements (Mueller & Plug, 2006). Given the established links between personality traits and job performance, the logical leap has been explored that personality directly impacts earnings due to associated differences in skills (Mueller & Plug, 2006). (This relies on the implicit assumption that personality affects behavior (Mueller & Plug, 2006)).

Personality also impacts wages indirectly through differing occupational choices that are made based on preferences influenced by personality traits (Mueller & Plug, 2006). Finally, personality may impact earnings due to labor market discrimination if men and women are rewarded or penalized differently for displaying the same traits (Mueller & Plug, 2006). One can see that these mechanisms tie to classic economic constructs of human capital, compensating wage differentials (occupational sorting), and discrimination.

Values

As mentioned previously, there has been conflicting evidence with regard to the presence and direction of gender differences in valuation of different aspects of work.
Several older studies assessing gender differences found that men placed greater importance than women on earnings (Brenner and Tomkiewicz 1979; Lueptow 1980; Peng et al. 1981; Herzog 1982; Major and Konar 1984), while others found job satisfaction to be more impacted by earning for females than males (Glenn and Weaver 1982), and others found no gender differences in this area (England, 1992; Walker et al., 1982). One more recently published longitudinal study shows evidence that although in the earlier cohort (aged in their mid-twenties in 1979) males placed significantly higher importance on money and work than females, in the second cohort, roughly 20 years younger, this difference reduced by a third (Fortin, 2008). From a theoretical perspective, this result aligns with the characteristics of gender role theory as context dependent and constantly evolving, thereby supporting the need for further scholarship in this area utilizing more recent data.

Four studies published relatively recently (in comparison to the rest of the literature in this area) present the closest analogs to including measurements similar to the centrality construct, though, as I will discuss, the differences are significant enough that I would not expect the results to be predictive to this study. All four studies examine the wage gap for early career individuals, from career onset to 10 years in (varying by study). Variables included in the models for these studies that may relate to centrality are values (Chevalier, 2007; Combet & Oesch, 2019), money/work importance and people/family importance (Fortin, 2008), and career orientation (Manning & Swaffield, 2008). These studies were limited to samples from the western world, including the U.K. (Chevalier, 2007; Manning & Swaffield, 2008), the U.S. (Fortin, 2008), and Switzerland (Combet & Oesch, 2019).
In the multi cohort (both U.S.) study by Fortin (2008) mentioned above, two separate composite variables were included in the Oaxaca Blinder decomposition, one to assess the level of importance placed on money/work, and the other to assess the level of importance placed on people/family. In both cases the measures included in the models were dichotomous with a value of 1 indicating ‘very important’ and 0 assigned to all others (Fortin, 2008). For the money/work composite survey participants indicated the importance in selecting a career of “Making a lot of money” “the chance to be a leader in one line of work” and the importance in life of “being successful at work” “having lots of money,” with response options of “not important” “somewhat important” and “very important” (Fortin, 2008, p. 895). The average of these responses was taken and then coded as a binary variable (Fortin, 2008). The variable for importance of people/family was created in the same way, though it contained two additional questions. Participants indicated the importance in selecting a career of “opportunities to be helpful to others or useful to society” “opportunities to work with people rather than things” and importance in life of “Helping other people in the community” “Ability to give children better opportunities” “Living close to parents and relatives” (Fortin, 2008, p. 895).

This study presents models for two cohorts at three periods of time: 1979 when the first cohort was age 25, 1986 when the first cohort was age 32, and 2000 when the second cohort was age 24 (Fortin, 2008). The raw wage gap (female disadvantage) for each of these analyses are roughly 23.7%, 22.9%, and 18.1% in 1979, 1986, 2000, respectively (Fortin, 2008). No significant gender differences in importance of people/family were found after the earliest survey (Fortin, 2008), meaning the initial differences diminished with age, and were never present for the younger cohort.
However, the gender differences in importance of money/work were significant for both cohorts at all three time periods, in fact, importance of money/work was found to be the most significant noncognitive factor to impact the wage gap, accounting for 1.7 log points of the 23.71 log point gap in 1979, 1.2 log points of 22.94 point gap in 1986, and ~1 log point of 18.11 point gap in 2000 (self-esteem, locus of control, and importance of people/family are the other noncognitive factors) (Fortin, 2008).

A major advantage of this study’s analysis of two cohorts from different time periods is the ability to assess across cohort changes over time. Whereas the change in the wage gap for the two periods assessed for the earlier cohort was not significantly decreased, comparing the earlier and later cohort she finds a significant decline (Fortin, 2008). She finds that importance of money/power explains a decreasing amount of the wage gap across cohorts because the gender differences in this area are decreasing (Fortin, 2008). However, the unexplained gap has not decreased significantly over time (1979, 1986, 2000) (Fortin, 2008).

Manning and Swaffield’s (2008) investigation of gender differences in early-career wages (10 years into careers), evaluates a sample from the U.K. at the age of 30 in the year 2000 (relatively close in age to Fortin’s (2008) second cohort, aged 24 in 2000). They include the construct of career orientation in their analyses, which is measured through a grouping of six questions included individually rather than developing a composite score. These questions include, “In your future job, how important is it to have high earnings?” “In your future job, how important is it to get ahead?” “Does getting married matter to you?” “Does having children of your own matter to you?” for which respondents have three possible responses: “doesn’t matter” “matters somewhat” or
“matters very much,” coded with values -1, 0, and 1, respectively for the first two questions and reverse coded for getting married and having children (Manning & Swaffield, 2008, p. 1012). Two other questions are also included to assess opinions of women’s role in society: “Women can do the same jobs as men” “Women's lib is a good thing,” for which respondents have also three possible answers: “agree fully” “agree partly” “disagree,” coded with values -1, 0, and 1, respectively (Manning & Swaffield, 2008, p. 1012).

They found a raw wage gap of roughly 18 log points (Manning & Swaffield, 2008) (meaning that females in this sample on average earn 18% less than men), which matches Fortin’s (2008) 18.1% raw gap for the cohort of the same time period. Within their sample they found significant gender differences for five of the six questions, the exception being ‘Does getting married matter to you’ (Manning & Swaffield, 2008). The signs of the significant differences were as expected, with women placing greater importance on having children relative to men, lesser importance on future earnings or ‘getting ahead,’ and stronger positive opinions towards gender equality of occupations and women’s lib (Manning & Swaffield, 2008).

In the decomposition model including this set of variables, the grouping is found to be collectively significant for female, explaining 4.3 log points of the wage gap, but not significant at the male coefficients (Manning & Swaffield, 2008). (For comparison sake, it should be noted that the decomposition estimates in Fortin’s (2008) study were based on a gender nondiscriminatory wage structure that works around the differences in coefficients that result from taking either male or female values as the reference group.) On the individual variable level, females “who report that having kids in later life as
mattering ‘very much’ to them have significantly lower earnings” (Manning & Swaffield, 2008, p. 1016). Manning and Swaffield’s (2008) assessment of their findings is that while these (and other included) variables tell us something about the forces driving the wage gap, they do not tell us everything. They find that “although men and women have similar earnings when entering the labour market, the women will be something like 8% behind the men ten years later even if they have been in continuous full-time employment, have had no children, do not want any and have the same personality as a man” (Manning & Swaffield, 2008, p. 1018).

Studies by Chevalier (2007) and Combet and Oesch (2019) both explore Solomon Polachek’s theory (see Polachek & Kim, 1994, and Polachek, 2006) that gendered choices, in particular the division of household labor, drives unobserved heterogeneity that underlies the wage gap (Chevalier, 2007). In the older Polachek source, the impact estimate cited indicates this heterogeneity “accounts for as much as 50% of the gender wage gap” (Chevalier, 2007, p. 820), whereas his later work is quoted as arguing “that this detrimental [household] division of labour is at the root of almost all the [gender] wage gap” (Polachek, 2006 as cited in Combet & Oesch, 2019). Both studies (Chevalier, 2007; Combet & Oesch, 2019) hold that these substantial assertions to warrant further empirical investigation and test this theory by examining early career cohorts in the U.K. (Chevalier, 2007) and Switzerland (Combet & Oesch, 2019).

Chevalier (2007) assess the impact of choice, career expectations, and career aspirations variables on the wage gap present from the onset of careers analyzing data from a cohort of young workers (employed full-time) who graduated from undergrad in 1995 and had, at the point of the study, no more than 42 months (3.5 years) of work
experience (data collected in 1998). Given the era of the data utilized here, outcomes should be comparable to Fortin’s (2008) second cohort and Manning and Swaffield’s (2008) sample (also from the U.K.). The collection of variables and how they were measured is unique once again. The survey asked respondents to indicate the level of importance for 12 items with regard to their long-term values on a 1-5 scale (“very important” “important” “not sure” “unimportant” and “not important at all”) (Chevalier, 2007, p. 826). These 12 items were listed as: “Career development” “Personal development” “Job satisfaction” “Financial reward” “Status and respect” “Valued by employer” “Socially useful job” “International experience” “Rewarding leisure” “Involvement in local issues” “Concern with ecology” and “Concern with current affairs” (Chevalier, 2007, p. 826).

Additionally, the survey contained eight other items relevant to assessing traits and expectations, which asked the respondent to rank their level of agreement with eight statements on a scale of 1-5 (“agree strongly” “agree somewhat” “not sure” “disagree somewhat” “disagree strongly”) (Chevalier, 2007, p. 826). These included: “I am extremely ambitious” “I do not expect to get main fulfillment from work” “I live to work” “I work to live” “I expect to work continuously until retirement” “I expect to take breaks for family reasons” “I expect my partner to take breaks” “I expect to change career several times” (Chevalier, 2007, p. 826).

For Chevalier’s (2007) fairly homogenous sample of young working graduates, the author found a raw wage gap of 12.6% (meaning that females in this sample earn on average 12.6% less than males), so a slightly smaller than the 18.1% and 18% raw gaps than in Fortin’s (2008) and Manning and Swaffield’s (2008) samples, respectively. This
difference could be a result in differences between source populations for the samples and is likely at least partially due to the exclusive focus on full-time working college graduates. (Chevalier only reports findings in terms of percentages, rather than log points, so I have calculated the corresponding log points here where appropriate for the ease of comparison.) Several decomposition models were reported. Collectively, these variables were found to have significant explanatory power in the wage gap model. In the favored model, 84% of the original 12.6% raw gap can be explained (Chevalier, 2007). Taken together, the 12 long-term values items accounted for 21% of the explained gap, while the eight trait & work/life expectation variables account for 12% (Chevalier, 2007). These percentages translate to 2.65 log points and 1.51 log points, respectively or roughly 4.16 log points collectively, which appears to be in the same ballpark of the 4.3 log points result found by Manning and Swaffield (2008) for their career orientation variable collection.

Statistically significant wage premiums and wage penalties were found for several variables. Both men and women who admit higher value for financial rewards or ambition may enjoy wage premiums up to 5% or 4%, respectively (Chevalier, 2007). Females that value status and respect highly enjoy a 1.7% wage premium, and males that rank highly in valuing international experience see a 2.6% premium (Chevalier, 2007). Some of the wage penalty findings seem less intuitive than these. Females, but not males, are found to suffer a 2.6% wage penalty for higher importance of career development, while males, but not females, are found to suffer a 1.7% penalty for higher ecological concern (Chevalier, 2007). Females are significantly more likely to place higher importance on doing a socially useful job than males, and presumably due to the
gendered nature of this value, males that report placing higher value on the socially usefulness of their work suffer a 1.5% wage penalty (no wage penalty found for females) (Chevalier, 2007). Curiously, an expectation to work continuously until retirement or an expectation that one will take career breaks for family reasons both have a negative impact on wages. The penalty for anticipating career breaks on the surface is only approaching significance, however, “28% of women strongly agree that they expect to take a career break for family reasons but only 2% of male graduates do” (Chevalier, 2007, p. 821). The gender difference in exhibiting this strong expectation to take a career break for family reasons, and the direction of the wage penalty, lead this to be the single most important variable of those discussed in the model, corresponding to 10% of the explained gap (Chevalier, 2007). This finding is of particular interest as it relates to Polachek’s assertion. Chevalier (2007) finds that the wage penalty females experience due to career breaks impacts wages even prior to the break being taken, support’s the essence of Polachek’s theory, that unmeasured heterogeneity driven by the gendered division of labor is important to the wage gap, but not the theorized magnitude of almost all (or even up to 50%) of the gender wage gap being accounted for by this.

Not all of these wage premium and penalties actually do much to explain the wage gap. Chevalier (2007) evaluated which variables exhibited both a significant difference in returns (wages) and significant gender differences found only four values/expectations variables to be meaningful in this way. These include: value placed on doing a socially useful job (women are more likely to exhibit this trait than men), the expectation one will change career several times (men are more likely to report this than women), the expectation one will take a career break (as just discussed), and the
expectation that one’s partner will take career breaks (men are a lot more likely to anticipate this compared to women) (Chevalier, 2007).

Combet and Oesch’s (2019) paper sets out to test Polachek’s argument that the anticipation of future family roles is the driving force of the persistent pay gap by investigating the research question: do male and female wages diverge prior to family formation among individuals matched in education level, field of study, and occupation? To embark on these analyses, they utilize two samples (one for the initial analysis and a second for robustness checks) of young workers in Switzerland, age 30 and below who are child-free (Combet & Oesch, 2019). The primary dataset presents a nationally representative sample, surveyed nine times over the course of 14 years (Combet & Oesch, 2019). Respondents were roughly age 16 at the first survey collection (2000), and age 30 at last surveyed collection (2014) (Combet & Oesch, 2019). Wage data for the first year an individual is in the labor force are used to calculate the dependent variable, log of gross monthly wage (Combet & Oesch, 2019). Unlike the other three papers discussed, this study actually takes wages at career onset, rather than 3.5 years in, 10 years in, or points in between. Taking a slightly different statistical approach from the studies previously discussed, these authors preprocess their data with the entropy balancing method in order to match data to evaluate wages between males and females with the greatest degree of similarity possible (Combet & Oesch, 2019).

Combet and Oesch (2019) utilized three indexes adapted from past literature to control for attitudes towards work, partnership, and family. These variables are labeled in the results: “Value orientation: partnership/family” “Value Orientation: work, intrinsic” “Value orientation: work, extrinsic” (Combet & Oesch, 2019, p. 339). Unfortunately for
this discussion, the actual questions included in these indexes are not reported, and the citation source the indexes were adapted from is unavailable thru U.S. library and database circulation, presumably since it is written in German.

Combet and Oesch (2019) find a raw wage gap for their sample based on their random effects model to be 4.9%, so comparatively a little less than half the 12.6% gap observed in Chavelier’s (2007) data, and less than a third of the estimated 18% raw gap reported in Fortin (2008) and Manning and Swaffield (2008). The results of their decomposition model indicate that in combination the three indexes that measured values towards work, family, and partnership account for a statistically insignificant portion of the gap at career onset roughly 4% (0.2 log points of the 4.9 log point wage gap) (Combet & Oesch, 2019). These finding are dramatically smaller than the collective variable estimates of 4.16 log points (Chevalier, 2007), 4.3 log points (Manning & Swaffield, 2008), and ~ 1 log point (Fortin, 2008), though like Manning and Swaffield, Combet and Oesch conclude that even at the onset of careers, among men and women equally matched, with shared values, the wage gap persists. Combet and Oesch’s interpretation of their results is that the insignificance of these variable in this model clearly disproved Polachek’s theory.

Drawing the findings of these four papers together, there is evidence that some measure of work values likely has a statistical relationship to the gender wage gap. The magnitude of the significance of these measures varies across different samples and possibly with the tool of measurement. As Muller and Plug (2006) also articulated, Combet and Oesch (2019) point out attitude variables “should only be relevant for earnings if they translate into concrete behavior” (p. 337 [original italics]). Even though
each of these studies looked at samples in early careers, before fertility decisions have been acted on, it is possible that each day/month/year into a person’s career, their day to day behavior (influenced by attitudes and values) compound, such that the magnitude of the impact these attitudes and values vary substantially from the point of starting salary to year 3, 5, 10, etc.

