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Self-Employment in Later Life: Implications for Financial, Physical, and Mental Well-Being

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by

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ABSTRACT OF THE DISSERTATION

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Professor Nancy Morrow-Howell, Chair

More than one in five working Americans aged 50 and older are self-employed, yet scholarship that examines the relationships between self-employment and personal health and financial well-being is limited. Using data from six biennial waves of the Health and Retirement Study, a nationally-representative panel study of Americans past 50 years of age, this quasi-experimental dissertation documents the characteristics of self-employed older adults in comparison to wage-and-salary workers, as well as compares self-employed and wage-and-salary workers in later life on a set of financial well-being and personal health outcomes. This study incorporates inverse probability of treatment weighting (also referred to as propensity score weighting) to control for selection into the "treatment" of concern, self-employment. Among older Americans, this dissertation revealed that age, being male, reporting better health, and having higher levels of risk tolerance were predictive of self-employment, among other factors. Further, it found strong evidence that self-employment leads to reduced earnings from work, with some evidence that it increases health and wealth. This dissertation builds upon previous work while contributing to discussions about the causal effects of later-life self-employment, as well as program and policy developments to support longer working lives.

<u>Chapter 1: Overview</u>

In a rapidly aging society, there has been increased attention in recent years on longer working lives. Recent coverage in the national media by *The New York Times*, *The Washington Post*, and *USA Today* all highlight the importance of the subject of longer working lives for many Americans, describing the duality of the desire and need to continue working well past traditional retirement age (e.g., Davidson, 2017; Farrell, 2017; Jordan & Sullivan, 2017). There are many reasons for this interest, including the growing share of the population that is approaching or already in retirement, the financial security of this group during retirement, and the desire for many to stay engaged in the workforce past traditional retirement age.

One way that older adults are staying engaged in the workforce later in life is through self-employment. Often called senior or silver entrepreneurship, the United States Senate Special Committee on Aging and the Small Business and Entrepreneurship Committee held a hearing on the "challenges and opportunities for senior entrepreneurs" in 2014 (Special Committee on Aging, U.S. Senate, 2014). Self-employment is considered one route to promoting financial security during retirement while simultaneously contributing to the economy, and over the past five to 10 years, programs designed to spur and support self-employment in later life have emerged from such organizations as AARP, Encore.org, Senior Entrepreneurship Works, and the U.S. Small Business Administration.

Much of the media attention on this subject has been positive in nature, emphasizing the financial benefits of working for oneself and the fulfillment of personal passions through this work (e.g., Rogers, 2017; Strauss, 2017; Zwilling, 2017). However, others have presented stories that discuss older adults' movement into on-demand services to secure supplemental income during retirement while promoting social engagement, such as driving for Uber (Olson, 2016), providing concierge services for older adults wishing to remain living at home (Moyer, 2017), and renting out rooms through Airbnb (Zipkin, 2016). For those who do start their own businesses, it has also been pointed out that the consequences of failing these ventures in later life, when there are fewer years to make up for the financial loss that a younger entrepreneur would have, are potentially dire (Harrison, 2015). While there are certainly potential benefits from self-employment in later life—perhaps for those with access to the right contacts and sources of support—it is currently difficult to have a clear discussion about this subject when there has been so little scholarship on it. As Halvorsen and Morrow-Howell (2017) described in their review of the literature and proposed research agenda, we know relatively little about the individual characteristics of self-employed older adults and the personal and environmental antecedents, workplace characteristics, and personal and societal outcomes from this work.

1.1 Definitions of Key Concepts

This section will define and operationalize two terms: self-employment and older adult. Much of the content in this section is a summation of scholarship published by Halvorsen and Morrow-Howell (2017).

1.1.1 Self-Employment and Entrepreneurship

Definitions of self-employment vary and in the applied social sciences are often shaped by the nature of the dataset being used. Self-employment can include several types of work and is defined as working for oneself, compared to working for another person or organization. Self-employment, in many regards, is a catch-all term for those who might describe themselves as consultants, small business owners, entrepreneurs, and social entrepreneurs (Pitt-Catsouphes, McNamara, James, & Halvorsen, 2017), as well as freelancers (Platman, 2004) and independent contractors (Weller, Wenger, Lichtenstein, & Arcand, 2015). Of course, the nature of the work among these types of self-employed positions may be very different from one another. A dataset often used to track self-employment statistics in the U.S., the Current Population Survey, simply asks if one is self-employed (Hipple, 2010). The dataset used for this dissertation and that is often used to study self-employment among older Americans (e.g., Zissimopoulos & Karoly, 2009), the Health and Retirement Study, defines self-employment as simply working for oneself (Health and Retirement Study, 2016).

One term that has a growing amount of scholarship devoted to it is entrepreneurship. While entrepreneurship has more theoretical underpinnings than self-employment, the two terms are often used interchangeably (e.g., Curran & Blackburn, 2001; Singh & DeNoble, 2003; Van Solinge, 2014). The term entrepreneurship, which is thought to have originated in France in the 17th or 18th centuries (Dees, 1998), has been defined in multiple ways. Bygrave and Hofer (1991) define entrepreneurship as a process, stating that an entrepreneur is "someone who perceives an opportunity and creates an organization to pursue it" (p. 14). Highlighting the view of Peter Drucker, a notable author and researcher in the fields of innovation and entrepreneurship, Dees (1998) describes an idealized version of entrepreneurship, in which simply starting a business for reasons of self-employment does not count as entrepreneurship if it is not innovative or change-oriented. In his classic text, *The Theory of Economic Development,* Schumpeter (1934) concurs, stating that an entrepreneur is "an agent who enables or enacts a vision based on new ideas in order to create successful innovations" (as cited in Dacin, Dacin, & Matear, 2010, p. 44).

Scholars of self-employment in later life have used various terms when describing those who work for themselves or start their own businesses. These include older entrepreneurs (Kautonen, 2008; Kautonen, Down, & South, 2008), grey/gray entrepreneurs (Harms, Luck, Kraus, &

Walsh, 2014; Weber & Schaper, 2004), seniorpreneurs (Maâlaoui, Castellano, & Safraou, 2013), and encore entrepreneurs (Civic Ventures, 2011; Crawford & Naar, 2016; U.S. Small Business Administration, 2015) as well as simply the self-employed (Zissimopoulos & Karoly, 2007b). Another study compared “career” and “later-life” older entrepreneurs, differentiating between those who had long run their own businesses and those who were new to it at later ages (Kerr, 2017).

Weber and Schaper (2004), in a review of the literature on older entrepreneurs, noted that aspects of the entrepreneurship definition are “hard to measure in the business world,” creating a category from which empirical measures are “too difficult to collect” (p. 152). *Innovation* and the *pursuit of opportunities*, two concepts often included in entrepreneurship definitions, are examples of this subjectivity. Also difficult to track in survey data and arguably subjective—yet argued to be important indicators of outcomes—are motivations for pursuing self-employment or entrepreneurship in later life, such as being “pushed” or “pulled” into entrepreneurship (Kautonen, 2008; Weller, Wenger, Lichtenstein, & Arcand, 2018), or being “constrained,” “rational,” or “reluctant” entrepreneurs (Singh & DeNoble, 2003). Indeed, after subjective aspects of these definitions are removed, self-employment—defined as working for oneself—becomes synonymous with entrepreneurship. However, some scholars have created two taxonomies of the self-employed, describing those who were previously unemployed as “necessity” entrepreneurs and those who were not as “opportunity” entrepreneurs (Ewing Marion Kauffman Foundation, 2017; Fairlie & Fossen, 2018). Following the direction of previous scholarship (Halvorsen & Morrow-Howell, 2017; Pitt-Catsouphes et al., 2017), this dissertation operationalizes self-employment as working for oneself. Limitations to this operationalization are discussed in Chapter 5, along with ideas for exploring new profiles of self-employed older Americans.

1.1.2 Older Adult and Later Life

The terms “older adult” and “later life” are certainly imprecise and can encompass several different age ranges. However, much of the literature on self-employment in later life includes those aged 50 and older (e.g., Curran & Blackburn, 2001; Harms, Luck, Kraus, & Walsh, 2014; Maâlaoui, Castellano, & Safraou, 2013; Platman, 2003; Weber & Schaper, 2004). As such, this dissertation will also consider Americans working at age 50 and older. Limitations to this operationalization and ideas for moving the field forward are discussing in Chapter 5.

1.2 Purpose of Dissertation

Broadly described, the purpose of this dissertation is to advance knowledge on the topic of self-employment in later life in two key areas: the characteristics of older self-employed Americans, including sociodemographic variables and metrics of their human, social, and financial capital; as well as to estimate the causal effects of self-employment in later life in comparison to working for someone else on two financial and two personal health factors. To accomplish this, I will conduct theoretically-driven analyses using six waves of data from the nationally-representative Health and Retirement Study.

1.3 Organization of Dissertation

This dissertation is organized as follows: Chapter 2 presents empirical scholarship that is relevant to the topic of self-employment in later life, including the topics of the aging of the population, longer working lives, financial security, rates of self-employment in later life, and our knowledge of the impact of pertinent programs and policies. It follows with a review of the theories and frameworks that have been used to understand this type of work. To close, it describes this dissertation’s research questions and hypotheses. Chapter 3 presents the methods of this dissertation, including an overview of the data source and sample, a description of the analytical strategy, and information about sensitivity analyses and diagnostics. Chapter 4 presents detailed findings of this dissertation, with Chapter 5 providing a discussion of the results in relation to the existing literature and their implications.

Chapter 2: Background and Significance

In this chapter, I present empirical and theoretical scholarship that is relevant to the topic of self-employment in later life, concluding with this dissertation's research questions and hypotheses. Sections 2.1 through 2.3, and sections 2.5 and 2.6, are updated and expanded from a literature review and conceptual article I previously published (Halvorsen & Morrow-Howell, 2017).