Centrality.

Role centrality is a psychological construct similar to the concepts of work and family values, career orientation, and expectations examined in the aforementioned studies. Role centrality is used as a measure of the level of importance one ascribes to a particular life role (Bagger & Li, 2012). Though I already described the research background for this construct I will revisit some key points and briefly expand upon that information here for the reader’s convenience.

Different researchers have linked the concept of role centrality to several constructs and theories including self-esteem, values, identity theory, role salience, and social identity theory, (Bagger & Li, 2012; Bagger, Reb & Li, 2014; Carlson & Kacmar, 2000; Carr et al., 2007; Eddleston, Veiga, & Powell, 2006; Liu & Ngo, 2017; Lobel & St. Clair, 1992; Lodahl & Kejner, 1965; Lu, Lu, Du, & Brough, 2016; Paullay, Alliger, Stone-Romero, 1994; Powell & Greenhaus, 2010; Xie, Shi, & Ma, 2017). Identity theory (Stryker, 1987; Stryker and Serpe, 1982) considers the implications of how people identify with the many roles they occupy and recognizes that these identities will not be valued equally (Bagger et al., 2014; Powell & Greenhaus, 2010). Role centrality describes the level of value placed on different roles. Researchers that start from the concept of values, individuals’ basic convictions that are enduring and resistant to change
(Rokeach, 1973), to explain role centrality describe it similarly as a means of value expression of individuals (Carlson & Kacmar, 2000; Carr, Boyar, & Gregory, 2007).

In this same vein, the concept of “role salience refers to the psychological importance of a particular role in a person’s life” (Thoits, 1991, as cited in Eddleston et al., 2006, p. 438). The terms role centrality, role salience, and even role involvement have been used fairly interchangeably within the literature (Gelb, 2014; Paullay et al., 1994). Identity salience as taken from social identity theory (Tajfel, 2010), varies only slightly from role salience, in that it “motivates attitudes and behavior in support of an identity” (Lobel & St. Clair, 1992, p. 1058). Essentially these are two facets of the same gem: Identity salience gets at the activation to engage and perform a role, whereas role centrality describes one’s psychological hierarchy of roles.

Research exploring the concept of centralities focused first on the work domain (Dubin, 1956; Lodahl & Kejner, 1965) and later the family domain (Lobel & St. Clair, 1992). Work and family centrality have almost exclusively been assessed as two ends of the same spectrum, and analysis have been based on the assumption that these centralities are reciprocally tied. From this perspective, a high interest in one has been deemed sufficient information to interpret a low interest in the other (Carlson & Kacmar, 2000; Carr, Boyar, & Gregory, 2008; Lobel & St. Clair, 1992).

However, Bagger and Li (2012) identify this assumption as a significant limitation to research in this area and point out theoretical and empirical findings that suggest these centralities are not mutually exclusive. Presumably as a result of Bagger & Li’s findings, more recent research has asserted that career and family centrality constructs “are considered as independent dimensions rather than as polar opposites, and
people can assign equal or unequal importance to” these roles (Liu & Ngo, 2016, p. 113).

Bhowon (2013) found that role salience levels were significantly positively correlated such that the higher the level of one role salience the more likely an individual also exhibits higher levels of the other role salience. Kossek et al. (2012) present the term dual-centricity to denote individuals with equally high levels of work and family centrality, while also acknowledging that other individuals may rate low on both work and family centrality and hold a primary identity outside of these two realms, such as “hobbyists, athletes, or church or community volunteers” (p. 114), referred to in this paper as other centrality, a centrality beyond the career or family spheres.

In the literature, centrality levels have been found to relate to a variety of variables such as career performance outcomes (merit wage increases) (Lobel & Clair, 1992), work-family/family-work conflict and enrichment (Bagger & Li, 2012; Carlson & Kacmar, 2000; Cinamon & Rich, 2002; Gelb, 2015; Weer, Geenhaus, & Linnehan, 2010), job satisfaction (Carr, Boyar, & Gregory, 2008; Kim, 2016), job attitudes (Lodahl & Kejner, 1965), organizational commitment (Carr, Boyar, & Gregory, 2008), job tenure (Dubin et al., 1975), and retention (Carr, Boyar, & Gregory, 2008; Liu & Ngo, 2017) among others. Following the train of logic laid out in previous psychological construct/wage gap studies, the established connection between centralities and variables with proven and obvious connection to wages (i.e. performance outcomes) provides the theoretical justification to bring these areas of research together.

**Research objective.**

As stated in the introduction of this paper, the objective of this study follows line of inquiry laid out by the recent research preceding it (Chevalier, 2007; Mueller & Plug,
2006; Nyhus & Pons, 2012) to explore the question: What portion of the unexplained gender wage gap can role centralities explain? As mentioned previously, we can only expect levels of role centrality to impact the wage gap if one’s internal hierarchy of roles effects their behavior, thus the underlying assumption is that centrality levels influence behavior. It is likely that some of the impact is already present in the wage equation insofar as centrality levels influence choices with measurable outcomes, such as attainment of higher education, job tenure, or employment status.

However, the persistence of the wage gap residual suggests the presence of effects residing below the surface potentially impacting the issues of selection bias or acting via mechanisms that are difficult to observe such as discrimination or micro level models of compensating wage differentials. Although it is beyond the scope of this study to identify which unmeasured behavioral outcomes are at play, assessing the impact of centrality levels on wages within a model controlling for human capital factors will uncover the portion of the unexplained gap, present due to these under the surface effects, that can be explained by these variables.

Furthermore, thanks to the rich collection of psychological construct measures available in the dataset, I am also able to test whether role centrality levels are in fact the correct construct to focus on relative to a variety of subjective assessments of one’s life, romantic partnership, and household labor.
Method

Data and Measurement.

Sample.

This study utilized the same dataset as described in papers 1 and 2. As discussed in the previous chapter, this choice was made to enable a robust examination of several aspects of life for this population using a variety of methods, while keeping the sample characteristics and measurement tools consistent across studies. This unique proprietary dataset is derived from a survey conducted in 2014, focused on couples and collected by a Center\(^1\) at the author's institution. A professional services company was employed to administer the survey and collect responses from a random sample of 500 men and 500 women from across the United States. The 56 question survey took participants approximately 8-10 minutes to complete, and includes details regarding respondents’ family situation, scales assessing centrality levels, life satisfaction, and perceived partner support, and limited demographic data. A major strength of this dataset is the depth to which family dynamics and psychological constructs (role centrality, life and relationship satisfaction) are probed, as reliable measurements of these items are generally absent from broader datasets used in wage studies.

Survey respondents were sourced from actively managed market research panels. All survey participants were in or had been in committed long-term relationships (specified in the survey as marriage or any domestic partnership with a shared household) and held a minimum of an associate degree. These survey results do not present paired

\(^1\) This survey was funded by Bentley University’s Center for Women and Business. It was written by Dr. Susan Adams and conducted by Qualtrics in 2014.
data, that is, the 500 men and 500 women were not in relationships with corresponding survey respondents. Only one member of each couple was surveyed.

The full sample was reduced from 1000 to 826 during the cleaning process to maintain focus on individuals actively in the workforce. Eliminating individuals age 60+ and retired reduced the sample by 100 respondents. An additional 74 observations were eliminated based on the data indicating: 1) that the respondent identified as a homemaker, or 2) the respondent indicated he or she was not currently employed and had no former job title. The sample comprised of 407 females and 419 males aged 21 to 75.

**DV - Annual Salary.**

Within the survey data, annual gross salary is reported in categories and category mid-points are used to define a continuous variable, as done in past studies with categorical wage data (Chevalier, 2007). Respondents are asked to report the highest level of income they sustained for at least three consecutive years. Multiple choice options required respondents to select one for five annual salary ranges (Less than $100,000/year; $100,000-$250,000; $251,000-$500,000; $501,000-$1 million/year; or More than $1 million/year). Because of the small number of observations in the top category (N=4) these were combined with the category below it. Mid-points were assigned for the first four categories ($50k, $175K, $340k, and $750k). Dropping wage outliers from the analysis is consistent with practices in the wage gap literature (Combet & Oesch, 2019; Manning & Swaffield, 2008). Removing the observations altogether versus folding them into the next highest category did not produce substantive differences in the results.
These data offer interesting opportunities for analysis. It essentially reports on a person’s real market wage rate, not just what they are earning at the moment. (Blau & Kahn, 2017). Similar to Combet and Oesch’s (2019) choice to use only the first wage observation for each individual upon entry into the workforce to limit unobserved heterogeneity, analyzing only the highest realized annual wage reduces the noise produced by gender differences in weekly hours or career-breaks (Blau & Kahn, 2017). If a fair market would be one in which a person’s market value of their work is not impacted by their gender, then this analysis brings us closer to measuring what the market is willing to pay for each individual’s skillset. This should theoretically narrow the observed wage gap for this sample relative to other studies.

Consistent with the prior literature, the natural log of wages is taken as the dependent variable, as the “log transformation is used to address the high degree of skew present in individual earnings data” (Tharp et al., 2019, p. 8). Past research varies in regard to the time unit of wages taken for analysis, with gross hourly wages being the most frequent denomination Blau & Kahn, 2017; Fortin, 2008; Manning & Swaffield, 2008; Mueller & Plug, 2006; Nyhus & Pons, 2012), and gross monthly wages (Combet & Oesch, 2017) or gross annual wages (Chevalier, 2007; Tharp et al., 2019) being relied upon if hourly wages cannot be accurately estimated with the available data. Gross annual wages are utilized in this analysis as no data on actual hours worked is available.

Relying on annual rather than hourly wages introduces the risk of statistical bias that may lead to an overestimation of the wage gap in a sample of all workers, given that females on average work fewer hours than men (Chevalier, 2007), although this is less likely in this dataset because the wage is measured as highest sustained annual earnings,
not current earnings. However, excluding part-time workers or people experiencing a career gap blinds the analysis to a significant portion of the female workforce, which creates its own issues in estimation. To address both of these concerns all analyses were run on the subset of the data of observations limited to those reporting current full-time employment (N=473), as well for the full dataset of individuals in the workforce (N=828). Both versions of the analyses are reported with estimates labeled to indicate the exclusively full-time (FT) sample and the whole workforce (WW) sample.

**IVs - Psychological Constructs / Subjective Variables.**

*Career Centrality.*

Career centrality was assessed using a scale adapted from Eddleston et al. (2006). Their instrument is an adaptation of “Lodahl and Kejner’s (1965) job involvement scale with the word career substituted for job” (Eddleston et al., 2006, p. 439) and the addition of one item based on Lobel and St. Clair’s (1992) Career identity salience scale. On a 7-point Likert scale respondents indicate their level of agreement with three statements (“A major source of satisfaction in my life has been my career,” “Most of the important things that have happened to me have involved my career,” “Most of my interests have been centered around my career,” strongly disagree = 1, strongly agree = 7). These responses are summed to establish the career centrality variable, though an average of the values (Eddleston et al., 2006) was also tested and produced equal coefficients in the models. Higher scores indicate higher levels of career centrality. The Cronbach alpha for this instrument in the whole workforce (WW) sample is .82, and .79 within the full-time only sample.
Family Centrality.

Family centrality was assessed with the same three-item scale as Career centrality, with the word family taking the place of career. Again, these responses are summed to establish the family centrality variable. The Cronbach alpha for this instrument in the whole workforce (WW) sample is .89, and .86 within the full-time only sample. Higher scores indicate higher levels of family centrality.

Other Centrality.

In order to take into consideration the possibility of centralities beyond career or family, other centrality was assessed with a single item measured. On a 7-point Likert scale respondents indicate their level of agreement with the statement: “A major source of satisfaction in my life has come from activities related to personal interests beyond work and family such as hobbies, reading, pets, exercise/personal care, time with friends, volunteer work, etc.” (1 = strongly disagree, 7 = strongly agree). High scores indicate higher levels of role centrality beyond career or family.

Life satisfaction.

Life satisfaction was assessed with a single item measured on a 7-point Likert scale as supported in the literature (Cheung & Lucas, 2014; Cummins, 2005). Respondents rated their level of satisfaction based on the following statement: ‘All things considered, how satisfied are you with life as a whole?’ (very dissatisfied = 1; very satisfied = 7).

Relationship satisfaction.

In four other items measured, respondents were asked about the quality of their relationship from their own perspective and their perceptions of their partner’s opinions.
On a 5-point Likert scale, respondents ranked their agreement with the statements “My current (or most recent) partner and I have had a good relationship” and “I really have felt like part of a team with my current (or most recent) partner” (strongly disagree = 1 to strongly agree = 5).

*Partner’s relationship satisfaction and Partner’s life satisfaction.*

On a 7-point Likert scale, respondents were asked to assess their partner’s level of satisfaction with the relationship (one item) and life as a whole during their relationship (one item) (very dissatisfied = 1 to very satisfied = 7).

*Partner support-overall.*

Overall perceived partner support (labeled *Partner Support-Overall* in figures and tables) was measured with a three-items based on Heikkinen’s (2014) study results of the spousal roles of employed partners of highly successful managers. Each item examines a particular support action or area (“My current (or most recent) partner has shown support for my career by "being" supportive (e.g., as a discussion partner, expressing acceptance of new career opportunities for me, participating in my business-related social activities, helping presentation practices),” “My current (or most recent) partner has shown support for my career by helping me maintain a life beyond work (e.g., considering the impact of work assignments and promotions on family life before accepting them – both of us make decisions as a couple),” “My current (or most recent) partner has supported my life-related desires (e.g., personal time, time with friends, hobbies).” On a 5-point Likert scale, respondents indicate the frequency at which they receive each type support (never = 1; all of the time = 5) (α = .89 for WW; α = .885 for FT).

*Partner support-domestic chores and satisfaction w/ family labor division.*
As mentioned previously, there are several types of support (i.e. emotional, informational, tangible assistance (Cutrona & Russell, 1987)). Tangible support, specifically in the area of domestic division of labor was assessed, aligning with the wealth of studies examining domestic gender specialization discussed in the literature review section (Blau & Kahn, 2017). Two items are used to measure the frequency of support and satisfaction with the established division of labor. Just as for the items included in the overall partner support scale, on a 5-point Likert scale, respondents indicate the frequency at which they receive domestic labor support from their partner: “My current (or most recent) partner has shown support for my career by managing or taking care of most of the domestic chores (children, extended family, housekeeping)” (never = 1; all of the time = 5). For the second item, on a 7-point Likert scale, respondents indicated their level of agreement with the statement: “I have been satisfied with the way my current (or most recent) partner and I have divided family labor” (strongly disagree = 1, strongly agree = 7).

Controls - Demographic and Human Capital / Objective Variables.

Gender¹.

Survey respondents were asked to select their gender from two options. The traditional binary designations of female or male were the only options presented, and the question was mandatory to proceed with the survey, so 100% of the sample declared one of these genders. The dummy variable coding designates female=1, male=0.

¹ Engaging in the extensive conversation surrounding the distinctions between biological sex and socially constructed gender is outside the scope of this project, but it is recognized that there is much to be said on this topic. In this dissertation self-reported sex is used as a proxy for gender. This is so common in the gender wage gap literature, most studies at this point do not specifically articulate how gender is measured. See Badgett and Folbre (2003) for an example that specifies sex was the reported data used for gender.
Age.

Respondents indicated their actual age at the time of the survey, and ages ranged from 21 to 75. The median age is 40 and an average age of 41.6, with a large standard deviation of 13.15 years. Age data within the sample does not adhere to a normal distribution and are significantly positively skewed (see histogram in Figure 2).

Family status - # of Relationships, # of Children, Stepchildren.