2.1 Work and Financial Security in an Aging America

The American population is aging at a rapid pace. In 2014, approximately 110 million Americans were aged 50 and older, making up 34 percent of the U.S. population; of those, more than 46 million were aged 65 and older. By 2050, the number of Americans aged 50 and older is expected to reach more than 160 million—more than 40 percent of the total population (U.S. Census Bureau, 2014). The Pew Research Center (2010) estimates that for the 19 years between 2011 and 2030, roughly 10,000 Americans have already turned or will turn 65 every day. Globally, the world population is also experiencing increased numbers of older adults, with those aged 50 and older estimated to increase from about one in five (21%) to almost three in 10 (28%) people between 2010 and 2030. By 2050, those aged 50 and older are anticipated to make up more than one-third of the world population (U.S. Census Bureau, Population Division, 2010). The U.S.—like much of the world—is rapidly aging.

While millions of individuals are approaching their retirement years, many are financially ill-prepared to cease work entirely. A consistent finding among scholars is that Americans, by and large, have not saved enough to retire and have a low level of confidence in their ability to retire comfortably. A 2017 study revealed that three in 10 (30%) American workers aged 55 and older, including their spouses, had not personally saved anything for retirement, excluding Social Security or employer-provided funds (Employee Benefit Research Institute & Greenwald &

Associates, 2017). In total, approximately one in six (18%) had less than $1,000 in savings and investments, with a similar number (19%) having between $1,000 and less than $50,000 and about a quarter (26%) having between $50,000 and less than $250,000 in savings and investments. About one third (35%) had $250,000 or more saved for retirement. A previous report found that only one in five (20%) American workers aged 55 and older were "very confident" that they would have enough money to live comfortably throughout their retirement years (Employee Benefit Research Institute & Greenwald & Associates, 2016). The recession that began in 2008 made financial matters worse for older adults. By the third quarter of 2011, for example, nearly two in five (38%) unemployed Americans aged 62 and older had been out of work for at least one year, compared to less than one in 10 (7%) in 2007 (Johnson, 2012). While the recession hit younger adults harder, more late-career workers lost their jobs than in previous recessions, resulting in a high level of Social Security claims (Munnell & Rutledge, 2013). Given these prospects, it is clear why retirement security was chosen as one of the 2015 White House Conference on Aging's four main focus areas (U.S. Department of Health & Human Services, 2015).

Globally, there remains a need, for many, for continued income during retirement. Results from a 2017 survey of 16,000 workers in 15 countries in the Americas, Asia, Australia, and Europe revealed that no country received a high score for its residents' preparedness for retirement, while just more than half (53%) of countries were given a medium score. In the six consecutive years that this report has been published, no country has ever received a high score in its index, which is based on six questions asked of workers that include "Thinking about how much you are putting aside to fund your retirement, are you saving enough?" and "How able are you to understand financial matters when it comes to planning for your retirement?" (Aegon Center for

Longevity and Retirement, 2017, pp. 6-7). Further, responsibility for retirement security is continually shifting away from governments and companies to individuals themselves throughout the world (Aegon Center for Longevity and Retirement, 2017; Natixis Investment Managers, 2017).

Concerns about financial security during retirement may be one reason why older adults are remaining in the work force longer. In the U.S., for example, the proportion of adults aged 55 and older in the workforce is projected to increase by nearly 10 percent in the 30-year span from 1994 (at 30.1%) to 2024 (at 39.4%) (U.S. Bureau of Labor Statistics, U.S. Department of Labor, 2015). This is a reverse of the long-running trend toward lower labor force participation rates among older adults. For example, while the participation rate for men aged 55 to 72 has increased since the mid-1980s, it is still far under the rate from the previous hundred years (Burtless & Quinn, 2002; Munnell, 2015).

Another way to consider this trend is by looking at the average retirement age. In the U.S., the average retirement age for men in 1910 was 74, compared to 63 in 1983—"a drop of about 1.5 years per decade" (Burtless & Quinn, 2002, p. 3). However, since the 1980s, this trend toward earlier retirement ages has stopped and possibly reversed to about age 64 in 2013 (Munnell, 2015). Further, it appears as though the average retirement age for women has increased dramatically over the past half-century from about 55 in the 1960s to 62 in 2013, although that figure is harder to track due to the changing work patterns and labor force participation rates of women (Munnell, 2015). Reasons for longer working lives are varied and include the outlaw of mandatory retirement ages for most American workers, changes in Social Security benefit calculations that stopped penalizing workers for working past normal retirement age and delays in the Social Security normal retirement age, increased health and education among older adults, less physically demanding jobs, joint decision making between husbands and wives, the decline of employer-sponsored post-retirement health insurance coverage, and reductions of defined-benefit employer pensions (Munnell, 2015; Quinn, Cahill, & Giandrea, 2011).

2.2 Rates and Trends in Later-Life Self-Employment

The increasing population of older Americans, combined with financial insecurity and a general trend toward longer working lives, are likely major reasons for self-employment being such a prominent form of work in later life. It has also been shown to be a “bridge” to retirement, providing a flexible way to continue earning income (Cahill, Giandrea, & Quinn, 2013). Using data from the Current Population Survey (CPS), the Ewing Marion Kauffman Foundation (2017) found, for example, that Americans between the ages of 55 and 64 made up more than one-quarter (25.5%) of the newly self-employed in 2016. Further, this data shows that for each year since tracking began in 1996, Americans between the ages of 55 and 64 had higher rates of self-employment activity than the average for all adults between the ages of 20 and 64. This is no small number: By multiplying the projected 40.5 million Americans between the ages of 55 and 64 in 2016 (U.S. Census Bureau, Population Division, 2017) by the 0.35 percent monthly startup rate of Americans in this age group for the same year (Ewing Marion Kauffman Foundation, 2017), it is revealed that approximately 145,121 businesses were started *each month* by Americans in this ten-year age range in 2016 alone.

Considering Americans in the labor force, the percentage of workers who are self-employed has been shown to increase with age among both men and women (Hipple, 2010). Among Americans in the labor force in 2014, for example, just 7.2 percent of working individuals aged 16 to 49 were self-employed, compared to 12.8 percent for those aged 50 to 54, 21.1 percent of those aged 65 to 69, and 30.2 percent of those aged 75 to 79 (Pitt-Catsouphes et al., 2017). Of course, these statistics only include those who are still working, a group whose numbers decline rapidly after traditional retirement age (U.S. Bureau of Labor Statistics, U.S. Department of Labor, 2015). Among the entire older adult population both in and out of the labor force, the self-employment rate has also increased: A 4.2 percent self-employment rate among all Americans aged 62 and older in 1988 rose to 5.4 percent by 2015 (Wilmoth, 2016). Further, the U.S. Small Business Administration's Office of Advocacy (2014) reported that just more than half (50.9%) of American business owners were age 50 or older. Similar rates exist in Europe. Using data from 11 countries in the Survey of Health, Ageing, and Retirement in Europe, for example, scholars have shown that the rates of self-employment increase with age among those who remain in the workforce (Hochguertel, 2010). Further, more than two in five of those who are self-employed in several European countries, including Germany, Sweden, and the United Kingdom, are aged 50 and older (Hatfield, 2015).

Important descriptive statistics regarding self-employment in later life have been published. Annual reports by the Kauffman Foundation have shown that self-employment is more common among older adults than younger adults (Ewing Marion Kauffman Foundation, 2017) and seminal studies by scholars with the RAND Corporation have shown that older self-employed adults are more likely to be male, married, and have higher levels of income, assets, and educational attainment, yet also less likely to have workplace pensions and health insurance (Zissimopoulos & Karoly, 2007b, 2009). The authors also found that those who become self-employed after the age of 50 are more likely to be female than those who became self-employed before the age of 50 and, among retirees, those who are male and married are more likely to transition to self-employment than wage-and-salary work. Certain industries have been found to attract older business owners, such as running bed and breakfasts, where the vast majority are age 50 or older (Crawford & Naar, 2016).

2.3 Outcomes of Work and Self-Employment in Later Life

While self-employment is not specifically considered in much of the published scholarship on the health outcomes of work in later life, research does suggest that paid work is positively related to well-being. A two wave analysis of older adults using the Health and Retirement Study (HRS) found that employment was associated with lower odds of reporting poor or fair health (Calvo, 2006). Using seven waves of the HRS, scholars found that fully retiring—completely leaving the paid workforce—was negatively associated with several physical and mental health indicators (Dave, Rashad, & Spasojevic, 2006). A more recent review of previous research found that work, in general, leads to more positive physical and mental health outcomes in later life (Staudinger, Finkelstein, Calvo, & Sivaramakrishnan, 2016). Among the self-employed, an older study of 564 Israeli business owners aged 25 to 65 revealed that the stress of managing one's own business was negatively related to health and well-being (Lewin-Epstein & Yuchtman-Yaar, 1991).

However, the context and meaning of work in later life may mediate this positive relationship. In a study of Americans aged 59 to 69, Calvo (2006) found that while having jobs with higher physical demands and stress or lower job satisfaction did not change the positive relationship between work and self-rated health, these factors were associated with worsened mood. A study of individuals aged 50 to 83 found that while being involved in paid work was not associated with greater or poorer psychological well-being than not working, workers with higher levels of engagement (e.g., feeling "bursting with energy" at work and "enthusiastic" about one's job) reported better psychological well-being than nonworkers; conversely, workers with lower levels of engagement reported worse psychological well-being than nonworkers (Matz-Costa, Besen, James, & Pitt-Catsouphes, 2014). The authors argued that these results support the role quality perspective, in which psychological well-being varies according to workplace engagement, but do not support the role occupancy perspective, in which simply working would be associated with higher psychological well-being. As such, there is reason to believe that self-employment in later life can produce positive well-being, yet the experience of the work and the quality of the engagement may mediate this relationship.