Respondents in the dataset can be assumed to be fairly homogenous with regard to marital/partnership status because a qualifying question for participation was “are you or have you been in a committed relationship (i.e. marriage of any domestic partnership with a shared household),” thus the dataset excludes individuals who are single, not-cohabitating, never married. However, a variable to report the number of committed relationships, as defined above, respondents have been in is included. This variable is capped such that respondents selected from four options (1, 2, 3, 4 or more).

As discussed in the literature review section, men and women experience different wage effects with parenthood. Variables for number of children including adoptions, and a separate variable indicating if one’s partner has children from another relationship are included. The variable for partner’s children is binary (yes/no) (labeled Stepchildren in tables), whereas the number of children variable is continuous but capped (selections available: 0, 1, 2, 3, 4, 5 or more). The majority of sample respondents (71.9%) have at least one child, with an average of 1.46 children per household. A total of 210 individuals report having one child (25.42% of the sample), 240 have two children (29.06% of the sample), and 143 reported 3, 4, 5 or more children, collectively.
Education.

The survey targeted college educated individuals, thus “Do you have a college degree?” was an initial screening question, and “Associate degree” was the lowest level of education available for respondents to select. Respondents were asked to indicate their highest level of education (Associate degree = 2; Bachelor degree = 3; Master degree (including MBA) = 4; Professional doctorate (e.g. MD, DDS, EdD, Law, Engineering) = 5; Academic doctorate (PhD) = 6). In the cleaning and coding process, all terminal degrees (professional doctorate and academic doctorate) were combined to one category (=5) so that the variable is truly ordinal by education level.

Partner education.

When indicating the highest education level of their partners, respondents selected one of six options (High school or some college with no degree = 1; Associate degree = 2; Bachelor degree = 3; Master degree (including MBA) = 4; Professional doctorate (e.g. MD, DDS, EdD, Law, Engineering) = 5; Academic doctorate (PhD) = 6). Just as was done for the respondent education variable, all terminal degrees (professional doctorate and academic doctorate) were combined to one category (=5).

Education equality.

A binary dummy variable was created to indicate education equality within partnership (equal =1; unequal = 0). Equality was determined based on school level (undergraduate, graduate, and terminal) rather than specific degree type. Associate and Bachelor degrees were considered equal as both reside at the undergraduate level, and Professional doctorate and Academic doctorate were also equal as both types fall into the terminal degree level.
Employment status.

Respondents selected among five options to indicate current status of employment (Employed full-time, not including self-employment=1; Employed part-time, not including self-employment=2; Self-employed=3; Not employed=4; Retired=5). As mentioned in the description of the dataset, observations were removed from the initial 1000 observations if the individual was 60+ year old and indicated a retired employment status, and if the individual indicated not employed as their employment status and listed no former job title. This excluded 174 observations collectively. Individuals under the age of 60 that indicated they were retired were retained in the dataset because they are still working age and potentially had an exceptionally successful career if they have been able to retire early. Only 35 of these observations (4.24% of the whole workforce sample) fall into this category and are obviously among the observations excluded in the full-time only sample. Observations of individuals currently not employed but working age are included in the whole workforce sample because unemployed individuals are considered part of the labor force per the technical definition (Bureau of Labor Statistics, 2014). Furthermore, since the survey collected data on the highest level of income for at least three consecutive years, there is wage rate data for even those individuals who are not currently employed.

Industry.

Survey respondents were asked to select all industries in which they currently work or have worked in the past. Each of the eight industry options were used to create dummy variables with 1 = participation in an industry and 0 = no participation. Only 65
of the 826 respondents indicated employment in more than one industry. See Table 15 for industries list details and sample breakdowns.

Means and standard deviations for all variables broken down by gender and sample are reported in Table 16.

**Empirical Model.**

I follow the standard procedure for wage differential decomposition used most frequently in wage gap research originally laid out by Oaxaca-Blinder (Oaxaca 1973; Blinder 1973). If $\ln W_m$ is the mean log wages for males and $\ln W_f$ is the mean log wages for females, then the total difference between these can be decomposed with the equation:

$$\ln W_m - \ln W_f = X_m \hat{\beta}_m - X_f \hat{\beta}_f$$  

(1)

$X_m$ and $X_f$ denote the average values of the independent variables for males and females, and $\hat{\beta}_m$ and $\hat{\beta}_f$ parameter estimates from the respective male and female wage equations (Nyhus & Pons, 2012). Restated in other words, “the average gender gap in earnings can be decomposed between the mean difference in observed characteristics and the difference in the returns to these characteristics” (Chevalier, 2007, p. 824).

The results of the Oaxaca-Blinder decomposition break the wage differential into two parts: an ‘explained’ part that can be accounted for by measured variables (i.e. education), and an ‘unexplained’ part, also known as the residual, which cannot be accounted for by known wage determinants (Jann, 2008).

One challenge in comparing decomposition results from various studies is the fact that the selection of reference group (males or females) will vary the results (Blau & Khan, 2017; Chevalier, 2007; Fortin, 2008). Authors have chosen to address this issue in
a variety of ways. Using males as the reference group has historically most often reported, thus some authors choose to run analysis for both reference groups, but only mention results from the female wage equation if of significant difference from those of the male equation (Blau & Khan, 2017). Other authors report results from both reference groups side by side for comparison (Manning & Swaffield, 2008). Still others use methods to pool the data or use weights to approximate gender nondiscriminatory estimates (Combet & Oesch, 2019; Chevalier, 2007; Fortin, 2008; Nyhus & Pons, 2012; Mueller & Plug, 2006).

However, there has been considerable debate about the best method for doing this, and some commonly used methods have been shown to produce extreme results (Fortin, 2008). To best navigate this debate, I have chosen to present results based on the male wage equation, the female wage equation, and a pooled model based on methodology laid out by Jann (2008) and utilized in the most recent publications in this area (Combet & Oesch, 2019; Tharp et al., 2019). All models have been estimated using STATA/SE 13.0 for Mac statistical software with the oaxaca command, specifying robust standard error estimation. I will primarily focus on the pooled model results in this discussion except where noteworthy differences between the models occurs, but corresponding results for all other models are presented in figures and tables.

Results

Gender differences within the samples.

Table 17 and Table 16 display the differences in means for both the whole workforce (WW) and full-time only (FT) samples, and the means and standard deviations broken down by gender for each sample. The significance of differences is reported in
Table 17 are based on results from t-tests ran to analyze the presence of gender differences for each individual variable. I find in both the WW and FT samples that males are significantly older than female respondents, on average have higher levels of education, and indicate their partners have higher levels of education. In the WW sample males are also significantly more likely to have a partner with equal levels of education relative to females. Consistent with the literature, in the WW sample females are significantly less likely to be employed full-time than males, and more likely to be employed part-time. In the FT sample, females are also more likely to have a partner with children from a previous relationship. Gender differences in the participation in several industries were also found significant. Females are more likely than men to be employed (now or in the past) in professional services, retail/wholesale, or social/government service. Males are more likely than females to be employed (now or previously) in technology or utilities (though the difference in the utilities industry is not significant in the full-time only sample).

Role centrality levels also vary significantly by gender. Aligned with traditional gender norms, males in the WW and FT samples exhibit higher career centrality and lower family centrality compared to females. Females also exhibit higher other centrality than males in the WW sample, but the difference is not significant when the analysis is limited to the FT sample.

Finally, in the FT sample males agree more strongly than females in assessing their romantic partnership as a ‘team.’
Earnings equation results.

Table 18 reports the Ordinal Least Squares (OLS) estimates for the whole workforce (WW) sample of the log annual wage equation for the male, female, and pooled samples respectively, for both the minimal specification and full specification models. Table 19 reports this same information for the current full-time only sample. Results for the male, female, and pooled equations are largely similar. A total of 13 variables are found to significantly impact wages in at least one of the 12 estimated models. Eight of these variables were identified when assessing gender differences in the sample, but four other variables emerged as significant to the wage gap even though they do not exhibit significant gender differences. This is potentially a result of gender differences in the rewards or penalties females and males experience when exhibiting the same traits or behavior, also referred to as gender-specific returns (Chevalier, 2007).

Almost all of the variables identified as significant in the minimal specification models remain significant in the full specification models, which suggests that the additional variables are not redundant, but rather improve the explanatory power of the models by adding new information. As anticipated from the comparison of means, several objective control variables are significant in all or most of the minimum specification and full specification WW sample models. These include age, children (own and stepchildren), education, education equality with partner, and several industries (life science, social/government service, and utilities). In the FT sample, with regard to industries, social/government service is the only industry found to be significant across all six models (p<.01). The negative coefficient indicates a wage penalty associated with this industry, and we know from the difference in means that females are more likely to
be in this industry than males. The utilities industry appears like is may also be significant in the FT sample, but only in the female reference group models (p<.01). For FT female workers there is a significant positive relationship between participation in the utilities industry and wages found in both the minimal and full specification models. Participation in the life sciences industry is positive and significant to wages for the WW sample in the male (p<.05) and pooled (p<0.1) minimal specification models and the male full specification model (p<0.1), but not significant in any of the FT sample models or the two female and pooled full specification model for the WW sample.

Analysis of the relationship between log wages and subjective measures reveals career centrality to have a positive and significant impact on wages in all models where these measures are included (p<.01). In the pooled regression of the WW sample, I also find a significant positive relationship of life satisfaction to wages (p<0.1), and in the pooled regression of the full-time only sample I find identifying as a team with one’s partner to also have a positive and significant impact on wages (p<0.1). In the male regression of the full-time only sample, the perception of one’s partner’s life satisfaction is also positive and significant (p<0.1). Stronger levels of agreement with the assessment of one’s relationship as a good relationship were found to have a significant negative relationship with wages for the full-time only sample, in both the male and pooled equations (p<.05).

Adjusted r-squared and F-test results are listed at the top of both Table 18 and Table 19. All of the models are found to be significant at or below the 0.1% level (p<.001), and, per the adjusted r-squared values, the addition of subjective measures improved the model fit in all cases. The subjective measures explain an additional 3.66%
of the variance in wages for females, and 1.04% for males in the whole workforce sample (2.59% and 2.32% for female and males in the full-time only sample, respectively).

**Wage gap decomposition results.**

Table 20 and Table 21 report the results of the gender wage gap decomposition. Table 20 presents results from the models based on the whole workforce (WW) sample, while Table 21 displays equivalent models run for the current full-time workers only (FT) portion of the larger sample. The raw wage differentials are 20.68 log points and 15.19 log points for the WW and FT samples, respectively. The WW sample value is similar to other research on U.S. samples such as Fortin (2008), while the FT sample value is close to the 12.6 log point gap Chevalier (2007) identified for his U.K. sample, also exclusive to college graduates employed full-time. The upper portion of each table, labeled Panel A, displays the results from decomposing a bare bones model specification including only objective variable measures, whereas the lower portion (Panel B) shows results for the full models including both objective variables as well as the measurements of psychological constructs. As explained above, results for the models using male wages as the reference group, female wages as the reference group, and a pooled nondiscriminatory estimation are presented side by side in each panel. Calculations of robust standard errors are reported in parentheses beneath each co-efficient.

Panel A of Table 20 shows that 49.2% (10.18 log points) of the gender gap for the pooled model can be attributed to differences in objective variables such as age, education level, and industry. In the same column, in panel B we can see that adding centrality, satisfaction, and family labor division variables accounts for 14.8% (3.07 log points) collectively and contributes to a model that explains 9.3% more of the gap overall.
(58.5% vs. 49.2%). Career centrality significantly contributes to the wage gap decomposition of the WW sample regardless of the reference group, accounting for 3.13 log points in the male reference group equation, 2.43 log points in the female equation, and 2.77 log points in the pooled equation.

**Additional decompositions.**

Given the categorical nature of the wage data available in this dataset, there could be some concern regarding the smaller sample sizes of higher categories leading to biased results. To address this, I have run 12 additional decompositions to check the robustness of the OLS decomposition results.

The dependent variable in each of these models is a binary variable for annual salary, indicating whether the respondent earns less than $100k per year (coded 0) or greater than or equal to $100k per year (coded 1). This split point was selected for several reasons. For one, when taking the midpoints of the salary categories, the mean income for the whole workforce sample is $106,749.4, and the average male and average female annual wages fall to either side of this threshold ($188,878.3 and $94,262.9, respectively). (These data are skewed above national averages, but the survey population exclusive to college graduates is likely a large reason for this since the average mid-career salary for college grads in the U.S. is $80,450 (Zetlin, 2019), compared to the national mean annual wage of $51,960 (Bureau of Labor and Statistics, 2019)). Secondly, this split point provides the closest approximation of a balanced sample with 31.84% of respondents falling into the > or = to $100k bucket for the WW sample (38.48% in the Full-time only sample). Finally, the ‘six figures’ salary has long been a normative
threshold for those who are perceived as ‘well off’ in the U.S. relative to the greater population, and thus has intuitive appeal for interpretation.

While logit models are perhaps the most common approach for multivariate analysis of binary dependent variables in management literature, linear binary regression is often used in economics due to the comparative ease in interpretation (Von Hippel, 2015). The traditional Oaxaca-Blinder decomposition has been extended beyond OLS models to accurately accommodate non-linear models, such as logit and probit models, among others (Fairlie, 2003; Powers & Pullum, 2006; Powers, Yoshioka, & Yun, 2011). Decomposition analyses were conducted for binary linear as well as logit models for the male, female, and pooled reference groups in both samples (WW and FT). Results are displayed in Table 22 and Table 23.

Taking this binary version of the salary variable, the analysis shows a raw gap of 14.33 log points for the WW sample, and 10.27 log points for the FT sample. (This is consistent across both the binary linear and logit models.) Comparison of the binary linear and logit models reveals these results are extremely similar with regard to the sign and significance of co-efficients, thus for ease of interpretation and comparison sake I will focus on reporting the binary linear results here. Consistent with the previous OLS decomposition models, in the WW sample, the three areas that showed the greatest explanatory power were industries, education variables, and career centrality.

Collectively, industries accounted for 4.08 log points (p<.01) of the 14.33 log point gap in the pooled model. Education variables accounted for 2.09 log points together (p<.01), and career centrality explained 1.81 log points (p<.01) (both in the pooled model for the WW sample). Current employment status was also significant (p<0.1) in the
pooled model, but not in the male or female equation models. Similar to the OLS decomposition result, the 54.7% of the gap (7.84 log points) is explained by the variables in the pooled model for the WW sample (58.5% was explained in the OLS decomposition).

Also similar to the OLS decomposition results, 51.9% of the gap is explained in the pooled equation model for the FT sample (53.6% in the OLS decomposition), and the same factors are significant. Education variables collectively and industry variables collectively explain 2.26 log points (p<0.05) and 2.74 log points (p>0.1), respectively. However, career centrality explains only 1.42 log points in the pooled model and, just as was found in the OLS decompositions, is not significant in any of the FT sample models.

The alignment of the results from the binary linear and logit models with the original OLS decomposition models build confidence in the robustness of the findings from these analyses.

**Discussion and Limitations**

**Discussion.**

**Career centrality.**

Within this study, calculations for the raw wage gap range from 10.27 log points based on the binary linear and logit models of the full-time only (FT) sample, to 20.68 log points in the whole workforce (WW) OLS models of the log of annual wages. These estimates fall within the range observed in similar studies (4.9% (Combet & Oecsh, 2019) to 23.7% (Fortin, 2008)), and at the upper end align with the U.S. estimate that females earn roughly 79% of what males earn annually (Blau & Khan, 2017). Results from the Oaxaca-Blinder decomposition analyses show that career centrality level can
account for 11.7% to 18.2% of this gap when included in the wage gap equation (dependent on sample and model specifications). Within these samples, males exhibit higher levels of career centrality than females, and this difference is statistically significant for both the WW and FT samples. Because career centrality is associated with higher wages in the labor market, males’ higher propensity toward this centrality represents an advantage.