Overall, self-employed older adults have been shown to be successful in their work. With the five-year survival rate of new businesses remaining consistently around 50 percent (U.S. Small Business Administration Office of Advocacy, 2014), some studies have shown that older entrepreneurs may be more successful than younger ones when considering business survival rates (Headd, 2003; Robb et al., 2010). However, while research has shown that older self-employed adults tend to work longer and are wealthier than those working for someone else, on average, they are also less likely to receive key benefits connected to many workplaces, such as pensions and health insurance (Zissimopoulos & Karoly, 2007b). Given the difficulties of finding new work past the age of 50 for those who lost their jobs, self-employment has been documented to be a destination—whether desired or not—for older unemployed adults (Cahill & Quinn, 2014). Finally, while adjusting for self-selection bias in this line of research using Heckman's sample selection framework (1979), it was found that self-employed men would have generally received higher incomes had they remained working for someone else (Hamilton, 2000). This study found that respondent labor market experience, a variable that considered age and years of education, was higher among the self-employed than those in standard wage-and-salary positions, yet that this experience had a greater effect on wages for those in wage-and-salary positions than those in self-employment. The author pointed to the nonpecuniary motivations for pursuing self-employment, such as being one's own boss, as an explanation for this finding.

Although a major form of work in later life, scholarship that looks at relationships between self-employment and key financial, physical, and mental health outcomes, while controlling for or directly modeling key sociodemographic variables, is limited. Further, given practical and ethical constraints, controlled trials to compare the effects of later-life self-employment and other types of work have not been conducted, leaving the question, "Compared to what?" when assessing the relationships between self-employment and its outcomes.

2.4 Programs and Policies to Support Self-Employment in Later Life

A few studies have considered how programs and policies may encourage or support self-employment in later life. The national nonprofit organization, Encore.org (formerly known as Civic Ventures), created The Purpose Prize in 2005 to support and highlight the work of social entrepreneurs aged 60 and older (see https://www.encore.org/prize for more information); this program was acquired by AARP in 2016, after which the age of eligibility for awards dropped to 50 (Encore.org & AARP, 2016). Investigating the outcomes of this program, researchers found that involvement in The Purpose Prize as winners or fellows may have positively influenced organizational outcomes, such as media coverage and revenue (Pitt-Catsouphes, Berzin, McNamara, Halvorsen, & Emerman, 2016). While this type of prize program is laudable, it would be difficult to sustain or replicate on a large scale, as $100,000 prizes were awarded every year to up to five older adult social entrepreneurs, with smaller prizes, ranging from $10,000 to $50,000, awarded as well (Encore.org, 2016).

In 2012, AARP and the U.S. Small Business Administration (SBA) began a partnership to provide in-person and online training and support for Americans aged 50 and older interested in starting new businesses (U.S. Small Business Administration, 2012). By 2015, the program stated that it had "educated more than 300,000 existing and budding encore entrepreneurs," although it is unclear how many of these individuals would have received services from existing SBA and AARP programs had this newly-branded programming not existed (U.S. Small Business Administration, 2015). As of this writing and after reviewing the SBA and AARP websites, it appears the last in-person events under this program were held the summer of 2016 and that no formal or informal evaluations of this program has been published.

In the United Kingdom, a case study described the impact of the Prince's Initiative for Mature Enterprise (PRIME), a program that encouraged self-employment among those aged 50 and older while targeting those who were unemployed, receiving disability benefits, former caregivers, and retirees. PRIME provided entrepreneurship assistance—sometimes financial—and advice to participants. Through self-evaluation reports, interviews with staff, and results from a survey of PRIME service recipients, the authors found that the program may have played a positive social and economic role for potential older entrepreneurs (Kautonen et al., 2008). However, this program ended in 2014 (Business in the Community, 2014), although a related program, which provides mentoring to help older adults transition into new paid and unpaid work, including self-employment, exists in Wales (see http://www.primecymru.co.uk for more information).

Pivoting from programs to policies, local and national public policies may encourage or discourage self-employment in later life, as well as lead to better or worse outcomes. The Ewing Marion Kauffman Foundation (2016), for example, highlighted how public policies that provide social insurance are linked to higher self-employment rates, such as increasing access to health insurance and food stamp (SNAP) benefits. To increase entrepreneurial opportunities across the lifespan, the foundation recommended policies that strengthen social insurance programs, facilitate asset accumulation, and decrease the bias toward incumbent entrepreneurs (such as occupational licensing). Indeed, Fairlie, Kapur, and Gates (2011), using data from the Current Population Survey, found that self-employment rates increased from just before turning 65 years old to just after—when individuals become eligible for Medicare health insurance—while increases were not found for turning other ages between 55 to 75. This provides evidence for what the authors called "entrepreneurship lock," noting that health insurance in the United States is so often tied to employers until one becomes eligible for Medicare. Due to the implementation of the Affordable Care Act, it is expected that the transition to self-employment will ease for those younger than 65 (Blumberg, Corlette, & Lucia, 2014), although initial findings—which do not focus solely on or which sometimes excludes those aged 50 to 64—find mixed results (Bailey, 2017; Heim & Yang, 2017). More broadly, scholars have questioned the "glorification of entrepreneurship" in our society and, in particular, by our policymakers, citing the lack of research on the effects of entrepreneurship on families and the billions of dollars spent on programs aimed to increase entrepreneurial activity (Jennings, Breitkreuz, & James, 2013).

2.5 Relevant Theories

While the literature on self-employment in later life is largely atheoretical, scholars interested in later-life self-employment have drawn upon theories and concepts from several disciplines to explain the antecedents of and, to lesser degrees, the experiences during and outcomes from self-employment in later life.

It has been suggested that self-employed older adults may be more likely to be successful in their work than younger adults due to the accumulation of skills, experiences, wealth, and other assets that accumulate over the lifespan. Often, these assets have been described as human capital, which includes previous work and life experience, education, and health; social capital, which includes personal and professional networks and being married; and financial capital, which includes income, wealth, and access to loans (e.g., Bleakley, 2010; McDonald & Mair, 2010; Meyskens, Allen, & Brush, 2011; Weber & Schaper, 2004). All else being equal, this line of thinking posits that someone with more project management experience or a higher level of education (i.e., human capital), for example, might be more successful at managing the daily complexities of starting a new venture than someone with less experience or education. Further, someone with more liquid assets, such as savings and investments, or a higher credit score that might facilitate better terms on a loan (i.e., financial capital), may be better able to handle the financial ups and downs of a new startup than someone with fewer liquid assets or a lower credit score. Finally, someone with a large personal and professional network or with a reputation for being smart in business (i.e., social capital) may be better able to leverage business partners and develop a robust client base than someone with a smaller network or unknown reputation. While not directly related, these assets are logically linked to age, given that older adults have had more time to develop them.

Of course, human, social, and financial capital may not increase indefinitely and, in fact, may decrease after retirement, making it difficult for those who chose to pursue self-employment at a point in time after official retirement. For example, a curvilinear relationship between social networks and time has been documented, with retirement marking the time when social networks stop growing and begin to decline (McDonald & Mair, 2010). Another exception is health, an aspect of human capital, which tends to decline with age (Bleakley, 2010; Federal Interagency Forum on Aging Related Statistics, 2016).

Drawing from the psychological and business literature, the concept of risk aversion or risk tolerance has been discussed in relation to self-employment. Within the literature, there is disagreement about the relationship between self-employment and risk aversion, with few studies considering age in this relationship. Although mixed, Xu & Ruef (2004) note that studies have found a link between lower risk aversion and self-employment. However, many of these studies are limited due to their small, non-representative samples. Using data from a representative group of early-stage American entrepreneurs (n=803 nascent entrepreneurs and n=431 general population) from the Panel Study of Entrepreneurial Dynamics, they found that early-stage small business owners (called "nascent entrepreneurs" in the study) were more risk averse (i.e., less risk tolerant) than the general population in the pursuit of financial gain. This study also found that older nascent entrepreneurs were more risk averse than younger entrepreneurs. Using the longitudinal Health and Retirement Study of older Americans, Sahm (2008) found that while there is a great deal of variation in risk aversion between older adults, there is little variation within them over time.

Several different bodies of work inform the relationship between self-employment and personal outcomes among older Americans. For example, scholars have begun to think about work characteristics and their impact on older adults. Appannah and Biggs (2015), in their review of the literature and proposed framework, offered several factors that influence the aging-friendliness of an organization's culture. These include flexibility in the workplace (e.g., part-time work, working from home, and phased retirement) and job design (e.g., lower stress, interesting and meaningful work, and autonomy), as well as inclusion in training and development activities and supportive leadership. Self-employed older adults may, due to the very nature of their work, have more control over these factors and therefore may have more positive outcomes. Much of the focus on later-life self-employment has been on the motivations for pursuing this type of work, instead of the nature of the work and workplace itself. However, some studies have examined key aspects of the workplace, such as the number of employees, hours worked per week, tenure on the job, receiving pension coverage, industry, and occupation (Zissimopoulos & Karoly, 2007b, 2007a, 2009). As such, Halvorsen and Morrow-Howell (2017) called for more research to examine the work experiences of self-employed older adults.

The relationship between self-employment and personal outcomes may also be explained by work motivation and job autonomy. Although much of the scholarship on work motivation has focused on younger adults or not considered age at all, some studies have examined the relationship between work motivation and age (Bertolino, Zacher, & Kooij, 2015; Kanfer & Ackerman, 2004; Kooij, Down, & South, 2007). For example, a review of 33 studies on the motivation to continue working among older workers found a negative association between work motivation and chronological age, biological age (e.g., physical health), and the sense of being “old” (Kooij et al., 2007). Considering only self-employment, a cross-sectional survey of nearly 14,000 adults between the ages of 18 to 64 from 21 developed countries showed that the motivation to be self-employed followed an inverted U shape, with the peak age of motivation around age 22 with a steady decline after that (Minola, Criaco, & Obschonka, 2016). However, actual rates of self-employment among working Europeans (Hochguertel, 2010) and Americans (Hipple, 2010; Pitt-Catsouphes et al., 2017) increase with age, suggesting that there are more considerations than motivation to pursuing self-employment among older adults.

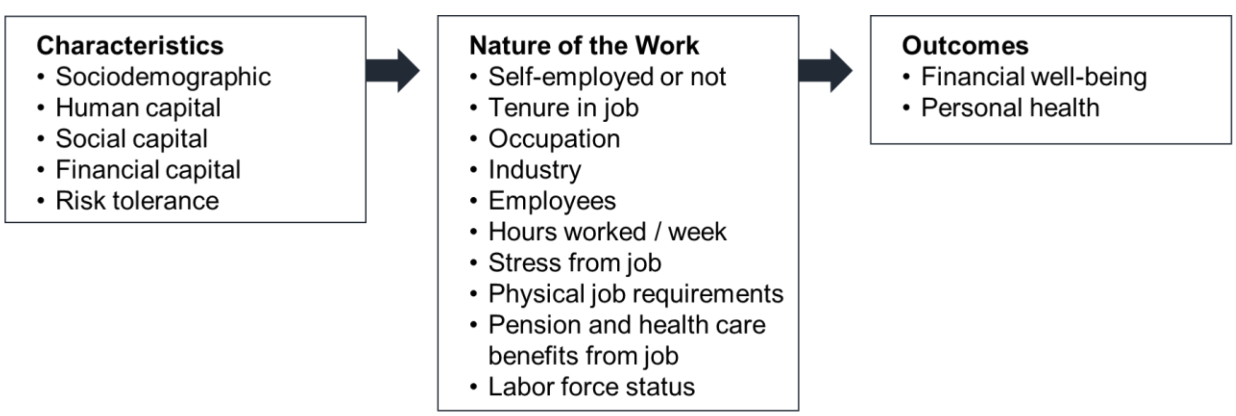
Interestingly, a Swedish study of “hybrid entrepreneurs”—those who simultaneously engage in wage-and-salary work and entrepreneurial ventures—revealed findings that were counter to the drop in entrepreneurial motivation with age that was documented by Minola, Criaco, & Obschonka (2016). The authors identified a U shape when assessing age and the intention to move from part-time to full-time entrepreneurship within one year, suggesting that the relationship between age and entrepreneurial motivation may be different among those considering moving into entrepreneurship for the first time and those who are already part-time entrepreneurs who are considering moving in these roles full time (Thorgren, Sirén, Nordström, & Wincent, 2016). There may be additional factors that influence the relationship between age and the motivation to move into self-employment, too. For example, cultural differences between countries, such as the degree to which countries encourage the collective distribution of resources and avoid uncertainty, has been found to moderate the relationship between self-employment motivation and age (Minola et al., 2016).

Autonomy, or having a high level of control over one’s work, has been shown to be an important aspect of work in later life and linked to work motivation, positive job attitudes, and well-being (Ng & Feldman, 2015). However, the authors found conflicting results on how chronological age influences the relationship between job autonomy and work outcomes in a meta-analysis of more than 400 empirical articles. Job autonomy was found to have a stronger relationship in older workers than younger workers when considering job self-efficacy, self-rated job performance, and emotional exhaustion; however, job autonomy was also found to have a weaker relationship in older workers than younger workers when considering job satisfaction, work engagement, job stress, and poor mental health. Further, the relationship between job autonomy and self-employment was not considered in this study.

2.6 Conceptual Framework

Guided by the theories and concepts previously described and adapted from the conceptual framework and research agenda proposed by Halvorsen and Morrow-Howell (2017), Figure 1 lists several characteristics that have been identified as important to self-employment in later life. These include sociodemographic factors; human, social, and financial capital; risk tolerance; and labor force status. It also lists variables that are a part of and important to the work experience itself, including being self-employed or in wage-and-salary employment, occupation and industry, time on the job, having employees, and access to health and insurance and retirement plans through the job. These attributes, which have been suggested to relate to the aging-friendliness of the workplace, might influence the relationship between antecedents and outcomes (Appannah & Biggs, 2015; Halvorsen & Morrow-Howell, 2017). Indeed, a major assumption of this dissertation study is that the work environment, in addition to personal characteristics, has an impact on outcomes; this is an extension of previous arguments on the productive engagement of older adults (N. Morrow-Howell & Greenfield, 2016). Finally, this model illustrates how work in later life might result in a set of financial well-being and personal health outcomes.

Figure 1. Conceptual Model of Predictors and Outcomes of Work in Later Life



2.7 Research Questions and Hypotheses

Using six biennial waves of the nationally-representative Health and Retirement Study (HRS) of Americans over the age of 50, this dissertation study has two major aims: to document the characteristics of self-employed older adults, and to examine how self-employment in later life impacts older adults' financial well-being and personal health in comparison to wage-and-salary work. To complete the second aim, selection into self-employment is controlled for using inverse probability of treatment weighting. The two primary research questions for this study are listed next, along with their associated hypotheses. Due to the limited published scholarship related to Question 2, the hypothesis proposes a relationship between self-employment and only one outcome variable.

Q1. **What are the characteristics of self-employed older adults, in comparison to those in wage-and-salary work, among older Americans working at baseline?** Characteristics include sociodemographic variables (e.g., age, gender, race, and ethnicity); levels of human (e.g., education and health), social (e.g., marital status and number of people in the household), and financial (e.g., total household income and wealth) capital; and risk tolerance.

> ***H1.*** Within this sample of working Americans aged 50 and older, human, social, and financial capital, as well as age and identifying as male and white, are positively associated with being self-employed. Given the mixed findings on risk tolerance among self-employed older adults, I provide no hypothesis for this characteristic.

Q2. **How does self-employment in later life influence financial well-being and personal health, in comparison to wage-and-salary work, among those working at baseline?**

Financial well-being is operationalized as individual earnings through one's work and total household wealth, and personal health is operationalized as self-reported health and total number of depressive symptoms.

H2. Similar to Hamilton's (2000) findings among working adults throughout the lifespan, I hypothesize that within this sample of working Americans aged 50 and older, self-employment leads to reduced income, on average, compared to wage-and-salary employment. I do not propose hypotheses for the remaining three outcomes, given this study's exploratory nature.

To conclude, while self-employment is a prominent form of work in an increasingly aging society, the scholarship on the characteristics of older adults who pursue it and the outcomes from this work, while considering the nature of the work, remain to be developed. This dissertation, through an analysis using data from six waves of the nationally-representative Health and Retirement Study of Americans over the age of 50, aims to fill this gap.

Chapter 3: Methods

This chapter outlines my dissertation's methods, including the data and sampling strategy used, measurement of all variables, and analytical strategy for both research questions.

3.1 Data and Sampling Strategy

3.1.1 Data Source

This study will use data from six waves of the biennial Health and Retirement Study (HRS), from 2004 to 2014. (At the time of final analysis for this dissertation, 2016 data was not yet released by the RAND Corporation, although I plan to include the 2016 wave before pursuing publication.) Commencing in 1992 and funded by the National Institute on Aging (grant number NIA U01AG009740), researchers from the University of Michigan collect data from a nationally-representative sample of approximately 20,000 community-dwelling Americans, over the age of 50, and their family members every two years. Questions aim to assess the financial, physical, and mental well-being of older Americans, their work histories, and family characteristics, among other topics.

Using the HRS dataset has several benefits. First, the HRS is one of the largest longitudinal studies in the U.S. on older adults, providing a descriptive, nationally-representative sample. Second, because it surveys Americans older than 50, it tracks individuals before and into retirement. Third, the wide array of instruments that make up the HRS cover a multitude of topics, including concepts important to this study. And finally, the HRS uses a steady-state sampling design to introduce a younger cohort every six years, enabling me to include Americans who had just passed the age of 50 in my baseline year (Sonnega et al., 2014; Survey Research Center, 2008).

The data used in this dissertation were substantially derived from Version P of the RAND HRS data file, a cleaned and pre-organized dataset that includes newly-created and imputed variables of total wealth, total household income, and individual weekly wages, among others. The database, developed at the RAND Center for the Study of Aging and funded by the National Institute on Aging and the Social Security Administration, is publicly and freely available after registering to use the HRS. Four variables regarding formal and informal volunteering that were not in the RAND HRS data file were pulled from the RAND Enhanced HRS Fat Files, which have the benefit of mirroring the format of the RAND HRS data file by collapsing the raw variables from each wave of the HRS into a single respondent-level dataset.

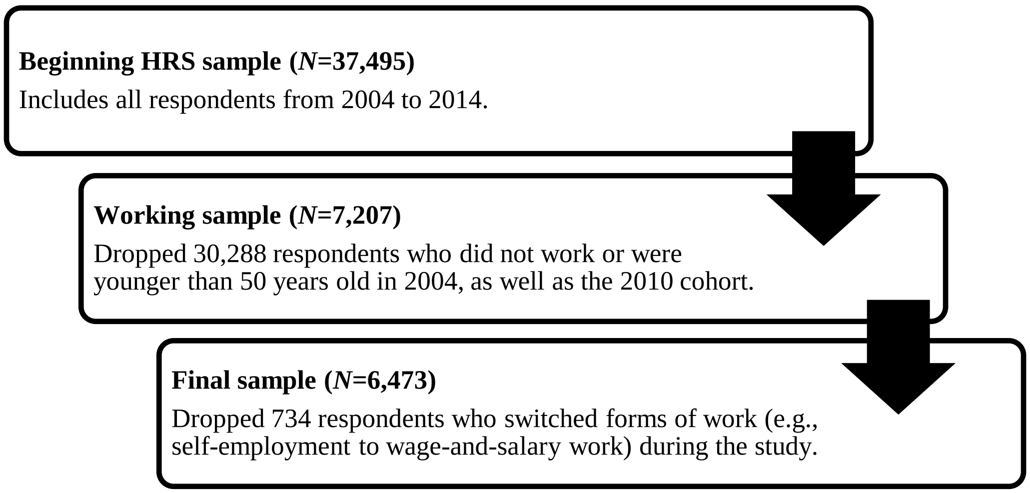
3.1.2 Sampling Strategy

Using Version P, which was released in September 2016, I reduced the larger RAND HRS data file to only include observations from the six biennial waves within the timeframe of interest, 2004 through 2014 (waves 7 through 12). These years were chosen to keep the sample as current as possible while maximizing available information from the younger cohort of older adults added in 2004. Then, the four variables from each of the six RAND Enhanced HRS Fat Files were merged with this larger dataset. As shown in Figure 2, a total of 37,495 unique individuals are in this larger sample.

To answer my research questions, this sample was further reduced by including only those who reported working for pay at baseline, as the inverse probability of treatment weights used in this dissertation, which require a binary treatment variable (i.e., self-employment and wage-and-salary employment), were created from the baseline data. This group of individuals was then followed for five additional waves, through 2014. As a result, the cohort that entered the study in

2010 was not included in this analysis. After these exclusion criteria were met, the sample included 7,207 unique individuals.