These values fall between estimates for similar variables examined in past studies. On the high end, groupings of career orientation variables have been found to account for 23.75% collectively (Manning & Swaffield, 2008). Likewise, Chevalier (2007) found a collection of eight work/life expectation variables and a collection of 12 long-term values variables to account for 12% and 21% of the gap respectively, or 33% all together. On the other end of the spectrum, Fortin’s (2008) similar single variable assessing importance of money/work accounted for only 5.5% of the wage gap in the most recent cohort. These differences may be largely due to the differences in the number of variables included to calculate these percentages. However, Combet and Oesch (2019) also reports the collective impact of 3 indexes and finds that values towards work, family, and partnership together account for a statistically insignificant 4% of the gender wage gap in their study.

As Blau and Khan (2017) found, differences in sample populations and measurement tools are likely driving the variation in these numbers. The estimates found here (11.7% to 18.2%) fall within the range of past findings, suggesting that the true impact of career centrality level on the U.S. gender wage gap is likely to be in this 4-24% ballpark.
Family centrality.

The findings of this study also run contrary, at least in part, to Polacheck’s theory that a very large portion of the wage gap can be attributed to gendered choices, in particular the division of household labor (Chevalier, 2007). The significance of career centrality level to account for a part of the wage gap, as well as the significant gender differences observed for this variable, do point toward the importance of gendered choices. However, the insignificance of family centrality level (also a gendered construct) and the family labor variables suggest that the home is not where gendered choices are translating to pay outcomes. For a variable to have a significant impact on the gender wage gap there must either be large gender differences for that variable or the returns (wage penalties or premiums) must be gender-specific (Chevalier, 2007).

In both the WW and FT samples significant gender differences are not found for either of the two division of family labor variables and significant gender differences in returns are not suggested by the regression or decomposition results for any of the models. Although significant gender differences were found for family centrality level in both samples, this variable also did not significantly impact wages in any of the models. Just as the intention or expectation toward having a family in the future has been found to result in wage penalties long before actions toward that end are initiated (Combet & Oecsh, 2019; Manning & Swaffield, 2008), these results suggest that the wage gap may have little to do with the practical day to day outcomes of the division of family labor or even the level of prioritization placed on one’s family role. Like human capital theory or the compensating wage differential construct, the gender division of family labor is insufficient in accounting for the unexplained wage gap.
General discussion.

Including all psychological construct / subjective variables reduces the unexplained portion of the wage gap by 25.8% in the pooled model for the FT sample (range of 21.7%-34.1% across the three models) and 9.3% in the pooled model for the WW sample (range of 7.2%-17% across the three models). These results suggest that a portion of the unexplained wage gap can be attributed to differences in levels of role centralities, degrees of various satisfaction (including relationship satisfaction), and the division of household labor within romantic partnerships, with level of career centrality being the single most influential variable among these.

As mentioned previously, there has been a flawed assumption in most of the role centrality literature that career and family centrality are two sides of the same spectrum. Similarly, in the economic literature, Becker (1985) theorized that the greater domestic commitment of women leads them to put less energy into work which translates to lower earnings, due to the choices in allocation of energy (a finite resource) among different activities. A handful of centrality articles have presented a departure from this assumption (Bagger & Li, 2012; Bagger, Reb, & Li, 2014, Eddleston et al., 2006; Kossek et al., 2012; Liu & Ngo, 2017).

The results presented here add support to this relatively recent development in the literature. While there is a significant relationship identified between career centrality and wages, the relationships between family centrality or other centrality and wages are not significant in any of the regression or decomposition models. If career and family centrality were in fact two ends of the same spectrum, then we would expect that a positive relationship between career centrality would be matched with a correspondingly
negative and significant relationship between family centrality and wages. However, the empirical findings here present do not align with this. In addition to the insignificance of family and other centrality in the model, it is worth pointing out that mean family centrality levels are considerably higher than the means for career centrality level for both men and women (Table 16) but there are smaller differences in these levels between genders (Table 17).

From a theory-based perspective, the results of this study point to the continued influence of traditional gender roles in modern America. On average, females still exhibit lower levels of career centrality and higher levels of family centrality than males. These findings are consistent in both the WW and FT samples. It is interesting to note that in comparing averages between the WW and FT samples, both males and females in the FT sample present slightly higher levels of career centrality and higher levels of family centrality (Table 16). Although these tiny differences (only fractions of one standard deviation) are unlikely to be statistically significant.

**Limitations.**

As with all research, this study is not without limitations. In general, empirical studies on the earnings effects of noncognitive traits struggle with the scarcity and high degree of variation among studies in this area, which makes it difficult to find patterns or make generalizations, as well as concerns regarding the exogeneity of self-reported ex-post measures as the potential that measures of these constructs may be “both causes and consequences of labor market outcomes” (Mueller & Plug, 2006, p. 4). This endogeneity may lead to biased estimates and an overestimation of the explained component of the gender wage gap (Chevalier, 2007).
Regarding concerns of endogeneity issues, the cross-sectional nature of the dataset is a challenge, because it is not possible to capture the impact of one’s workforce experience on levels of centrality, and thus cannot be relied upon for causal inferences (Nyhus & Pons, 2012). However, like personality, there is substantially more convincing evidence to support that levels of role centrality are relatively stable for an individual over time than to the contrary. Several studies that analyzed panels over 12 year time periods found no significant changes in work centrality (Mannheim, 1993), the meaning of work concept (Harpaz & Fu, 2002), or leisure-orientation and work-orientation (Snir & Harpaz, 2002; and Snir & Harpaz, 2005). Mauno and Kinnunen (2000) looked at job and family involvement levels and found no significant changes over a course of three years (three waves of surveys). Furthermore, Swaffield (2000) considered work orientation and home orientation and found “that yearly variations in motivations are not correlated with wage variation, but that the average motivation over a 6-year period correlates with permanent wage” (Chevalier, 2007, p.822).

While there is some conflicting evidence to support the notion that centralities do change over time, as suggested by the change model of role centrality, the studies supporting this idea have only presented data with samples surveyed only twice, at an interval of one year apart (Norton et al., 2002; Norton et al., 2005). It appears mostly likely, based on this collection of evidence, that role centrality levels may exhibit some variation in the short-term, but these variations balance to non-significance over a longer time horizon. In keeping with Arvey, Harpaz, and Liao, (2004) and Chevalier (2007), based on this evidence, role centrality is a relatively stable individual characteristic, and as such can be assumed to be exogenous to wages in the same time period.
As discussed in the literature review section on discrimination, the results presented here cannot be utilized to draw conclusions regarding the presence, severity, or absence of discrimination. Role centrality levels as variables are subject to the same limitations as other variables, such as area of study and occupational choices: it is impossible to rule out the possibility that these variables reflect female response to discrimination (Chevalier, 2007). It is worth noting that even when the psychological constructs are measured before the time of employment and found to be stable over time, discrimination could still be an underlying factor, as these measures (like attitudes and values) could be influenced by the anticipation of discrimination (Blau & Kahn, 2017). The issue of scarcity of research can only be resolved incrementally, with each new study such as this one. Acknowledging the concern of too much variation, just as Mueller and Plug (2006) utilized the established five-factor model to measure personality traits to draw together a scattered pattern of research, here I introduce the use of an established measurement scale to assess levels of centrality into the wage gap literature. This lays the foundation for better consistency in the measurement of role values in future research. Furthermore, I have sought to reference and rely on the extant literature to guide this research, as well as pull together disparate but interrelated research to compare results across studies.

Despite these limitations, as Mueller and Plug (2006) argue, studies such as the one presented here have value in their ability to shed light on the importance of noncognitive traits, and there is ample room for exploratory studies due to the infancy/scarcity of this research area. Furthermore, as one can see from the review of the literature, the studies that do exist almost exclusively report on datasets from the year
2000 or before. Therefore, this paper participates in a much needed effort to bring this literature more up to date.

**Conclusion**

While the unexplained portion of the wage gap is often attributed to discrimination, this residual could also be the result of omitted variables capturing differences in productivity, prioritization, or preferences (Nyhus & Pons, 2012). This paper contributes to our understanding of the wage gap residual by exploring the impact of differences in levels of role centrality.

Consistent with several previous studies assessing related or similar variables, I find that level of career centrality is positively related to wages for all genders, and accounts for at least a moderate portion of the gap left unexplained by human capital characteristics. The results do not indicate a similar relationship between wages and family centrality, nor do I find direct relationships between wages and any other psychological construct included in the models.

Regarding estimation of the gender wage gap, I find that the raw wage gap to be 20.68% in the OLS decomposition models for the whole workforce sample, 15.19% in the OLS decomposition models for the sub-sample of only full-time workers, 14.33% in the logit and binary linear decomposition models for the whole workforce, and 10.27% in the logit and binary linear decomposition models for full-time. The results from estimations of models that include human capital and demographic variables as regressors indicate that the unexplained part of this gap is 54.3%, 45.1%, or 50.8% (depending on the reference group used for the equation, Males, Females, or Pooled) in the OLS decomposition models for the whole workforce sample. In the equivalent
models of the full-time only sample 84.3%, 70.3%, or 72.3% of the gap is unexplained. The inclusion of centrality level, satisfaction, and family labor variables reduces the unexplained portion of the gap to 47.1%, 28.1%, or 41.5% (WW sample) or 50.2%, 48.6%, or 46.5% (FT sample), respectively. The greatest part of this reduction is attributable to gender differences on career centrality. Therefore, the gender wage gap may partly be explained by the fact that level of career centrality, found to be higher on average in males than females, appears to be rewarded in the labor market. I do not, however, find any gender difference in the rewards females and males receive for possessing higher career centrality, as I find that all genders receive wage premiums for increasing levels of this centrality.

The results of this study support the theoretical development conceptualizing role centralities as largely independent, as opposed to two ends of a spectrum, as well as confirm the continued influence of gender roles in U.S. society. These findings also run counter to Polachek’s theory, leading to the conclusion that the division of family labor is not directly significant to the gender wage gap. Therefore, just like the other classic theorizing on the topic, the gender division of labor is alone insufficient to fully explain the gap.

I do not interpret the results here to lead to any conclusions regarding the presence, absence, magnitude or impact of discrimination on either the explained or unexplained portion of the gap. Furthermore, I refrain from drawing any causal inferences in particular due to the cross-sectional nature of this dataset. Despite these limitations, this study’s results support the call to continue this line of academic inquiry. Future research would benefit from greater standardization of measurement tools and
exploration of more recent datasets. Better understanding of the causes of the wage gap may assist in the development of policies or social change movements that target reducing and eliminating the differential outcomes of these causes.

As Blau and Kahn (2017) also point out, there is fertile ground for further research in this area to answer the many remaining questions that this study cannot. For example, given the significant impact of career centrality on the gender wage gap, research testing the effectiveness of interventions to address this portion of the wage gap is needed. It would be helpful to better understand the circumstances, if any, in which centrality levels are malleable on a long term horizon, and if it is possible to close the gender gaps in centrality levels in present or future developing generations.
Chapter 5: Contributions, Themes & Connections, and Conclusion

Themes and Connections

All three papers in my dissertation feature role centrality and gender as key variables of interest. The first is a replication study testing hypotheses to examine the gender differences within modern the dual-career couple member’s experience, reexamining several of the imbalances between genders within dual-career families that have previously been reported. The second conducts an exploratory quantitative analysis of the variables that best predict life satisfaction for individuals in dual-career couples. The third paper analyzes the role centrality construct as it relates to the gender wage gap.

Life satisfaction, role centrality, income and the experience of life within dual-career romantic partnerships are the common themes of this dissertation. These papers related to one another as follows. All papers are linked by use of a shared dataset and evaluation of several of the same variables including role centrality, gender, income, partner support. My final paper extends the preceding analyses and narrows in on the gender wage gap and the ability to explain part of the unexplained wage gap with role centrality levels. The sequence of this dissertation starts with confirmatory analysis (hypothesis testing), proceeds to exploratory empirical analysis, and concludes with an econometric analysis. An organizing framework is displayed in Table 24 and Figure 5.

Motivation and Collective Findings

Returning to the motivation of this dissertation, I have succeeded in my aim to add to the broad collective body of knowledge about gender and the workforce. In regard to the question of why the dual-career couple phenomenon has not brought with it the anticipated gender equality, I find that traditional gender roles appear to continue to effect
the levels of priority placed on central life roles. For the shift in family structure to
catalyze further societal change it would need to carry with it changes in behaviors and
beliefs, and it appears that whatever changes in behaviors and beliefs the dual-career
couple phenomenon brought with it has been insufficient because of the persistence of
traditional gender roles. Furthermore, levels of role centrality matter to both life
satisfaction and the gender wage gap. Career centrality can account for a statistically
significant portion of the gender wage gap not explained by human capital traits, and both
family centrality and career centrality have greater impact on life satisfaction than income
has on life satisfaction for individual in dual-career couples.

Collectively these results suggest there might be a mediation or moderation
relationship between centrality level, income, and life satisfaction. It is possible that
centrality moderates the relationship between income and life satisfaction such that the
extent to which financial success resulting from career success improves one’s life
satisfaction is influenced by one’s levels of career and/or family centralities. The research
and theory within role centrality literature that asserts that levels of centralities critically
moderate the impact of circumstances or occurrences in a certain life domain on the
significance of one’s psychological outcomes (Dubin, 1956; Martire, Stephens, &
Townsend, 2000) align with this hypothesis. These conclusions not only add to the
existing body of knowledge but also lay down empirical support and direction for future
research.

**Contributions**

This dissertation contributes to academic scholarship and society at large in a
number of ways.
It continues to progress the study of role centrality. This research area stemmed from studies conducted exclusively in the workplace (Dubin, 1956; Lodahl, 1965), but later expanded to inquiry of the impact of role centrality in life outside of work (Paullay et al., 1994). There is a dearth of studies that measure centrality for multiple roles and a prevalence of studies that assume career and family centralities are directly oppositional (Bagger & Li, 2012). This creates significant gaps in the literature. In fact, the assumption of mutual exclusivity of roles has been so pervasive in this line of study, that even some very recent work has fallen prey to this flaw (for an example, see Xie, Shi, & Ma, 2017). By separately measuring both career centrality and family centrality and including a measure of role centrality beyond these two realms, this dissertation addresses multiple shortcomings of past literature. Furthermore, role centrality has been considered most frequently in the work-family conflict literature, so the work presented here incorporating it into investigation of the characteristics of modern dual-career couples assists with expanding the application of this construct. The final paper of this dissertation expands the application of the role centrality construct still further by investigation the presence or absence of gender wage gaps within and between groups with aligned role centrality levels.

This dissertation also adds to the academic literature on social support. The majority of studies on social support stem from research questions of whether, or to what degree, social support impacts psychological or physiological health given X context (Broadhead et al., 1983; Callaghan & Morrissey, 1993; Clavél, 2017; Coker et al., 2003; Coyne & Downey, 1991; Cutrona, 1989; Cutrona & Russell, 1987; Feeney & Collins, 2015; Gottlieb & Bergen, 2010; Graham & Barnow, 2013; House, Landis, & Umberson,
However, the understanding of how other variables relate to social support in intimate relationships is extremely limited (Clavél et al., 2017). Therefore, exploring gender differences in perception of partner support, both overall and in the area of domestic responsibilities specifically, contributes to addressing this gap in the literature. This dissertation also contributes to the social support literature by focusing on the specific support within a dual-career couple, because the research on close relationships and research on social support have only been drawn together on rare occasions (Feeney & Collins, 2015).