Figure 2. Sample Flow Chart



Unweighted descriptive statistics for the work status of the sample of older adults who were working in 2004 (baseline) show that the average number of waves worked was 3.57 (*SD*=1.84; *range*: 1 to 6). If the respondents worked the entire time between waves, this means that the average number of years worked among respondents working at baseline over the 10-year period was about seven years. On average, individuals in this sample were self-employed for 0.87 waves (*SD*=1.68; *range*: 0 to 6) and had wage-and-salary work for 2.71 waves (*SD*=2.10; *range*: 0 to 6). In other words, respondents were more likely to work in wage-and-salary employment. Accounting for all six waves included in this study and not just working years, respondents were self-employed 14% of the time (*SD*=0.28) and in wage-and-salary work 45% of the time (*SD*=0.35). The remaining time includes those who were not working due to retirement, unemployment, disability, or other reasons; as well as those who did not respond to follow-up waves and those who died between waves or moved into an institutional setting.

To incorporate inverse probability of treatment weighting within the proposed analyses for Question 2, a binary "treatment" condition for self-employment was created. Under ideal conditions, a sample that includes only long-term self-employed and wage-and-salary workers would be created to better ascertain the direct effects of these types of work on older adults. However, given real-world issues that include retiring from work, changing jobs, study non-response, death, and other factors, developing this type of sample becomes problematic. In the sample of 7,207 individuals who reported working at baseline, for example, only 5% (*SD*=0.22) and 16% (*SD*=0.36) of respondents remained self-employed or in wage-and-salary work, respectively, during the 10-year period captured by the six waves. This seems natural, as this is the time of life when many people may leave the workforce. This type of sampling strategy would dramatically reduce the sample size and call into question the generalizability of my findings. I then conducted a series of tests to determine a rule for placement into the self-employment "treatment" condition and wage-and-salary employment "control" condition, with the goal to balance this study's needs for maximizing information (i.e., the number of observations in the analysis) and precision (i.e., at what point does the inclusion of different categories of work or no work add too much noise to the analysis?). Six possible strategies are described in detail in Appendix A.

Given these options, I chose to utilize data from respondents who reported being *either* self-employed *or* in wage-and-salary employment during all waves *with reported work* (named Strategy 1B in Appendix A). In other words, this strategy allows respondents to leave the workforce but does not allow them to switch from self-employment to wage-and-salary work, or vice versa. As such, it does not include respondents who worked in both self-employment and wage-and-salary work during the study period, as that would prevent a clear link between the outcomes assessed in Question 2 and self-employment. This is a conservative decision in that it only considers respondents whose work during the study's timeframe was in a single category, yet it also includes those who were not working in, did not respond to, or left the study due to death or institutionalization by subsequent surveys. This also allows for the estimation of treatment effects after one leaves the workforce. This method will include observations from 90% (*N*=6,473) of respondents who reported working at baseline, a reasonable number that maximizes the available information. This includes 5,090 respondents working in wage-and-salary work (78.6%) and 1,383 who in self-employment (21.4%) at baseline.

Because of this rule, approximately 10% (*N*=734) of respondents were dropped from analysis because they reported working as self-employed *and* in wage-and-salary positions in different waves. In other words, these respondents switched from self-employment to wage-and-salary work, or vice versa, within this 10-year timespan. Figure 2 illustrates the creation of the final sample, which includes respondents aged 50 and older who were working at baseline (2004) and who did not switch forms of work (e.g., self-employment to wage-and-salary) between waves.

As shown in Table 1, individuals excluded from the sample were different on a range of factors from those who remained in the study. On average, they were more likely to have worked for more waves than those who remained in the sample (4.42 vs. 3.48) and were about one year younger (59.42 vs. 60.51 years) and less likely to be female (42.9% vs. 51.7%). While they reported a higher number of years of education, this difference is less than six months, on average. They were not statistically different from the final sample in terms of race or ethnicity. Understanding the characteristics of respondents who switch from one type of work to another is a separate line of questioning that is worthy of another study. However, for this study, I determined that the benefits of having "pure" self-employed and wage-and-salary groups outweighed the costs of excluding the relatively few individuals who were employed in both forms of work during the study's period.

Table 1. Comparing Included and Excluded Samples

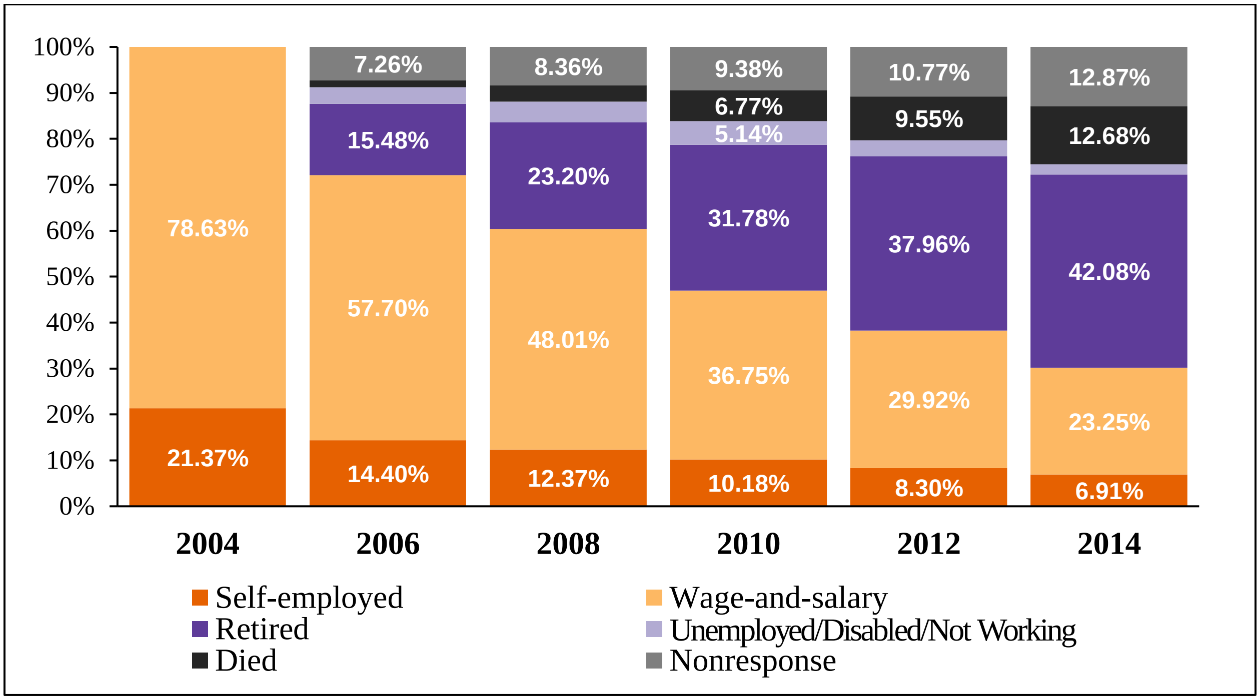
	Included *M*(*SD*) or *%*	**Excluded** *M*(*SD*) or *%*	*p*
Respondents	89.8% (*N*=6,473)	10.2% (*N*=734)	
Waves worked			
As self-employed	0.74 (1.68)	2.04 (1.23)	<0.001
As wage-and-salary	2.74 (2.17)	2.37 (1.33)	<0.001
Total	3.48 (1.86)	4.42 (1.41)	<0.001
Demographics			
Age (Years)	60.51 (0.10)	59.42 (0.25)	<0.001
Education (Years)	13.20 (0.04)	13.66 (0.11)	<0.001
Gender			<0.001
Female	51.7%	42.9%	
Male	48.3%	57.1%	
Race			0.092
White	79.7%	83.1%	
Black	14.2%	11.6%	
Another race	6.1%	5.3%	
Ethnicity			0.965
Not Hispanic	91.2%	91.1%	
Hispanic	8.8%	8.9%	

Note: Percentages may not add up to 100% due to rounding.

3.1.3 Final Sample Characteristics

Figure 3 shows the work and life status, by wave, of the final sample of 6,473 respondents. Each column adds up to 100%. By the 2014 wave, about three in 10 (30.2%) of the respondents who reported working at baseline remained in the workforce, with 447 maintaining their status as self-employed (32.3% retention) and 1,505 as wage-and-salary workers (29.6% retention). The number of respondents who retired grew steadily across the waves, resulting in 42.1% of the sample being retired by 2014. Reporting one's status as unemployed, disabled, or otherwise not being in the labor force remained low throughout the four follow-up waves (*min:* 2.2% in 2014; *max:* 5.1% in 2010). Although not the subject of this study, it is possible that the slight uptick in these statuses by 2010 was a result of the recession that began around 2008. Indeed, research has shown similar results among older Americans in the same period (Johnson, 2012). By 2014, about 1 in 8 (12.7%) of respondents had died, with a similar number (12.9%) not responding or otherwise requesting to be dropped from the survey.

Figure 3. Work and Life Status by Wave



Notes: N=6,473 for each wave. Only categories with values of more than 5 percent are labeled. For quick-reference, respondents who reported working (self-employment or wage-and-salary employment) are in shades of orange, those who reported not working (retirement or unemployment/disabled/otherwise not working) are in shades of purple, and nonresponse indicators (death or living-yet-nonresponse) are in shades of grey.

Sample Descriptive Statistics by Wave

Appendix B lists the sample descriptive statistics for each of the five waves. In all but the final few rows, the entries consider only those who remained in and responded to the study in that wave. By this study's design, a full 100% of the sample was working in 2004; however, by 2014, about three in five (59.5%) of respondents had stopped working. Overall, slightly more than one in five of working respondents were self-employed at each wave. At baseline, the sample's average age was 60.51 years (*SD*=7.67) and just over half (51.7%) of respondents identified as female at baseline. Overall, about four in five (79.7%) respondents identified as white or

Caucasian, with nearly one in seven identifying as black or African American (14.2%). Less than one in 10 respondents identified as Hispanic (8.8%) and just more than one in five (22.4%) were veterans.