Theoretically and empirically, it contributes to the body of work on dual-career couples. It adds to the theorizing on the dynamics within dual-career couples grounded in new home economics, resource bargaining, gender relations theory, and the perspectives and hypotheses developed from these theories by evaluating gender differences within a modern sample of the population. This dissertation also addresses the disconnection in this literatures’ focus on housework labor hours and the construct of social support. Prior research on how dual-career couples interact have frequently assessed housework labor hours (Bertrand et al., 2015; Brines, 1994; Carlson & Lynch, 2015; Grunow et al., 2012; Gupta, 2007; Heisig, 2011; Killewald & Gough, 2010; Lachance-Grzela & Bouchard, 2010; Maret & Finlay, 1984; Sayer, 2005), but have overlooked a partner’s participation in these responsibilities as one part of a multi-faceted partner support construct. Finally, this dissertation contributes theoretically to the academe by drawing together a broad array of theories to enhance knowledge of the variables impacting working women and men, and particularly those in dual-career couples.
Empirically, this dissertation presents three key contributions. First, this dissertation pursues a replication study to test a series of hypotheses based on past research to strengthen the foundation of knowledge for theory development on gender differences within dual-career couples.

Second, it applies machine learning to investigate life satisfaction of individuals in dual-career relationships for the first time. Life satisfaction studies have rarely ventured methodologically beyond traditional statistical techniques. All statistical analysis methods offer differing advantages and drawbacks, thus there is no one best method for all questions (Caruana & Niculescu-Mizil, 2006; Ho & Pepyne, 2002). Looking at data from a different technique can illuminate different facets of an empirical question to provide researchers more comprehensive understanding. As explained by Galletta (2016), the use of statistical methodology beyond the common parametric techniques provides an alternative perspective to complement existing research on the factors influencing life satisfaction.

Third, by applying the construct of role centrality to analysis of the gender wage gap this dissertation evaluates the explanatory properties of this construct to understand one of the most salient effects of continued gender inequality that the modern labor force must contend with.

For the public and practitioners, this dissertation contributes in three ways. First, the results and conclusions presented here may be of particular interest to couples’ counselors or mental health professionals assisting clients navigating the modern dual-career lifestyle. Understanding the gendered propensity toward different centrality levels and the relationships between these centralities and the critical life components of income
and life satisfaction may help these professionals provide better advice, because uncovering what is going on under the surface in people’s lives often plays a large part in counseling or therapeutic processes.

Second, life satisfaction is a popular subject for even the none academic reader, evidenced by the plethora of continuous investigation of variables and group comparison reports geared to the nonacademic reader. Given the substantial portion of the general population in dual-career relationships, inquiry of what impacts their life satisfaction specifically is likely to garner similar fascination. Logically people are generally interested in findings that are directly and specifically applicable to them. Findings identifying variables with the greatest impact on life satisfaction, to the extent that these variables are controllable, may be useful to members of dual-career couples to improve their well-being. Likewise, to the extent to which these findings relate to factors employers have control over, (such as the gender pay gap, the gender leadership gap, and personnel policies), family conscious employers could gain further incentive to make changes that improve norms for this population.

Finally, uncovering mechanisms that impact the gender wage gap but retain some degree of flexibility may start to breakdown assumptions of inevitable inequity that are demotivating and demoralizing to women, thereby standing to improve professional female self-efficacy.

Conclusion

The one line takeaway from this project is that role centrality levels matter. This mechanism, while relatively stable as a construct, falls into the category of factors that are theoretically ultimately malleable. It seems plausible, if not clearly likely, that I, an
individual, could willfully change my centrality levels in hypothetically the same way a
person can willfully change their personality. Improving our understanding of
mechanisms, which are both stable enough to be meaningfully predictive and yet flexible
enough that one could potentially exercise her agency on, is of value to academics and
the general population alike. I hope you, the reader, find the information presented in this
project interesting or helpful in some way. Thank you for your time.
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## Tables and Figures

### Table 1. Stylized facts sources

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<thead>
<tr>
<th>Hypothesis</th>
<th>Study</th>
<th>Sample</th>
<th>Sample size</th>
<th>Construct examined</th>
<th>Measurement tool</th>
<th>Key relevant finding</th>
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<tbody>
<tr>
<td>HY1</td>
<td>Mauno and Kinnunen (2000)</td>
<td>Central Finland, 3 waves survey: T1=1995, T2=1996, T3=1997</td>
<td>N=109</td>
<td>Job and family involvement</td>
<td>*Involvement scale, (Kanungo, 1982)</td>
<td>Men were found to be more involved with their jobs than were the women</td>
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<td></td>
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<td>24% M 76% F</td>
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<td>HY2</td>
<td>Cinamon and Rich (2002)</td>
<td>Tel Aviv area, Married computer workers and lawyers (N=178; N=35, respectively)</td>
<td>N=213</td>
<td>Life role salience</td>
<td>Life role salience scale (Amatea, Cross, Clark &amp; Bobby, 1986)</td>
<td>Women were found to be overrepresented in the family centric and dual (work and family centric) profiles</td>
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<td></td>
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<td>59% M 41% F</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>HY3</td>
<td>Kossek, Ruderman, Braddy, and Hannum (2012)</td>
<td>U.S. based managers, from Center for Creative Leadership: 2011 data</td>
<td>N=592</td>
<td>Work identity/Family identity</td>
<td>Other centricity not measured with its own instrument</td>
<td>Males accounted for 61% of the ‘nonwork-eclectics’ cluster (individuals with both work and family identity scores at least one standardization below the mean) (cluster size; N=128)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>39% M 61% F</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Author(s)</td>
<td>Location</td>
<td>Sample Description</td>
<td>N</td>
<td>Gender</td>
<td>Centrality of Work</td>
<td>Relative Work Centrality Measure</td>
</tr>
<tr>
<td>-----------</td>
<td>-----------</td>
<td>---------------------</td>
<td>---</td>
<td>--------</td>
<td>-------------------</td>
<td>-------------------------------</td>
</tr>
<tr>
<td>Snir and Harpaz (2002)</td>
<td>Israel, Representative samples of labor force, 1981 and 1983 data</td>
<td>N=1915 (total)</td>
<td>57.7% M 42.3% F</td>
<td>Centrality of work</td>
<td>Relative work centrality measure</td>
<td>Across two samples, 63% of leisure oriented individuals were male (Roughly 20% of all participants fell into this category, N=381)</td>
</tr>
<tr>
<td>van Daalen, Sanders, and Willemsen (2005)</td>
<td>Netherlands, Individuals in dual-earner families, telepanel &quot;CentERpanel&quot; (specifically not paired data)</td>
<td>N= 459, 61% M 39%</td>
<td>Perceived social support from: spouse, colleagues, relatives, friends</td>
<td>Two 8-items scales (Parasuraman, Greenhaus &amp; Granrose, 1992)</td>
<td>Men received greater social support from their spouses and women received greater support from colleagues, relatives, and friends</td>
<td></td>
</tr>
<tr>
<td>Clavél (2017)</td>
<td>Iowa State U. students, Dating or cohabitating young adults; 2 week daily diary study</td>
<td>N=120, 60 couples</td>
<td>Perceived social support from partner</td>
<td>Social Provisions Scale (SPS), for romantic partners (Cutrona &amp; Russell, 1987)</td>
<td>Within the heterosexual romantic couples in this study women were on average less satisfied than men with the support they received from their romantic partners</td>
<td></td>
</tr>
<tr>
<td>Eagly and Wood (2011)</td>
<td>Literature Review - Social Role Theory</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>Despite shifts in the stringency of gendered social roles, women still perform more domestic work and spend fewer hours in paid employment than men</td>
<td></td>
</tr>
<tr>
<td>Lachance-Grzela &amp; Bouchard, 2010</td>
<td>Literature Review - Women's household workload in the US</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>United States household labor remains persistently divided along traditionally gendered lines</td>
<td></td>
</tr>
</tbody>
</table>

*measurement tool matches this study*
Figure 1. Theoretical Model

- **Role Centrality**
  - Career
  - Family
  - Other

- **Perceived Partner Support**
  - Overall
  - Domestic

Figure 2. Age Frequency Histogram with Normal Curve

- **Histogram**
  - Mean = 41.61
  - Std. Dev. = 13.166
  - N = 826

<table>
<thead>
<tr>
<th>Frequency</th>
<th>VAR004 Your current age</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>20</td>
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<tr>
<td>10</td>
<td>30</td>
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<tr>
<td>20</td>
<td>40</td>
</tr>
<tr>
<td>30</td>
<td>50</td>
</tr>
<tr>
<td>40</td>
<td>60</td>
</tr>
<tr>
<td>50</td>
<td>70</td>
</tr>
<tr>
<td>60</td>
<td>80</td>
</tr>
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</table>
Table 2. Spearman Correlations Among Variables

<table>
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<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Being Supportive</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Maintaining Balance</td>
<td>.728**</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Hobbies/Personal Time</td>
<td>.689**</td>
<td>.712**</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>4 Domestic Chores</td>
<td>.483**</td>
<td>.493**</td>
<td>.463**</td>
<td>1</td>
</tr>
</tbody>
</table>

Note: **p<0.01 (2-tailed)
N=826

Table 3. Description of Instruments

<table>
<thead>
<tr>
<th>Scale-measure</th>
<th># of items (range)</th>
<th>Cronbach α</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Career Centrality</td>
<td>3 (3-21)</td>
<td>0.82</td>
<td>13.09</td>
<td>4.2</td>
</tr>
<tr>
<td>Family Centrality</td>
<td>3 (3-21)</td>
<td>0.89</td>
<td>17.84</td>
<td>3.36</td>
</tr>
<tr>
<td>Other Centrality</td>
<td>1 (1-7)</td>
<td>NA</td>
<td>5.64</td>
<td>1.18</td>
</tr>
<tr>
<td>Partner Support-Overall</td>
<td>3 (1-5)</td>
<td>0.83</td>
<td>3.79</td>
<td>0.88</td>
</tr>
<tr>
<td>Partner Support-Domestic</td>
<td>1 (1-5)</td>
<td>NA</td>
<td>3.48</td>
<td>1.11</td>
</tr>
</tbody>
</table>

N=826
Figure 3. Chi-square Q-Q plot for squared Mahalanobis distances of model residuals to test multivariate normality.
Table 4. Spearman Correlations between Dependent Variables

<table>
<thead>
<tr>
<th></th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Career Centrality</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Family Centrality</td>
<td>0.074*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Other Centrality</td>
<td>0.095**</td>
<td>0.182**</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 Partner Support-Overall</td>
<td>-0.026</td>
<td>-0.009</td>
<td>-0.041</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>5 Partner Support-Domestic</td>
<td>0.001</td>
<td>0.004</td>
<td>-0.044</td>
<td>0.739**</td>
<td>1</td>
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</tbody>
</table>

Note: *p<0.05, **p<0.01 (2-tailed)

** Indicate correlations at the .01 significance level (2-tailed)

N=826

Table 5. MANCOVA Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pillai</th>
<th>F</th>
<th>df</th>
<th>Residual df</th>
<th>p</th>
<th>ηp2</th>
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</thead>
<tbody>
<tr>
<td>Model</td>
<td>0.42</td>
<td>9.34</td>
<td>40</td>
<td>4085</td>
<td>&lt;.001</td>
<td>0.42</td>
</tr>
<tr>
<td>Gender</td>
<td>0.02</td>
<td>3.58</td>
<td>5</td>
<td>813</td>
<td>.003</td>
<td>0.02</td>
</tr>
<tr>
<td>Age</td>
<td>0.01</td>
<td>1.91</td>
<td>5</td>
<td>813</td>
<td>.090</td>
<td>0.01</td>
</tr>
<tr>
<td>Education</td>
<td>0.01</td>
<td>2.39</td>
<td>5</td>
<td>813</td>
<td>.036</td>
<td>0.01</td>
</tr>
<tr>
<td>Employment Status</td>
<td>0.01</td>
<td>2.32</td>
<td>5</td>
<td>813</td>
<td>.042</td>
<td>0.01</td>
</tr>
<tr>
<td># of Relationships</td>
<td>0.03</td>
<td>4.48</td>
<td>5</td>
<td>813</td>
<td>&lt;.001</td>
<td>0.03</td>
</tr>
<tr>
<td># of Children</td>
<td>0.09</td>
<td>16.50</td>
<td>5</td>
<td>813</td>
<td>&lt;.001</td>
<td>0.09</td>
</tr>
<tr>
<td>Life Satisfaction</td>
<td>0.17</td>
<td>32.77</td>
<td>5</td>
<td>813</td>
<td>&lt;.001</td>
<td>0.17</td>
</tr>
<tr>
<td>Log Annual Salary</td>
<td>0.04</td>
<td>7.03</td>
<td>5</td>
<td>813</td>
<td>&lt;.001</td>
<td>0.04</td>
</tr>
</tbody>
</table>

DVs: Career Centrality, Family Centrality, Other Centrality, Partner Support-Overall, and Partner Support-Domestic

N=826
### Table 6. Analysis of Variance Table for Career Centrality by Gender

<table>
<thead>
<tr>
<th>Term</th>
<th>SS</th>
<th>df</th>
<th>F</th>
<th>p</th>
<th>ηp²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>2396.84</td>
<td>8</td>
<td>20.19</td>
<td>&lt; .001</td>
<td>0.1651</td>
</tr>
<tr>
<td>Gender</td>
<td>63.22</td>
<td>1</td>
<td>4.26</td>
<td>.039</td>
<td>0.0052</td>
</tr>
<tr>
<td>Age</td>
<td>74.30</td>
<td>1</td>
<td>5.01</td>
<td>.026</td>
<td>0.0061</td>
</tr>
<tr>
<td>Education</td>
<td>140.14</td>
<td>1</td>
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<td>.002</td>
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<td>Employment Status</td>
<td>119.21</td>
<td>1</td>
<td>8.03</td>
<td>.005</td>
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</tr>
<tr>
<td># of Relationships</td>
<td>107.01</td>
<td>1</td>
<td>7.21</td>
<td>.007</td>
<td>0.0087</td>
</tr>
<tr>
<td># of Children</td>
<td>56.83</td>
<td>1</td>
<td>3.83</td>
<td>.051</td>
<td>0.0047</td>
</tr>
<tr>
<td>Life Satisfaction</td>
<td>630.19</td>
<td>1</td>
<td>42.47</td>
<td>&lt; .001</td>
<td>0.0494</td>
</tr>
<tr>
<td>Log Annual Salary</td>
<td>480.13</td>
<td>1</td>
<td>32.35</td>
<td>&lt; .001</td>
<td>0.0381</td>
</tr>
<tr>
<td>Residuals</td>
<td>12124.16</td>
<td>817</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

N=826

### Table 7. Analysis of Variance Table for Family Centrality by Gender

<table>
<thead>
<tr>
<th>Term</th>
<th>SS</th>
<th>df</th>
<th>F</th>
<th>p</th>
<th>ηp²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>1836.3</td>
<td>8</td>
<td>25.02</td>
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<td>0.1968</td>
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<td>Gender</td>
<td>73.98</td>
<td>1</td>
<td>8.06</td>
<td>.005</td>
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<tr>
<td>Age</td>
<td>14.39</td>
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<td>1.57</td>
<td>.211</td>
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<td>Education</td>
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<td>0.81</td>
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<td>0.0010</td>
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<td>1</td>
<td>0.23</td>
<td>.631</td>
<td>0.0028</td>
</tr>
<tr>
<td># of Relationships</td>
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<td>8.98</td>
<td>.003</td>
<td>0.0109</td>
</tr>
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<td>1</td>
<td>50.04</td>
<td>&lt; .001</td>
<td>0.0577</td>
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<td>1045.25</td>
<td>1</td>
<td>113.94</td>
<td>&lt; .001</td>
<td>0.1224</td>
</tr>
<tr>
<td>Log Annual Salary</td>
<td>7.69</td>
<td>1</td>
<td>0.84</td>
<td>.360</td>
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<td>Residuals</td>
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N=826
Table 8. Analysis of Variance Table for Other Centrality by Gender

<table>
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<th>Term</th>
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<th>df</th>
<th>F</th>
<th>p</th>
<th>ηp²</th>
</tr>
</thead>
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<tr>
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<td>6.11</td>
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<td>0.0564</td>
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<td>1</td>
<td>4.22</td>
<td>.040</td>
<td>0.0051</td>
</tr>
<tr>
<td>Age</td>
<td>2.26</td>
<td>1</td>
<td>1.69</td>
<td>.194</td>
<td>0.0021</td>
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<td>0.10</td>
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<td>0.0001</td>
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<td>0.21</td>
<td>.649</td>
<td>0.0003</td>
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<td>2.44</td>
<td>.119</td>
<td>0.0030</td>
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<td># of Children</td>
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<td>1</td>
<td>15.98</td>
<td>&lt; .001</td>
<td>0.0191</td>
</tr>
<tr>
<td>Life Satisfaction</td>
<td>40.39</td>
<td>1</td>
<td>30.18</td>
<td>&lt; .001</td>
<td>0.0356</td>
</tr>
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<td>1</td>
<td>0.02</td>
<td>.899</td>
<td>0.0000</td>
</tr>
<tr>
<td>Residuals</td>
<td>1093.65</td>
<td>817</td>
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</tbody>
</table>

N=826

Table 9. Analysis of Variance Table for Partner Support-Overall by Gender

<table>
<thead>
<tr>
<th>Term</th>
<th>SS</th>
<th>df</th>
<th>F</th>
<th>p</th>
<th>ηp²</th>
</tr>
</thead>
<tbody>
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<td>4.44</td>
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<td>0.71</td>
<td>.684</td>
<td>0.0109</td>
</tr>
<tr>
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<td>0.91</td>
<td>1</td>
<td>1.16</td>
<td>.281</td>
<td>0.0014</td>
</tr>
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<td>1</td>
<td>0.02</td>
<td>.888</td>
<td>0.0000</td>
</tr>
<tr>
<td>Education</td>
<td>0.44</td>
<td>1</td>
<td>0.56</td>
<td>.454</td>
<td>0.0007</td>
</tr>
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<td>Employment Status</td>
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<td>0.32</td>
<td>.573</td>
<td>0.0004</td>
</tr>
<tr>
<td># of Relationships</td>
<td>0.02</td>
<td>1</td>
<td>0.02</td>
<td>.878</td>
<td>0.0000</td>
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<td># of Children</td>
<td>1.76</td>
<td>1</td>
<td>2.25</td>
<td>.134</td>
<td>0.0027</td>
</tr>
<tr>
<td>Life Satisfaction</td>
<td>0.53</td>
<td>1</td>
<td>0.68</td>
<td>.411</td>
<td>0.0008</td>
</tr>
<tr>
<td>Log Annual Salary</td>
<td>0.21</td>
<td>1</td>
<td>0.27</td>
<td>.603</td>
<td>0.0003</td>
</tr>
<tr>
<td>Residuals</td>
<td>639.25</td>
<td>817</td>
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</tr>
</tbody>
</table>

N=826
### Table 10. Analysis of Variance Table for Partner Support-Domestic by Gender

<table>
<thead>
<tr>
<th>Term</th>
<th>SS</th>
<th>df</th>
<th>F</th>
<th>p</th>
<th>ηp²</th>
</tr>
</thead>
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<tr>
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<td>1.05</td>
<td>.396</td>
<td>0.0102</td>
</tr>
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<td>Gender</td>
<td>0.76</td>
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<td>0.62</td>
<td>.431</td>
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<td>Age</td>
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<td>0.0006</td>
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<td>1.09</td>
<td>.297</td>
<td>0.0013</td>
</tr>
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<td>Employment Status</td>
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<td>1</td>
<td>2.69</td>
<td>.102</td>
<td>0.0032</td>
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<td>0.59</td>
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<td>0.48</td>
<td>.488</td>
<td>0.0006</td>
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<td># of Children</td>
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<td>2.06</td>
<td>.152</td>
<td>0.0025</td>
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<td>1</td>
<td>0.00</td>
<td>.982</td>
<td>0.0000</td>
</tr>
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<td>0.99</td>
<td>.321</td>
<td>0.0012</td>
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<td>1005.76</td>
<td>817</td>
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</tr>
</tbody>
</table>

N=826

### Table 11. ANCOVAs Marginal Means

<table>
<thead>
<tr>
<th></th>
<th>Males (N=419)</th>
<th>SE</th>
<th>Females (N=407)</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Marginal Means</td>
<td></td>
<td>Marginal Means</td>
<td></td>
</tr>
<tr>
<td>Career Centrality</td>
<td>13.375</td>
<td>0.192</td>
<td>12.800</td>
<td>0.195</td>
</tr>
<tr>
<td>Family Centrality</td>
<td>17.530</td>
<td>0.151</td>
<td>18.152</td>
<td>0.153</td>
</tr>
<tr>
<td>Other Centrality</td>
<td>5.552</td>
<td>0.058</td>
<td>5.724</td>
<td>0.058</td>
</tr>
<tr>
<td>Partner Support-Overall</td>
<td>3.759</td>
<td>0.044</td>
<td>3.828</td>
<td>0.045</td>
</tr>
<tr>
<td>Partner Support-Domestic</td>
<td>3.447</td>
<td>0.055</td>
<td>3.510</td>
<td>0.056</td>
</tr>
</tbody>
</table>

Controls: Age, Education, Employment Status, # of Relationships, # of Children, Life Satisfaction, and the log of Annual Salary

### Table 12. Description of scaled instruments

<table>
<thead>
<tr>
<th>Scale-measure</th>
<th># of items (range)</th>
<th>Cronbach α</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Life Satisfaction</td>
<td>1 (1-7)</td>
<td>NA</td>
<td>5.58</td>
<td>1.27</td>
</tr>
<tr>
<td>Career Centrality</td>
<td>3 (1-7)</td>
<td>0.82</td>
<td>4.36</td>
<td>1.4</td>
</tr>
<tr>
<td>Family Centrality</td>
<td>3 (1-7)</td>
<td>0.89</td>
<td>5.95</td>
<td>1.12</td>
</tr>
<tr>
<td>Other Centrality</td>
<td>1 (1-7)</td>
<td>NA</td>
<td>5.64</td>
<td>1.18</td>
</tr>
<tr>
<td>Partner Support-Overall</td>
<td>4 (1-5)</td>
<td>0.86</td>
<td>3.79</td>
<td>1.27</td>
</tr>
</tbody>
</table>
Table 13. Variables entered in CART model

<table>
<thead>
<tr>
<th>Objective Variables</th>
<th>Values</th>
<th>Reference to prior work</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Your gender</td>
<td>Binary ([F=1, M=2])</td>
<td>Borooah (2006); Sekaran (1983)</td>
</tr>
<tr>
<td>- The number of committed relationships you have had (Note: For the purpose of this study, the term committed relationship includes marriage or any domestic partnership with a shared household. Accordingly, the term partner includes, but is not limited to, a married spouse)</td>
<td>Capped numeric ([1, 2, 3, 4 \text{ or more}])</td>
<td>Borooah (2006)</td>
</tr>
<tr>
<td>- Your current age</td>
<td>Numeric</td>
<td>Borooah (2006); Sekaran (1983)</td>
</tr>
<tr>
<td>- Your age at the time of your FIRST committed relationship</td>
<td>Numeric</td>
<td>Bahr, Chappell, &amp; Leigh (1983); Levenson, Carstensen, Gottman (1993)</td>
</tr>
<tr>
<td>- Your partner's age at the time of your FIRST committed relationship</td>
<td>Numeric</td>
<td>Bahr et al. (1983); Levenson et al. (1993)</td>
</tr>
<tr>
<td>- Number of committed relationships that ended for reasons other than death</td>
<td>Capped numeric ([0 \text{ coded } 1, 1=2, 2=3, 3=4, 4 \text{ or more}=5])</td>
<td>Borooah (2006)</td>
</tr>
</tbody>
</table>

**Age difference within relationship**
- Partner >10 years younger \((Y=1/N=0)\) | Vera, Berardo, & Berardo (1985) |
- Partner 6-10 years younger \((Y=1/N=0)\) |
- Same age within 5 years \((Y=1/N=0)\) |
- Partner 6-10 years older \((Y=1/N=0)\) |
- Partner >10 years older (Y=1/N=0)

**Children**
- How old were you when your first child was born adopted? Numeric Pollmann-Schult (2014)
- Number of your children, including adoptions Capped numeric [0 coded 1, 1=2, 2=3, 3=4, 4=5, 5 or more=6] Sekaran (1983)
- Does your current (or most recent) partner have children from another relationship? (Y=1/N=0) Sekaran (1983)

**Education**
- Your highest level of education [Assoc. degree=2; Bachelor degree=3; Master degree=4; Professional/Academic doctorate=5;] Sekaran (1983)
- Highest level of education of your current (or most recent) partner Same as above but starting with [High school or some college with no degree =1] Guant (2006)
- Education Equality (Y=1/N=0) Guant (2006)
- Current employment status [Employed full-time, not including self-employment=1; Employed part-time, not including self-employment=2; Self-employed=3; Not employed=4; Retired=5] Borooah (2006); Galletta (2016)

**Industries**
*Industry(ies) in which you currently work or have worked (check all that apply)*
- Financial Services (including banking, insurance, securities, venture capital, real estate) (Y=1/N=0) Galletta (2016)
Industry(ies) in which your current (or most recent) partner is currently working or has worked (check all that apply)

- Life Sciences (including biotech, pharmaceuticals, medical devices) (Y=1/N=0)
- Manufacturing NOT in the life sciences, technology or utility fields (including design, creation, assembly of all products) (Y=1/N=0)
- Professional Services other than information technology and engineering (including accounting, architecture, law, management consulting, other business services) (Y=1/N=0)
- Retail-Wholesale (including restaurants, stores, sale of products online) (Y=1/N=0)
- Social and Government Services (including education, healthcare-including for profit, all nonprofit enterprises) (Y=1/N=0)
- Technology (including devices, hardware manufacturing, software, telecommunications, web and IT consulting, architecture, engineering services) (Y=1/N=0)
- Utilities (including distribution, manufacturing) (Y=1/N=0)

Galletta (2016)
- Financial Services (including banking, insurance, securities, venture capital, real estate) \((Y=1/N=0)\)

- Life Sciences (including biotech, pharmaceuticals, medical devices) \((Y=1/N=0)\)

- Manufacturing NOT in the life sciences, technology or utility fields (including design, creation, assembly of all products) \((Y=1/N=0)\)

- Professional Services NOT in the technology, science and engineering fields (including accounting, law, management consulting, other business services) \((Y=1/N=0)\)

- Retail-Wholesale (including restaurants, stores, sale of products online) \((Y=1/N=0)\)

- Social and Government Services (including education, healthcare—including for profit, all nonprofit enterprises) \((Y=1/N=0)\)

- Technology (including devices, hardware manufacturing, software, telecommunications, web and IT consulting, architecture, engineering services) \((Y=1/N=0)\)

- Utilities (including distribution, manufacturing) \((Y=1/N=0)\)
### Income

- **Your highest level of income for at least three consecutive years**
  - Less than $100,000/year = 1
  - $100,000-$250,000/year = 2
  - $251,000-$500,000/year = 3
  - $501,000-$1 million/year = 4
  - More than $1 million/year = 5

- **Highest level of income for at least three consecutive years of your current (or most recent) partner**
  - See above

### Subjective Variables

<table>
<thead>
<tr>
<th>Role Centrality</th>
<th>Values</th>
<th>References to prior work</th>
</tr>
</thead>
<tbody>
<tr>
<td>Family Centrality Average</td>
<td>See Above</td>
<td>Bhowon (2013); Eddleston, Veiga, &amp; Powell (2006)</td>
</tr>
</tbody>
</table>

### Role Identity

**How much does assuming each of the following roles affect your behavior?**

- **Provider**
  - Likert [1-3: Not at all = 1, Occasionally = 2, Frequently = 3]

- **Protector**
  - See above

- **Nurturer**
  - See above

- **Caregiver**
  - See above

- **Being a Gender Role Model**
  - See above

**How much does assuming each of the following roles affect your current (or most recent) partner’s behavior?**

- **Provider**
  - See above

- **Protector**
  - See above
- How often do you think that your current (or most recent) partner's gender-based identity has felt threatened in YOUR RELATIONSHIP (e.g., as the protector, provider, role model, caregiver, etc.)? Likert [1-5: Never=1; Rarely; Sometimes; Often; All the Time=5] Hiller & Philliber (1982)

- How often do you think that your current (or most recent) partner's gender-based identity has felt threatened at WORK (e.g., as the protector, provider, role model, caregiver, etc.)? Likert [1-6: Never=1; Rarely; Sometimes; Often; All the Time; Has not worked for pay=6] Hiller & Philliber (1982)

- My current (or most recent) partner has expected my career to be highly successful (i.e., financially, with high status and/or lifestyle). Likert [1-5, strongly disagree=1/strongly agree=5] Heikkinen (2012)

**Partner Support**

- My current (or most recent) partner has shown support for my career by "being" supportive Likert [1-5: Never=1; Rarely; Sometimes; Often; All the Time=5] Heikkinen (2012); van Daalen, Sanders, & Willemsen (2005)

- My current (or most recent) partner has shown support for my career by helping me maintain a life beyond work See above Heikkinen (2012); van Daalen, Sanders, & Willemsen (2005)
- My current (or most recent) partner has supported my life-related desires
  See above
  Heikkinen (2012); van Daalen, Sanders, & Willemsen (2005)

- My current (or most recent) partner has shown support for my career by managing or taking care of most of the domestic chores (children, extended family, housekeeping)
  See above
  Heikkinen (2012); van Daalen, Sanders, & Willemsen (2005)

- Overall Support Score
  Average of 4 items above
  van Daalen, Sanders, & Willemsen (2005)

- I have been satisfied with the way that my current (or most recent) partner and I have divided family labor.
  Likert [1-7, strongly disagree=1/strongly agree=7]
  Suitor (1991)

- Relationship Satisfaction
  Average of 2 items - Likert [1-5, strongly disagree=1/strongly agree=5]
  Norton (1983)
Table 14. Independent Variable Importance table for CART model