The labor force status variable in Appendix B shows that the number of full-time workers dropped from 65.0% in 2004 to 22.5% in 2014, with the number of part-time workers falling as well, from 13.8% in 2004 to 4.7% in 2014. There was a corresponding rise in the number of fully-retired respondents, from none in 2004 (by this study's design) to 56.5% in 2014. Partially retired respondents decreased from 21.3% of the sample in 2004 to 13.3% in 2014. RAND researchers created this variable from a series of questions in the HRS survey, as evidence of working, being retired, or being disabled could be combined with other statuses and sometimes be conflicting. As such, RAND researches attempted to view information from several responses while giving precedence to working and retirement (Bugliari et al., 2016, pp. 1399–1400).

Retention rates remained relatively high throughout the survey, with nearly three in four (74.5%) of the baseline respondents taking part in the final wave, ten years after the baseline wave, in 2014. By this time, about one in six (16.3%) of the baseline respondents had died or otherwise been dropped from the sample by request or other reasons.

3.1.4 Imputation of Missing Data

To maximize available information while reducing the number of observations dropped from analysis and potentially biased results, I imputed missing data. The financial indicators in this study were already imputed in a three-step process by RAND researchers, which included imputing exact dollar amounts when a value range was revealed by respondents; imputing a range when ownership, the holding of assets or debt, or receiving income was revealed by respondents; and imputing ownership if nothing was revealed by respondents. The imputation process was progressive, in that ownership was imputed where it was unknown, then ranges were imputed where only ownership was known or imputed, and finally exact amounts were imputed where ranges were known or imputed (see Bugliari et al., 2016, pp. 23–25, for more information).

The HRS, overall, has a history of high response rates (Health and Retirement Study, 2017). As shown in Appendix B, there are generally very few missing responses for the variables used in this study at baseline. By the final wave, about 9.2 percent of individuals who were presumed to be alive by HRS staff did not respond, which is the reason why several of the maximum missing percentages list that number. The largest sources of missing data are related to three variables: risk tolerance, occupation, and industry. This is because these questions were only asked of a few segments of respondents. Questions relating to risk tolerance were only asked of the newest cohort in Wave 7 and those younger than age 65 in Wave 8 (Bugliari et al., 2016, p. 1350), with a few exceptions, covering about just more than half (55.9%) of this sample. Questions relating to occupation and industry were altered over the course of the HRS due to changes in classification codes from the U.S. Census Bureau, with classifications for some respondents pulled from previous waves that did not align with the new codes (Bugliari et al., 2016, pp. 1482–1483, 1490–1491). As a result, the highest rates of missingness are at baseline for both occupation (41.7%) and industry (37.8%); however, these rates quickly drop to between 8.1 to 15.7 percent missing by the third wave.

Therefore, missing data was imputed for both non-respondents and responding individuals who did not answer select questions. Specifically, the *mi impute chained* command in Stata was used to create 20 datasets using multiple imputation by chained equations (“MICE”), which allows for separate models for each variable with missing values (Royston & White, 2011). Within the

MICE framework, I used predictive mean matching ("PMM"), a method that imputes missing data by using values from a linear prediction to sample from the observed data and closely matches the distribution of the observed data. This is especially helpful when the normality assumption is not met or when the relationship between variables is not linear, as multivariate imputation techniques are more sensitive to these issues (Kleinke, 2017; White, Royston, & Wood, 2011). As a result, all imputed values are plausible values and have a similar distribution to the observed data. Factors shown to be related to the variables with missing data were included in the imputation models; for example, gender, which has been shown to be related to risk tolerance among older adults, was included (Sahm, 2008).

Conditional imputation was incorporated for variables pertaining to characteristics of the workplace to prevent those who had left the labor force in later waves from receiving unrealistic values. For example, only those who were still working but had missing data related to occupation received imputed values for blue- or white-collar work; all others were automatically placed in the "not working" category for that variable. For most workplace-related variables, less than five percent of data were missing among those who were still working. As described previously, however, there were higher rates of missing data among those still working in the occupation and industry variables due to changes in how and to whom the questions were asked. The lowest and highest rates of missing data among those still working were 0.10 percent and 20.89 percent for occupation, respectively, and 0.38 percent and 35.69 percent for industry, respectively. As diagnostics confirmed that some of the best predictors of occupation and industry were previous and future waves, these were also used in the imputation equations.

One consideration while employing PMM is the size of the donor pool of observed values that are closest to the predicted value. While the default in Stata is to impute values using the nearest observed observation to the predicted value (*k*=1), this has been shown to perform poorly in several scenarios. Instead, as recommended by Morris, White, and Royston (2014), I directed Stata to randomly choose from one of the nearest 10 neighbors (*k*=10). Further, while PMM values are predicted using linear regression, this method can also be used to impute unordered categorical covariates and has been shown to be more robust to violations of the normality assumption, unlike multivariate imputation (Morris et al., 2014). Pragmatically, in my own analysis, the PMM procedure runs with far fewer errors than other forms of MICE.

While some scholars have recommended imputing a relatively low number of datasets—between three and 10, for example—others acknowledge that while this is likely to be more than sufficient, 20 datasets is preferable to reduce the amount of power falloff as a result of missing data (Graham, Olchowski, & Gilreath, 2007). Given increasing levels of computing power and speed, this should not be a problem. Additionally, once the missing data was imputed into 20 datasets, I reshaped it into long format in Stata before deleting observations beginning at the wave that respondents died or were dropped from the study. This way, data from these respondents were not used in final analysis. After deleting observations from the deceased and those dropped from the study, I reviewed the data from three randomly-chosen datasets using numbers from a random number generator to confirm that the imputed data contained plausible values with similar distributions to the complete observations; as such, there were no concerns for disproportionality among imputed and missing values. Finally, in outcome analysis, separate models for each of the 20 datasets were run, after which Rubin’s combination rules were applied to create a final set of model estimates (Rubin, 1987).

3.2 Measurement

Both time-variant and -invariant factors are included in this study. Brief descriptions of all variables used in this study are described below; however, see Appendix C for more detailed information.

3.2.1 Outcome Variables

For Question 1, the outcome variable has three categories that include being self-employed, working for someone else, or not working for pay. This categorical variable is derived from two sources. First, respondents were split into two groups using the labor force status variable created by RAND researchers for the RAND HRS data file: those who were working, and those who were not. Second, among those who are working, the question, "Do you work for someone else, are you self-employed, or what?" in Section J of the HRS was used to determine self-employment or wage-and-salary work (Bugliari et al., 2016, p. 1395; Health and Retirement Study, 2016). This phrasing is similar to that used by the Bureau of Labor Statistics and the U.S. Census Bureau's Current Population Survey. HRS researchers recoded respondents who said they ran their own businesses as self-employed.

Question 2 includes four outcome variables that represent two constructs: financial well-being and personal health. Financial well-being is measured using individual earnings from work and total household wealth, both measured in U.S. dollars. The individual earnings variable includes income only from one's job, including bonuses, overtime pay, commissions, and tips, as well as second job or reserve earnings and professional practice and trade income. It does not include income from other sources, such as savings, pensions, and Social Security retirement benefits. Total household wealth includes the net value of respondents' and, when applicable, their spouses' wealth, calculated as the sum of all wealth measures minus all debt. This includes retirement savings (i.e. IRA and Keogh accounts), stocks and bonds, checking and savings accounts, and real estate, among others, as well as the value of mortgages and other debt.

Personal health is measured using a self-rated health question and number of depressive symptoms. First, global self-rated health was assessed using answers to the question, “Would you say your health is excellent, very good, good, fair, or poor?” This scale was then reverse coded so that an increase in value relates to an increase in self-reported health. Additionally, the fair and poor categories were combined due to the low number of responses in the poor category (3.93% of the observed values), resulting in a four-level variable. Self-rated health, a subjective measure, has been shown to be an excellent and consistent predictor of more objective measures, such as physician visits and mortality (Miilunpalo, Vuori, Oja, Pasanen, & Urponen, 1997; Schnittker & Bacak, 2014). Second, total number of depressive symptoms was measured using the modified, eight-item Center for Epidemiologic Studies Depression Scale (“CES-D,” Radloff, 1977), which includes yes/no answers to questions such as, “Much of the time during the past week, you felt depressed” and “…you enjoyed life.”

3.2.2 Explanatory—or “Treatment”— Variable

Question 2 includes a binary self-employment indicator as the explanatory variable. When using propensity score analysis methods, this is often referred to as the “treatment” variable or condition, as propensity score analysis controls for selection into the treatment, enabling scholars to estimate treatment effects (Guo & Fraser, 2015). This type of variable is used only to answer Question 2, making this a quasi-experimental study. See the Analytical Strategy section of this chapter to learn more about how propensity score analysis was employed in this dissertation.

3.2.3 Predictor Variables

Individual characteristics are included in all final models for both Questions 1 and 2. These include sociodemographic characteristics; measures of human, social, and financial capital; and risk tolerance.

Sociodemographic variables include age in years, with binary indicators of gender, Hispanic ethnicity, and veteran status, and a categorical indicator of race (white, black/African American, and all other races). Additionally, an ordinal measure of risk tolerance is included. For this dissertation, risk tolerance is operationalized through a six-item categorical variable, ranging from least to most risk tolerant, that was asked mostly of respondents less than 65 years old. This question was developed by asking respondents to choose between two new hypothetical jobs, where one job guaranteed the current family income and the other provided a chance to increase—or lose—family income in amounts ranging from 75 percent (i.e., most risk tolerant) to 10 percent, or to take the job with guaranteed income (i.e., least risk tolerant). This line of questioning ended in 2006, making analysis from 2008 to 2014 difficult when considering risk tolerance. However, given the finding from previous research using the HRS that there is little change over time in risk tolerance among older adults (Sahm, 2008), baseline risk tolerance is considered. Finally, labor force status is included for Question 2; however, it is not included as a predictor in Question 1, as the outcome variable—self-employment, wage-and-salary work, or not in the workforce—is itself a form of labor force status and the models do not converge with its inclusion.

Human, social, and financial capital are captured through several variables. Human capital is assessed by years of education, measured continuously; self-rated health, a four-category variable that ranges from "poor/fair" to "excellent," as described in section 3.2.1; and a binary measure that asks if health problems have limited the kind or amount of paid work completed by respondents. Further, three binary measures of health insurance are included in Question 1: respondents who received their health insurance from the federal government, including Medicare, Medicaid, TRICARE, and other federal sources; from their employers; and from their spouses' employers. Given the larger number of covariates considered in Question 2, I include a single binary variable regarding health insurance, simply reporting if respondents have health insurance or not.

Five measures of social capital are considered, including a binary marital status indicator, if a spouse is in paid work, the number of people living in the respondents' households, and separate variables that measure the amount of formal and informal volunteering. Regarding volunteering as a form of social capital, Gonzales and Nowell (2016) argued that informal (defined as helping friends, neighbors, or relatives who did not live with respondents and did not pay for the help) and formal (defined as doing volunteer work for religious, educational, health-related or other charitable organizations) volunteering is "fundamentally social" (p. 3), increases the quantity and quality of an older adult's social connections, and—importantly for this study—is associated with movement into employment during the retirement years. It should be noted that the concept of social capital used in this dissertation is consistent with the individual-focused usage in the literature on productive engagement in later life (e.g., Gonzales & Nowell, 2016; McNamara & Gonzales, 2011; N. Morrow-Howell & Greenfield, 2016); however, there is a rich body of sociological scholarship on social capital that considers factors related to social norms, reciprocity, trust, and the structure of relationships between and among actors (e.g., Coleman, 1988) that may also play an important role in relation to self-employment in later life.

Financial capital is assessed through five variables. The first is annual individual earnings from work. Additional measures include total household wealth, described previously, as well as total household income, which measures income from respondents' and their spouses, but not other members of the household. Individual earnings are subtracted from total household income so as not to count it twice. Finally, two binary measures indicate if respondents were receiving Social Security retirement benefits and if they were receiving pension income at the time of the survey.

Question 2 also considers several variables that examine the nature of the work experience, important considerations when assessing the relationship between type of work (self-employment or wage-and-salary employment) and financial well-being and personal health outcomes from this work. Years of tenure in the current job is measured continuously, with those not working in subsequent waves coded as 0. Ordinal variables include level of stress on the job as well as job requirements for physical effort; lifting heavy loads; stooping, kneeling, or crouching; and having good eyesight, with increasing numbers (from 1 to 4) showing higher levels of that attribute and with those not working in subsequent waves coded as 0. Labor force status is included as a categorical variable (full-time work, part-time work, partly retired, fully retired, and otherwise not in the workforce). Five binary variables indicate the average hours worked per week over the course of the year (<35 and 35+), if respondents received a pension plan as a benefit from their current job; whether they worked alone or with others in their work location; whether respondents were in blue- or white-collar occupations, based off the 2000 Census codes and following the example set by Jacobs (2016); and whether respondents were in goods- or service-producing industries, based off the 2002 Census codes and following the example set by Kail and Warner (2013). Technically, each of these five binary variables have a third category for those who are not working in subsequent waves; however, that category was only included in one of the variables in outcome analysis while the remaining were dropped, due to the perfect prediction that is caused by their redundancy.

Additionally, all final models include controls for proxy interview status, if the respondent died at some point during the study, and if the respondent did not respond to at least one wave in the study. Further, all final models include sampling weights, which are discussed in section 3.3.4.

3.3 Analytical Strategy

The aims for this study are two-fold: Among Americans aged 50 and older, Question 1 compares the characteristics of self-employed and wage-and-salary workers. Then, Question 2 assesses how self-employment influences financial well-being and personal health, in comparison to wage-and-salary work. In all cases, regression models appropriate to the outcome variable are employed.

3.3.1 Correcting for Serial Correlation

Because this dissertation uses longitudinal data, observations—or waves—are nested within individuals. Further, individuals are nested within households, as both members of married or partnered households are individually tracked in the HRS. While clustering does not affect model coefficients, it introduces bias in the standard error estimates. This, in turn, decreases trust in hypothesis tests by usually, but not always, estimating standard errors that are too small (Kennedy, 2008). While there are several approaches to handling this type of clustering, such as multilevel or mixed-effects modeling, I used the cluster-robust estimate of the variance-covariance matrix to determine standard errors and, as a result, final model test statistics. This type of sandwich estimator allows for correlation within the identified clusters as well as heteroskedasticity (Angrist & Pischke, 2009; Cameron & Trivedi, 2010), and works best when there are many clusters, a threshold that my sample exceeds. For example, Angrist and Pischke

(2009), while careful not to suggest a hard-and-fast rule, recommended that datasets have at least 42 clusters. In comparison, my sample has more than 5,000. Further, my analysis controls for clustering within the household by including the household identifier as the cluster variable, following the authors' recommendation to use the highest-level clustered-covariance estimator. Using the household identifier as the cluster variable then allows for correlation within both households and individuals.

3.3.2 Model Building and Testing

Final models include both time-variant and -invariant factors. Major time-variant factors include labor force status, work characteristics (e.g., hours worked/week and working alone or with others), self-rated health, marital status, and total household wealth, among others. Major time-invariant factors include gender, race, Hispanic ethnicity, and education, among others. For both aims, univariates were analyzed for all variables (see Appendix B), as well as bivariate associations between the outcome, treatment, and predictor variables (see Appendix D). I also ran tests to increase my confidence that the specific assumptions for each model are reasonably met, described throughout this section. Model fit was determined by *F* tests. In all cases, the alpha level for indicating significant relationship is 0.05. Results shown in Tables 2 and 3, as well as in Tables 9 and 10 in Appendix F, list exponentiated coefficients that are called relative risk ratios (*RRR*) for multinomial logistic regression, odds ratios (*OR*) for ordered logistic regression, and incidence rate ratios (*IRR*) for negative binomial regression. Accounting for serial correlation, cluster-robust standard errors are listed in all multivariate tables. Finally, results will be described in terms of the direction and significance of the documented relationships to aid theory development. For this dissertation, a discussion of the marginal effects and predicted probabilities from my final models will be avoided, given ongoing questions about the limitations of using Rubin's combination rules with predicted probabilities in multiply-imputed datasets and the chances of invalid results (StataCorp, 2017).

To answer Question 1, multinomial logistic regression is employed, as the outcome variable has three distinct categories: self-employment, wage-and-salary work, and not working. Before the analysis, univariates of all variables were assessed to determine if data transformations were necessary, after which I transformed individual earnings, total household wealth, and total household income from all sources (minus individual earnings) due to a high level of skewness, discussed in the next paragraph. After the models were completed, parameter and significance estimates indicated when the hypotheses were supported.

As Question 2 has four outcome variables, different methods are necessary. For both financial well-being variables, I transformed the variables using the inverse hyperbolic sine function (IHS) before conducting regression analysis. This can be expressed as:

Equation 1. Inverse Hyperbolic Sine (IHS) $= \text{arcsinh}(x) = ln\left(x + \sqrt{x^2 + 1}\right)$

For the individual earnings outcome variable, the IHS transformation can account for the non-trivial number of respondents who report zero earnings in some years—unlike in a log transformation, where the log of zero is undefined—as well as the positive skewness of the data. For the total household wealth outcome variable, the IHS transformation accounts for the large number of respondents who report negative household wealth (as defined by assets minus debts), as well as the positive skewness of the data. The IHS transformation, which was first proposed by Johnson (1949), can handle extreme values in dependent variables, including negative and zero values, performing better than the more commonly-used tactic of taking the log of values after adding a constant (Burbidge, Magee, & Robb, 1988; Friedline, Masa, & Chowa, 2015). As a form of sensitivity analysis, all final models for total household wealth were run with and without housing assets included; as the results were largely similar, I chose to keep housing assets as a part of this variable and present those findings in Chapter 4.

Regarding personal health outcomes, self-rated health was measured using a four-item ordinal variable. As such, ordered logistic regression was used, which accounts for the rank order of the data while not assuming equal differences between the possible values (Kennedy, 2008). A key assumption of ordered logistic regression is that the coefficients are equal in a series of cumulative logit models in which the response variable is recoded into a series of binary variables (Williams, 2016). In other words, the coefficients should have the same relationship with the outcome variable, no matter how it is dichotomized (e.g., fair/poor health compared to good health and better, or good health or worse compared to very good health or better). To test this assumption, I used the Brant test of coefficients (Brant, 1990), rejecting the null hypothesis of equal coefficients for the entire model. This significant result was expected once considering the large sample size in my study and the high number of covariates in my final model. Following the guidance set forth by Williams (2016), I carefully considered the direction of the coefficients and their magnitudes, and ultimately determined that the spirit of this assumption was met, making the need for partial proportional odds models unnecessary.

Depressive symptoms, which were measured using a modified CESD scale with answers ranging from 0 to 8, required the use of negative binomial regression due to overdispersed nature of the data. Poisson regression should not be used, as the variance of total depressive symptoms (at t=1: V=2.85) was not equal to the mean (t=1: M=1.09), a strong assumption of Poisson regression that, if not met, can dramatically reduce the standard errors and lead researchers to believe in the existence of more statistically-significant explanatory variables than might actually exist (Kennedy, 2008).

Question 2 incorporates two additional estimation procedures. First, all models include a form of propensity score analysis, called inverse probability of treatment weighting, to help correct for selection into self-employment and wage-and-salary work by including a time-invariant factor for self-employment ("treatment") or wage-and-salary work ("control"). This procedure will be described in detail in the next section. Additionally, lagged dependent variables (LDVs) from the prior wave are included to prevent the biasing of coefficients that can result from serial correlation that is not controlled for using sandwich estimators. After including LDVs, however, the magnitude of the coefficients for the explanatory variables can be reduced to values below what the real magnitudes may, in reality, be (Angrist & Pischke, 2009; Keele & Kelly, 2006). This may also reduce the magnitude of the estimated treatment effect in Question 2. Given the consequences of *not* including LDVs—serial correlation of errors that lead to an overestimation of the magnitude of explanatory variables—I decided to keep them in my models, with the understanding that the estimated magnitude of the coefficients for the explanatory and treatment variables are likely more conservative, and the estimated magnitude for the coefficients for the LDVs are likely higher, than in reality.