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Importance</th>
<th>Normalized Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>RelateSat2</td>
<td>.057</td>
<td>100.0%</td>
</tr>
<tr>
<td>VAR054 Family Centrality Average</td>
<td>.034</td>
<td>59.7%</td>
</tr>
<tr>
<td>VAR048 Career Centrality Average</td>
<td>.014</td>
<td>24.4%</td>
</tr>
<tr>
<td>VAR056 Other Centrality</td>
<td>.008</td>
<td>14.9%</td>
</tr>
<tr>
<td>VAR004 Your current age</td>
<td>.007</td>
<td>11.7%</td>
</tr>
<tr>
<td>VAR005 Your age at the time of your FIRST committed relationship.</td>
<td>.005</td>
<td>8.4%</td>
</tr>
<tr>
<td>VAR015 How old were you when your first child was born adopted?</td>
<td>.004</td>
<td>7.5%</td>
</tr>
<tr>
<td>VAR041 Your highest level of income for at least three consecutive years</td>
<td>.004</td>
<td>6.4%</td>
</tr>
<tr>
<td>VAR020 Highest level of education of your current (or most recent) partner</td>
<td>.004</td>
<td>6.3%</td>
</tr>
<tr>
<td>VAR016 (Actual Values) Number of your children, including adoptions</td>
<td>.003</td>
<td>5.9%</td>
</tr>
<tr>
<td>VAR042 Highest level of income for at least three consecutive years of your current (or most recent) partner</td>
<td>.003</td>
<td>5.8%</td>
</tr>
<tr>
<td>VAR077 My current (or most recent) partner has supported my life-related desires (e.g., personal time, time with friends, hobbies)</td>
<td>.003</td>
<td>5.5%</td>
</tr>
<tr>
<td>VAR060 How much does assuming each of the following roles affect your / behavior? - Nurturer</td>
<td>.003</td>
<td>4.5%</td>
</tr>
<tr>
<td>VAR075 My current (or most recent) partner has shown support for my career by &quot;being&quot; supportive (e.g., as a discussion partner, expressing acceptance of new career opportunities for me, participating in...)</td>
<td>.003</td>
<td>4.4%</td>
</tr>
<tr>
<td>VAR011 Partner 6-10 years older</td>
<td>.002</td>
<td>4.3%</td>
</tr>
<tr>
<td>VAR061 How much does assuming each of the following roles affect your / behavior? - Caregiver</td>
<td>.002</td>
<td>4.2%</td>
</tr>
<tr>
<td>VAR080 I have been satisfied with the way that my current (or most recent) partner and I have divided family labor.</td>
<td>.002</td>
<td>4.2%</td>
</tr>
<tr>
<td>VAR079 Overall Support Score</td>
<td>.002</td>
<td>4.0%</td>
</tr>
<tr>
<td>VAR006 Your partner’s age at the time of your FIRST committed relationship.</td>
<td>.002</td>
<td>3.9%</td>
</tr>
<tr>
<td>VAR078 My current (or most recent) partner has shown support for my career by managing or taking care of most of the domestic chores (children, extended family, housekeeping).</td>
<td>.002</td>
<td>3.6%</td>
</tr>
<tr>
<td>VAR062 How much does assuming each of the following roles affect your / behavior? - Being a Gender Role Model</td>
<td>.002</td>
<td>3.5%</td>
</tr>
<tr>
<td>VAR067 How often do you think that your current (or most recent) partner’s gender-based identity has felt threatened in YOUR RELATIONSHIPÂ (e.g., as the protector, provider, role / model, caregiver, etc.)...</td>
<td>.002</td>
<td>3.3%</td>
</tr>
<tr>
<td>VAR034 Industry(ies) in which your current (or most recent) / partner is currently working or has worked (check all that / apply)-Life Sciences (including biotech, pharmaceuticals, medical devices)</td>
<td>.001</td>
<td>2.5%</td>
</tr>
<tr>
<td>VAR040 Industry(ies) in which your current (or most recent) / partner is currently working or has worked (check all that / apply)-Utilities (including distribution, manufacturing)</td>
<td>.001</td>
<td>2.2%</td>
</tr>
<tr>
<td>VAR033 Industry(ies) in which your current (or most recent) / partner is currently working or has worked (check all that / apply)-Financial Services (including banking, insurance, securities, venture capital, real estate)</td>
<td>.001</td>
<td>2.1%</td>
</tr>
<tr>
<td>VAR043 High Income Couple</td>
<td>.001</td>
<td>2.0%</td>
</tr>
<tr>
<td>Variable</td>
<td>Coefficient</td>
<td>Effect Size</td>
</tr>
<tr>
<td>----------</td>
<td>-------------</td>
<td>-------------</td>
</tr>
<tr>
<td>VAR038 Industry(ies) in which your current (or most recent) partner is currently working or has worked (check all that apply): Social and Government Services (including education, healthcare—including for profit, all nonprofit enterprises)</td>
<td>0.001</td>
<td>1.7%</td>
</tr>
<tr>
<td>VAR002 Your gender</td>
<td>0.001</td>
<td>1.5%</td>
</tr>
<tr>
<td>VAR076 My current (or most recent) partner has shown support for my career by helping me maintain a life beyond work (e.g., considering the impact of work assignments and promotions on family life before...)</td>
<td>0.001</td>
<td>1.5%</td>
</tr>
<tr>
<td>VAR012 Partner &gt; 10 years older</td>
<td>0.001</td>
<td>1.5%</td>
</tr>
<tr>
<td>VAR073 How much does assuming each of the following roles affect your / current (or most recent) partner's behavior? - Being a Gender Role Model</td>
<td>0.001</td>
<td>1.4%</td>
</tr>
<tr>
<td>VAR032 Industry(ies) in which you are currently working or have worked / (check all that apply) / - Utilities (including distribution, manufacturing)</td>
<td>0.001</td>
<td>1.4%</td>
</tr>
<tr>
<td>VAR009 Partner 6-10 years younger</td>
<td>0.001</td>
<td>1.2%</td>
</tr>
<tr>
<td>VAR069 How much does assuming each of the following roles affect your / current (or most recent) partner's behavior? - Provider</td>
<td>0.001</td>
<td>1.2%</td>
</tr>
<tr>
<td>VAR003 The number of committed relationships you have had (Note: For / the purpose of this study, the term committed relationship includes / marriage or any domestic partnership with a shared household. / Accor...)</td>
<td>0.001</td>
<td>1.1%</td>
</tr>
<tr>
<td>VAR068 How often do you think that your current (or most recent) partner's gender-based identity has felt threatened at / WORK (e.g., as the protector, provider, role model, caregiver, / etc.)?</td>
<td>0.001</td>
<td>1.1%</td>
</tr>
<tr>
<td>VAR021 Industry(ies) in which you are currently working or have worked / (check all that apply) / - Technology (including devices, hardware manufacturing, software, telecommunications, web and IT consulting, architecture, engineering services)</td>
<td>0.001</td>
<td>1.0%</td>
</tr>
<tr>
<td>VAR074 My current (or most recent) partner has expected my career to be highly successful (i.e., financially, with high status and/or lifestyle).</td>
<td>0.001</td>
<td>0.9%</td>
</tr>
<tr>
<td>VAR030 Industry(ies) in which you are currently working or have worked / (check all that apply) / - Social and Government Services (including education, healthcare—including for profit, all nonprofit enterprises)</td>
<td>0.000</td>
<td>0.9%</td>
</tr>
<tr>
<td>VAR022 Education Equality Adjusted</td>
<td>0.000</td>
<td>0.6%</td>
</tr>
<tr>
<td>VAR070 How much does assuming each of the following roles affect your / current (or most recent) partner's behavior? - Protector</td>
<td>0.000</td>
<td>0.6%</td>
</tr>
<tr>
<td>VAR010 Same age within 5 years</td>
<td>0.000</td>
<td>0.5%</td>
</tr>
<tr>
<td>VAR019 Your highest level of education</td>
<td>0.000</td>
<td>0.5%</td>
</tr>
<tr>
<td>VAR023 Current employment status</td>
<td>0.000</td>
<td>0.5%</td>
</tr>
<tr>
<td>VAR025 Industry(ies) in which you are currently working or have worked / (check all that apply) / - Financial Services (including banking, insurance, securities, venture capital, real estate)</td>
<td>0.000</td>
<td>0.4%</td>
</tr>
<tr>
<td>VAR072 How much does assuming each of the following roles affect your / current (or most recent) partner's behavior? - Caregiver</td>
<td>8.926E-5</td>
<td>0.2%</td>
</tr>
<tr>
<td>VAR026 Industry(ies) in which you are currently working or have worked / (check all that apply) / - Life Sciences (including biotech, pharmaceuticals, medical devices)</td>
<td>7.444E-5</td>
<td>0.1%</td>
</tr>
</tbody>
</table>

Growing Method: CRT
Dependent Variable: VAR057 All things considered, how satisfied are you with your life as a whole? 
N=662
Figure 4. Dual-Career Couple Life Satisfaction Classification Tree

VAR054 Family Centrality Average
Improvement=0.003

VAR054 Family Centrality Average
Improvement=0.005

VAR054 Career Centrality Average
Improvement=0.004

VAR054 Your current age
Improvement=0.005

VAR055 Your age at the time of your FIRST committed relationship.
Improvement=0.003

VAR07 All things considered, how satisfied are you with your life as a whole?

Node 0
Category % n
1.000 0.5 2
2.000 1.5 12
3.000 8.5 16
4.000 15.5 31
5.500 20.0 40
6.000 27.0 43
7.000 10.0 17
Total 14.0 159

RelateSat2
Improvement=0.038

Node 1
Category % n
1.000 1.3 2
2.000 8.2 13
3.000 16.4 26
4.000 19.5 31
5.500 27.0 43
6.000 17.0 27
7.000 16.7 17
Total 14.0 159

Node 2
Category % n
1.000 0.8 4
2.000 2.6 13
3.000 2.6 13
4.000 5.0 25
5.000 17.5 88
6.000 66.9 236
7.000 26.5 134
Total 76.0 503

Node 3
Category % n
1.000 0.9 2
2.000 0.9 2
3.000 0.9 2
4.000 0.9 2
5.000 0.9 2
6.000 0.9 2
7.000 0.9 2
Total 10.9 72

Node 4
Category % n
1.000 0.7 2
2.000 0.7 2
3.000 0.7 2
4.000 0.7 2
5.000 0.7 2
6.000 0.7 2
7.000 0.7 2
Total 11.1 82

Node 5
Category % n
1.000 0.8 4
2.000 0.8 4
3.000 0.8 4
4.000 0.8 4
5.000 0.8 4
6.000 0.8 4
7.000 0.8 4
Total 14.1 292

Node 6
Category % n
1.000 0.5 1
2.000 0.5 1
3.000 0.5 1
4.000 0.5 1
5.000 0.5 1
6.000 0.5 1
7.000 0.5 1
Total 10.9 72

Node 7
Category % n
1.000 1.4 1
2.000 1.4 1
3.000 1.4 1
4.000 1.4 1
5.000 1.4 1
6.000 1.4 1
7.000 1.4 1
Total 10.9 72

Node 8
Category % n
1.000 4.2 1
2.000 4.2 1
3.000 4.2 1
4.000 4.2 1
5.000 4.2 1
6.000 4.2 1
7.000 4.2 1
Total 3.0 24

Node 9
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 10
Category % n
1.000 1.4 2
2.000 1.4 2
3.000 1.4 2
4.000 1.4 2
5.000 1.4 2
6.000 1.4 2
7.000 1.4 2
Total 10.9 72

Node 11
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 12
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 13
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 14
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 15
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 16
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 17
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 18
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 19
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 20
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 21
Category % n
1.000 0.0 0
2.000 0.0 0
3.000 0.0 0
4.000 0.0 0
5.000 0.0 0
6.000 0.0 0
7.000 0.0 0
Total 0.0 0

Node 22
Category % n
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<th>% of FT Sample (N=473)</th>
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Table 16. Means and Standard Deviations

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Note: *p<0.1, **p<0.05, ***p<0.01
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**OLS Estimates for the log of annual wages - Current Full-time Only Sample**

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Note: *p<0.1, **p<0.05, ***p<0.01
Table 20. Decompositions - Whole workforce sample

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Note: Robust standard errors in parentheses, *p<0.1, **p<0.05, ***p<0.01

Variables Included in Groupings:
Children: Number of children, Partner has child(ren) from past relationship
Education: Education, Partner’s Education, Education Equality
Satisfaction: Life Satisfaction, Good Relationship, Team w/ Partner, Partner’s Relationship Satisfaction, Partner’s Life Satisfaction, Partner Support-Overall
Family Labor: Partner Support-Domestic Chores/Children, Satisfaction with division of family labor

Table 21. Decompositions - Full-time sample
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<th>Coefficient</th>
<th>Standard Error</th>
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### Total Pay Gap

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<th>Standard Error</th>
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<td>**.1519</td>
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**Panel B. Full Specification**

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<th>Coefficient</th>
<th>Standard Error</th>
<th>Coefficient</th>
<th>Standard Error</th>
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<td>(.0114)</td>
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</tr>
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<td>(.0039)</td>
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<td>(.0018)</td>
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<td>.0706</td>
<td>(.0665)</td>
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<td>(.0726)</td>
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</tr>
</tbody>
</table>

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**Note:** Robust standard errors in parentheses, *p<0.1, **p<0.05, ***p<0.01

**Variables Included in Groupings:**

- **Children:** Number of children, Partner has child(ren) from past relationship
- **Education:** Education, Partner’s Education, Education Equality
- **Industry:** Financial Services, Life Science, Manufacturing, Professional Services, Retail/Wholesale, Social/Government Service, Technology, Utilities
- **Satisfaction:** Life Satisfaction, Good Relationship, Team w/ Partner, Partner’s Relationship Satisfaction, Partner’s Life Satisfaction, Partner Support-Overall
- **Family Labor:** Partner Support-Domestic Chores/Children, Satisfaction with division of family labor
Table 22. Decompositions of Binary Linear Models

<table>
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<th>Variable</th>
<th>Whole Workforce Sample</th>
<th>Full-time only Sample</th>
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<td>Male (N=419)</td>
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<tr>
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<tr>
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<td>***0.1433</td>
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<tr>
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</table>

Note: Robust standard errors in parentheses, *p<0.1, **p<0.05, ***p<0.01

Variables Included in Groupings:
Children: Number of children, Partner has child(ren) from past relationship
Education: Education, Partner’s Education, Education Equality

187
Satisfaction: Life Satisfaction, Good Relationship, Team w/ Partner, Partner’s Relationship Satisfaction, Partner’s Life Satisfaction, Partner Support-Overall
Family Labor: Partner Support-Domestic Chores/Children, Satisfaction with division of family labor

Table 23. Decompositions of Logit Models

<table>
<thead>
<tr>
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<th>Logit Decompositions</th>
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<tbody>
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<td>Whole Workforce Sample</td>
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<td>Male (N=419)</td>
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<tr>
<td>Age</td>
<td>-0.0031</td>
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</tr>
<tr>
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<td>(-0.0021)</td>
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</tr>
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188
Variables Included in Groupings:

Children: Number of children, Partner has child(ren) from past relationship
Education: Education, Partner’s Education, Education Equality
Industry: Financial Services, Life Science, Manufacturing, Professional Services, Retail/Wholesale,
Social/Government Service, Technology, Utilities
Satisfaction: Life Satisfaction, Good Relationship, Team w/ Partner, Partner’s Relationship Satisfaction,
Partner’s Life Satisfaction, Partner Support-Overall
Family Labor: Partner Support-Domestic Chores/Children, Satisfaction with division of family labor

Table 24. Organizing Framework

<table>
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<th>Paper Title</th>
<th>Level of Analysis</th>
<th>Key Constructs/Variables</th>
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<td>Phenomenon: Dual-Career Couples</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P1: Role Centrality and Perceived Partner Support in Dual-Career Couples: A Replication Study</td>
<td>Micro – Individual</td>
<td>Role Centrality, Partner Support, Gender</td>
</tr>
<tr>
<td>P2: Happily Ever After: Maximizing Life Satisfaction in Dual-Career Relationships</td>
<td>Micro – Individual</td>
<td>Life Satisfaction, Relationship Satisfaction, Role Centrality, Partner Support, Income, Gender</td>
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<tr>
<td>P3: Is Role Centrality a Key to the Gender Wage Gap?</td>
<td>Micro – Individual</td>
<td>Role Centrality, Gender, Income</td>
</tr>
</tbody>
</table>
Figure 5. Venn Diagram of Key Constructs/Variables

Paper 1

Role Centrality

Partner Support

Gender

Income

Relationship Satisfaction

Life Satisfaction

Paper 2

Paper 3
Appendix - Decision trees

According to the no-free-lunch impossibility theorem, there is no single universally best strategy or learning algorithm for all optimization problems, and therefore whether one method or technique outperforms another is dependent on the problem and the specialization of each tool (Caruana & Niculescu-Mizil, 2006; Ho & Pepyne, 2002). The CART decision tree method selected and employed in this analysis has been chosen for its ability to offer a novel informative perspective on this research area. As explained by Salford Systems (2019),

A decision tree is a flow chart or diagram representing a classification system or predictive model. The tree is structured as a sequence of simple questions, and the answers to these questions trace a path down the tree. The end point reached determines the classification or prediction made by the model, which can be a qualitative judgment (e.g., these are responders) or a numerical forecast (e.g., sales will increase 15 percent). (para. 1)

Decision trees are a class of predictive techniques within machine learning/data mining, in which “a target variable is singled out and the hope is to build a model with suitable predictors that explains or predicts the target variable well” (Haughton, Nguyen, & Senne, 2010, p. 90). It is in this way that decision trees are similar to other traditional methods of predictive modeling, such as linear or logistic regression (Haughton et al., 2010), and can be used to approach the same sort of research questions. However, tree-generating techniques are comparatively better than a number of other methods (logistic regression, discriminant analysis, and log-linear modeling) at identifying important predictors and significant interactions when analyses contain a myriad of variables (Haughton & Oulabi, 1997).
Decision trees have been in use since the first regression tree algorithm was presented by Morgan and Sonquist in 1963, though there has been a resurgence of interest in the method afforded to Breiman, Friedman, Olshen, and Stone’s 1984 book, *Classification and Regression Trees* (Loh, 2014). Google Scholar search indicates the Classification and Regression Trees (CART) algorithm and the authors’ subsequent methodological extension, bagging predictors, has been cited nearly 60,000 times collectively. CART has been used widely across social and life science disciplines, including research areas such as medical, predictive business analytics, market research, and economics among others (Eliashberg, Hui, & Zhang, 2007; Haughton et al., 2010; Haughton & Oulabi, 1997). However, decision trees are seldom seen in organizational behavior journals, thus this analysis offers the benefit of novelty among other advantages when applied to this topic.

Classification trees, and the CART method specifically, offer several advantages compared to other predictive analysis methods. First, these are nonparametric methods; meaning distribution assumptions of predictor variables are not necessary (Gordon, 2013; Haughton et al., 2010). “Thus CART can handle numerical data that that are highly skewed or multi-modal as well as categorical predictors with either ordinal or non-ordinal structure” (Lewis, 2000, p. 5 as cited in Haughton et al., 2010, p. 91). Furthermore, these methods are non-linear (Gordon, 2013). “Nature, or society, is rarely linear. In seeking to identify or quantify relationships between variables, a basic linear model is often inadequate, even as an approximation” (Haughton & Haughton, 2011). The challenge this presents is that assembling a model of nonlinear relationships, particularly when data are multi-faceted with complicated interactions, is exceptionally difficult and confusing to
interpret if achieved (Haughton & Haughton, 2011; Shalizi, 2006).

Classification and regression trees present an alternative to the complexities of non-linear regression by dividing and subdividing the data, a process called recursive partitioning, until it has been separated into groups that can be easily fit with simple models (Shalizi, 2006). This divides “populations into meaningful subgroups which will allow the identification of groups of interest and enhance the provision of products and services accordingly” (Gordon, 2013, p. 1). Through this process trees can “identify interactions and complex relationships between the target variables and predictors” (Haughton et al., 2010, p. 91) with outputs that are easy to interpret and present intuitive insights (Eliashberg et al., 2007; Gordon, 2013; Loh, 2014). Decision trees “produce rules that are easily interpretable in logical terms,” thus, the user-friendly nature of decision tree results gives it an advantage over other methods for examining questions directly relevant to business practitioners or people that are not trained statisticians (Giudici, 2005a, p. 291).

Decision trees can be used with all manner of variables, often simultaneously, with some variation among the different types of trees. In the CART methodology, both categorical and/or continuous exploratory variables can be used, whereas in CHAID, another tree algorithm, all dependent and explanatory variables must be categorical (Bagdatli Kalkan & Bahar Yucel, 2017; Haughton & Oulabi, 1997). For continuous variable outcomes regression trees are employed, and for categorical variable outcomes classification trees can be utilized (Gordon, 2013). Furthermore, the CART method is reportedly well equipped to be applied to a dataset even when there are missing values.
and is “robust to the effects of outliers” (Haughton & Haughton, 2011, p. 84; Shalizi, 2006; Shalizi, 2009).

Additional attractive aspects of these methods include fast computation speed (Loh, 2014; Shalizi, 2006), good prediction accuracy (Loh, 2014; Giudici, 2005a; Salford Systems, 2013), easy model training through fast and reliable learning algorithms (Hannak et al., 2012; Shalizi, 2006), and the wide availability of statistical software that includes these methods (Gordon, 2013; Haughton et al., 2010; Loh, 2014). In fact, bagged decision trees, a method extension to CART that has been found to substantially improve accuracy (Breiman, 1996a), has been found to perform “among the very best prediction models for both classification and regression problems” (Caruana and Niculescu-Mizil, 2006 as cited in Hannak et al., 2012, p. 480).

As with all statistical analysis methods, decision trees have utilization requirements. While decision trees make no distributional assumptions about the data, as discussed, datasets need to meet three key criteria for these methods to be applied. 1) The target (outcome) variable must be predefined, that is, consistent with all supervised learning techniques, a training dataset containing known values of the outcome variable must be available (Larose, 2005). 2) Because the learning part of the process happens by example, the algorithms require a rich and varied training sample, ideally representative of all the types of cases the model would need to predict outcomes for in the future (Larose, 2005). 3) For classification trees, the target variable values must be discrete (Larose, 2005).

Decision trees also present some limitations. One of the limitations particularly problematic in early algorithms was masking, in which only one of two or more highly
correlated variables would emerge in a tree, leading to spurious or inaccurate conclusions regarding the relative significance of variables (Loh, 2014). The CART algorithm addresses this issue by calculating scores to measure the importance of each variable that can help in identifying masking (Loh, 2014). However, even with the CART output, it is possible for some variables to mask others, thus researchers should look critically at tree results. Further analysis of theorized associations can be helpful to understand the full story being communicated by the data (for an example of this see Haughton et al., 2010). Haughton et al. (2010) also point out “if important situational variables are not included in the model” or the model is mis-specified, such as when a particular predictor variable/target relationship is not included, “the results of the model may be misleading” (p.93).

Gordon (2013) asserts that CART trees are less popularly used in research compared to traditional statistical methods due to the relative youth of the method and the scarcity of “tests to evaluate the goodness of fit of the tree produced” (p.1). Indeed, the preferred metrics for evaluating learning algorithms in general vary by research domain, with information retrieval, medicine, and marketing, each concentrated on Precision/Recall measure, ROC area, and Lift, respectively (Caruana & Niculescu-Mizil, 2006). These evaluation metrics do not always agree, which limits the researcher’s ability to confidently assess the fit of the model to the data.

Another limitation of the CART algorithm specifically, which is of particular concern when the sample size is small, is estimation instability, meaning that the structure of the tree produced is sensitive to slight changes in the training dataset (Eliashberg et al., 2007). The methodological extension, bootstrap aggregation, a.k.a.
*bagging*, was developed to address this issue (Eliashberg et al., 2007). “In a bagging procedure, the original data are repeatedly sampled with replacement, creating bootstrapped data sets” from which different trees are created and subsequently an average of the predictions of all trees lead to a final predictive tree model (Eliashberg et al., 2007, p. 885).

Loh (2014) points out in his review that an outstanding debate regarding decision trees is how missing values should be dealt with. The varied decision tree algorithms have been designed to approach this issue through several different techniques. Ding and Simonoff’s (2010) comparative analysis of these techniques found the method utilized in the CHAID and GUIDE algorithms performs best for classification trees with binary target variables but further comparative research is needed for other contexts (as cited in Loh, 2014).

Consistent with the no-free-lunch theorem, in studies comparing different predictive analyses, machine learning methods, and tree algorithms, the best method/algorithm depends on the metric being evaluated and the characteristics of the dataset or aim of the particular research study. Type 1 errors have been found to be relatively more likely with decision trees (CART, bagged-CART, CHAID) than in logistic regression for problems with binary outcome variables, such as credit scoring (designating good/bad credit), but less likely than with neural networks (Giudici, 2005a; Giudici, 2005b). Caruana and Niculescu-Mizil (2006) found bagged trees, random forests, and neural nets performed best testing 11 problems across eight metrics, but after applying calibration, boosted trees was found to be best overall and at predicting probabilities. Haughton and Oulabi (1997) found response lifts for CART and CHAID
models to be very close and fairly robust with respect to the size of the tree. However, Giudici (2005b) reports that based on misclassification rates the CART algorithm performs better than CHAID. Comparison of the CART vs. C4.5/C5.0 algorithms found these algorithms to be in agreement regarding the identification of the most important variables, but disagreement as to their order of importance (Larose, 2005). Finally, ensemble methods that generate forests of trees have been found to produce on average 10% better prediction accuracy compared to the best performing single-tree algorithm, but what is lost is the ability for the model to explain how the variables influence predictions (Loh, 2014). Thus, interpretability is the strongest argument for single-tree methods (Loh, 2014). For an in-depth review of decision tree methods history and variants, see Loh (2014).

**How it works.**

It is common when employing data mining methods, such as decision trees, for a sample to first be randomly partitioned into training (a.k.a. learning) and testing data sets (Breiman, 1996a; Nagadevara, Srinivasan, and Valk, 2007). A model is first developed with the training set and then tested on data from the test set (Gallette, 2016; Gordon, 2013; Nagadevara et al., 2007; Shalizi, 2009). Some software enables researchers to also partition out a validation set that serves to select the best model among many options before the test set is used to evaluate the final model (Gordon, 2013; Sarma, 2013). The training set generally contains the majority of observations because, as mentioned previously, it is important to the accuracy of the model for the training set to be rich, and ideally contain examples of all types of observations the model may encounter (Haughton & Haughton, 2011; Larose, 2005). However, when a sample contains too few
observations to be partitioned into training and testing sets, techniques such as cross validation are employed, where small proportions of the training data are left out in turns for evaluation of the model (Breiman, 1996a; Nagadevara et al., 2007).

Training set to test set ratios found in published research are often specified 80% training and 20% testing (Bogomolov, Lepri, Ferron, Pianesi, & Pentland, 2014; Bogomolov et al., 2013; Gallette, 2016) or roughly 70:30 (Bagdatli Kalkan & Bahar Yucel, 2017; Eliashberg et al., 2007; Hannak et al., 2010; Haughton & Oulabi, 1997). “Reserving more data for the training generally results in more stable parameter estimates” (Sarma, 2013).

After the sample has been partitioned into these sets there are essentially three stages in the tree making process: growing a tree, pruning, and testing model performance (Bagdatli Kalkan & Bahar Yucel, 2017; Sarma, 2013). The ways in which these stages are conducted varies among the differing tree algorithms.

**Growing.**

A tree starts at its root node, which contains the entire training dataset (Sarma, 2013). The dataset is then broken down through a series of questions regarding the features of the observations with the goal of creating groups with the maximum level of homogeneity among group members (Bagdatli Kalkan & Bahar Yucel, 2017; Shalizi, 2009). For example, a very simple tree (though the smallest possible would be a single node (Haughton et al., 2010)) might have a root node, one split, and two terminal nodes (a.k.a. leaf nodes) (Shalizi, 2006).

How splits are executed depends on the method employed. In CART, all splits are binary, meaning that only two child nodes are produced at each split (Medina-Borja &
Pasupathy, 2007). “If a predictor involves more than two categories, CART merges some of the categories in such a way as to obtain two child nodes that are as homogeneous as possible in the target variable” (Haughton et al., 2010, p. 90). In contrast, the C4.5 and CHAID algorithms don’t restrict the data to binary splits, meaning that each value of a categorical variable can split into its own branch resulting in trees that are bushier (wider) in appearance, with potentially many terminal nodes containing few observations (Larose, 2005; Loh, 2014; Medina-Borja & Pasupathy, 2007). Reminder, in the CHAID algorithm all variables are categorical (Haughton et al., 2010). In all methods, each split produces mutually exclusive child nodes (or potentially terminal nodes) that significantly differ from one another (Eliashberg et al., 2007; Medina-Borja & Pasupathy, 2007).

A potential advantage to the CART algorithm is that it mathematically determines the way variables are split into binary groups based on the homogeneity of the resulting nodes rather than this being specified by the researcher as is done in some other methods, such as CHAID (Haughton & Oulabi, 1997). For example, for the variable age, the algorithm may split the observations into ≤ 20 and >20, or it may split into ≤ 40 and >40; it determines the best splitting criteria based on the training data (Haughton et al. 2010). This also applies to categorical variables with more than two levels; a split could group levels 1&2 and 3&4 or it could group levels 1&4 and 2&3 (or any other possible combination) (Haughton et al. 2010). This has the advantage of avoiding split groups arbitrarily assigned by the researcher but could ignore the benefit of a seasoned researcher’s experience with similar data and past research findings in which optimal split groupings have been determined or supported theoretically (Haughton & Oulabi, 1997).
How the order in which variables are selected for splits also varies by method and tree type (classification versus regression). In CART, the algorithm considers all variables and selects the variable that will produce the most homogenous two child nodes (Haughton & Haughton, 2011). In CART, for a tree with a categorical outcome variable, this is based on a metric of purity, whereas in CHAID the order of the variables are determined by level of significance (p-value) in a contingency table at each junction (Haughton et al., 2010). With regard to purity, “CART measures the success of the split by the Gini coefficient for a categorical target variable (classification tree),” which is equal to zero when all observations in a node are of the same target variable class, “and the within sum of squares for a continuous target variable (a regression tree)” (Haughton et al., 2010, p. 90). Like the Gini coefficient used in CART, entropy is used as the impurity function in other common algorithms (Breiman, 1996b). In comparison, the entropy criterion tends to equalize sample size in the resulting nodes, whereas the Gini produces purer nodes with regard to the class of the target variable (Breiman, 1996b). It is through the process of splitting that “a set of important independent variables is revealed” (Medina-Borja & Pasupathy, 2007, p. 5).

Although the Gini Coefficient is the generally recommended measure of impurity for classification trees within the CART method (Haughton & Oulabi, 1997), the algorithm authors also discuss alternative measures including twoing and ordered twoing (Steinberg, 2009). The twoing rule compares the outcome variable distribution of the two child nodes and has been observed to perform better than the Gini for trees with categorical target variables with more than two classes or difficult-to-predict binary target variables (Steinberg, 2009). However, the shortcoming of the Gini, entropy, and twoing
measures when applied to multiclass ordinal target variables is a loss of known information; each class is assumed to be defined nominally and none of these measures can account for the ordering of classes (Frank & Hall, 2001).

The ordered twoing measure is a variation on the twoing rule that takes into account class orders. Essentially “it is a classification rule with characteristics of a regression rule as attempts to separate low-ranked from high-ranked target classes at each split” (Steinberg, 2009, p. 186). This measure is of particular interest for this study because the target variable, life satisfaction, has been measured on a 7-point Likert scale, which is naturally ordinal. While some researchers may argue that Likert scales with seven or more points can be treated as continuous variables for analysis, because an exact distance cannot be measured between sentiments (for example, agree, neutral, disagree), it is most accurate to treat these scales as ordered categorical variables (Lund Research Ltd., 2018).

**Pruning and testing model performance.**

Determining the best size for a tree is a process that has evolved since the earlier tree algorithms, which required researcher imposed stopping criteria that could be relatively arbitrary, leaving trees open to issues of over and under fitting (Loh, 2014; Shalizi, 2006). By growing the largest tree possible (overfitting the data) and then pruning until finding the model with the lowest cross-validation estimate of error (mean square error), the CART method is able to remedy this issue (Haughton & Haughton, 2011; Loh, 2014; Shalizi, 2009).

Recall that ideally one’s sample was large enough to partition out a portion of the data for testing (or two separate portions for validation and testing), to be used after the
model is built based on the training dataset. This testing dataset comes into play for pruning and model performance testing, unless a validation set takes its place in pruning.

For each pair of terminal nodes sharing a parent, the error is evaluated on the testing set (or validation set) to determine if the sum of squares would decrease if that pair of nodes were removed and only the parent node remained; if yes that pair is pruned, if no it remains in the tree (Shalizi, 2009). This pruning process is repeated until the error is no longer improved (Shalizi, 2009). Explained more technically, the pruning process is “based on the idea of weakest-link cutting, with the links indexed by the values of a cost-complexity parameter” (Loh, 2014, p. 331). The way all this plays out when using the CART algorithm is that it “creates a list of trees from the smallest tree with only one node to the largest tree with as many nodes as observations, and then selects the tree which predicts the dependent variable best” based on the test dataset (Haughton, Haughton, Mbaye, 2010, p. 70).
Vita

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This manuscript was typed by the author.