3.3.3 Inverse Probability of Treatment Weighting

To answer Question 2, inverse probability of treatment weighting was employed. In recent years, it has become increasingly common for social science researchers who use observational studies to utilize statistical adjustment methods that control for selection into the "treatment" of concern; in this case, self-employment. These methods are often grouped together into a category called propensity score analysis, or PSA. Propensity scores are the probabilities of receiving the treatment, conditional on an observed set of characteristics (Rosenbaum & Rubin, 1983).

In addition to more traditional covariance control methods, PSA techniques attempt to balance the covariates by treatment group, striving to mimic an important quality of randomized-controlled trials while estimating treatment effects. PSA techniques provide a practical way to estimate the counterfactual framework—or potential outcomes—of both the treatment and control groups (Guo & Fraser, 2015). As shown in Equation 2, after conducting propensity score balancing procedures, it is possible to estimate the average treatment effect (ATE) as the mean difference between the outcome measure of the treatment and comparison groups. Here, τ signifies the treatment effect, $W = 1$ signifies receiving the treatment, $W = 0$ signifies not receiving the treatment, and Y_1 and Y_0 signify the measured outcome variables for those who have and have not received the treatment (Guo & Fraser, 2015, p. 49).

Equation 2. Average Treatment Effect (ATE) $= \tau = E(Y_1|W = 1) - E(Y_0|W = 0)$

Although there are several PSA methods, this study used the inverse probability of treatment assignment as weights in outcome analysis. This method, called inverse probability of treatment weighting (IPTW), is also known as propensity score weighting (Guo & Fraser, 2015). This method provides three key benefits over other PSA methods: IPTW permits the inclusion of most or all observations, unlike other forms of propensity score analysis; it does not restrict outcome variables to be continuous and normally distributed; and in addition to estimating the ATE among the population of older workers overall, IPTW allows for the estimation of the average treatment effect *for the treated* (ATT). This estimates the treatment effect among the self-employed only, asking, “How would older self-employed Americans perform on a set of outcome variables had they *not* been self-employed?" Equation 3 shows the formula for determining ATT (Guo & Fraser, 2015, p. 49):

Equation 3. Average Treatment Effect for the Treated (ATT) = $E(Y_1 - Y_0 \mid X,\ W = 1)$

Two methods to derive the propensity scores were utilized. This first and most common method for determining propensity scores is through binary logistic regression (Guo & Fraser, 2015). However, simulation studies have shown that the propensity scores created through logistic regression can have subpar performance when compared to those created through machine learning, a general term for prediction and classification algorithms that have become more common as computer power increases (Lee, Lessler, & Stuart, 2009). Therefore, the second method for determining propensity scores in this dissertation is generalized boosted modeling (GBM), a machine-learning method that has been shown to outperform alternative methods for creating propensity scores when assessing prediction error and that is derived by using a regression tree method to capture nonlinear effects of pre-treatment variables (Lee et al., 2009; McCaffrey, Ridgeway, & Morral, 2004). Specifically, I used the Stata macro for the TWANG (Toolkit for Weighting Analysis of Nonequivalent Groups) package that was developed for the R statistical environment by researchers at the RAND Corporation (Griffin et al., 2014). Up to 10,000 iterations and interactions of up to three ways were considered. Unlike logistic regression, no consideration of functional covariate form was necessary, as GMB algorithms see covariates and their transformations, such as age, age^2, and log(age), identically (McCaffrey et al., 2004). As such, GBM-derived propensity scores are different than those from binary logistic regression due to the inclusion of interactions and nonlinear effects.

A key innovation in this dissertation is its use of 20 datasets through multiple imputation to handle missing data; however, special consideration must then be given to how and when the propensity scores are derived. Following the example set by Eulenburg and colleagues (2016), I first created propensity score weights within each of the 20 datasets before the results of the final outcome models were averaged using Rubin's combination rules. In practice, this means that I created four propensity score weights for each of the 20 datasets—ATE and ATT using logistic regression, and ATE and ATT using GBM—resulting in 80 sets of propensity scores for each respondent.

To create the propensity scores, variables that have been associated with self-employment in later life are used. While some scholars have suggested using all or many available variables within a dataset, consensus is forming around the strategy to include only variables that are associated with the treatment condition (Austin, 2011; Guo & Fraser, 2015). Following this strategy, this study includes sociodemographic variables (age, gender, race, Hispanic ethnicity, veteran status, and risk tolerance), as well as measures of human (education, self-rated health, a binary indicator of a low or high number of depressive symptoms, and health insurance status), social (marital status), and financial capital (total household wealth, total household income, and labor force status), which have been associated with later-life self-employment (e.g., Weller et al., 2015; Zissimopoulos & Karoly, 2007b). Further, a control for interview by proxy was included, as well as HRS sampling weights. Only data from 2004, the baseline year, were considered when creating the propensity scores, as variables measured in later years may have been influenced by the treatment condition at baseline (Austin, 2011). As such, while the model for Question 1 includes observations from all six waves of data, ranging from 2004 to 2014, the models for Question 2 include observations from the final five waves of data, ranging from 2006 to 2014, while using weights derived from the first wave in 2004.

A series of imbalance checks were conducted to determine if the covariates were properly balanced between treatment groups after taking into account the propensity score weights, as recommended by Guo and Fraser (2015). As shown in Appendix E, with few exceptions, both forms of propensity score weight derivation—GBM and logistic regression—balanced the selection covariates between the self-employment and wage-and-salary employment groups when considering both the ATE and ATT. Considering the unbalanced (pre-IPTW) sample, bivariate associations were found to be significantly different ($p < 0.05$) in 14 of the 16 covariates. With GBM-derived ATE weights, five of the covariates remained significantly different. Logistic regression-derived ATE weights, as well as GBM- and logistic regression-derived ATT weights, all resulted in two or fewer significant covariates after their application. Overall, the magnitude of the coefficients was lessoned after applying the propensity score weights. These findings increase my confidence in the weighting of the final models for Question 2.

My results for Question 2 are considered “doubly robust,” as they simultaneously attempt to estimate treatment effects in two ways: through traditional covariate control in regression analysis, and with weighting through IPTW. Doubly-robust estimation of treatment effects has been shown to improve upon both methods through their combination, increasing one’s confidence in the results in the event that one of the two models is misspecified (Bang & Robins, 2005). Therefore, I will first estimate the treatment effect using IPTW without covariates in the final model, followed by IPTW with covariates. Meaningful differences will be discussed.

My final analysis for Question 2, therefore, includes five weight-only models, as well as five doubly-robust models, for each of the four outcome variables. This results in 40 final models. These models estimate the ATE and ATT from logistic regression and GBM, as well as through regression with the HRS-provided sampling weights only. This is completed as a form of sensitivity analysis, with general agreement between each model's parameter estimates leading to higher confidence in the findings (Guo & Fraser, 2015). However, it should also be noted that recent research indicates that models using propensity scores created through GBM or other machine-learning methods are superior when estimating treatment effects, although I still consider propensity scores derived from logistic regression, as that is one of the most popular methods of propensity score analysis (Lee et al., 2009; Li, Handorf, Bekelman, & Mitra, 2016). As such, results that seek to estimate the ATE using GBM-derived propensity scores will be reviewed in Chapter 4 as the main models; however, results from models that seek to estimate the ATT from GBM-derived propensity scores, the ATE and ATT from logistic regression-derived propensity scores, and the relationship between self-employment and outcomes from simple and multivariate regression without IPTW are included in Appendix F as supplemental models. Major differences in results will be discussed.

3.3.4 Survey Weighting

The HRS was designed to be nationally-representative of the older, community-dwelling American population. However, certain groups, such as those who identify as black or African American and residents of Florida, are oversampled. To maintain the representativeness of the sample, individual-level survey weights provided by the HRS research team are integrated twice in this dissertation's analysis. Following the two-stage process used in IPTW, the survey weights are first incorporated when developing the propensity scores in each of the 20 datasets created through multiple imputation (Stage 1), and again when conducting outcome analysis before the estimates are averaged using Rubin’s combination rules (Stage 2). During the second stage, the survey weights and inverse probability of treatment weights are multiplied together, resulting in a new “grand” weight for outcome analysis (DuGoff, Schuler, & Stuart, 2014; Ridgeway, Kovalchik, Griffin, & Kabeto, 2015).

Chapter 4: Findings

To understand the characteristics of self-employed Americans in later life and how self-employment influences personal health and financial well-being, I will first present the results from bivariate tests of association between self-employment and the following factors: sociodemographic characteristics; measures of human, social, and financial capital; risk tolerance; and work characteristics. To control for potentially confounding variables when answering Question 1, I will then present the results from multinomial logistic regression to understand what factors are related to being self-employed when controlling for all other variables. Finally, to answer Question 2, I will present the results from a series of ordered logistic, negative binomial, and OLS regressions that incorporate a variety of weights to estimate how self-employment influences personal health and financial well-being.

4.1 Bivariate Results

As shown in Appendix D, just more than one in five (21.4%) respondents were self-employed at baseline. Within this nationally-representative sample of Americans aged 50 and older, the self-employed were nearly four years older than those in wage-and-salary work. They were less likely to be female and Hispanic, and more likely to identify as white and veterans. They also had higher levels of risk tolerance.

Considering human capital, they were slightly healthier and had slightly higher levels of educational attainment, but not meaningfully so. They were much less likely to report having health problems that limited their work. Regarding health care, they were less likely to have health insurance from any source, on average, yet more likely to have health insurance from a governmental source, such as Medicare, Medicaid, or TRICARE. There was no significant difference between the self-employed and those in wage-and-salary work in regard to the number of depressive symptoms reported.

Considering social capital, self-employed respondents were more likely to be married and more likely to participate in both formal and informal volunteer activities than those in wage-and-salary work. Although statistically significant, the number of household members does not appear to be a meaningful factor, as the effect size was small.

The bivariate results from the financial capital variables are particularly interesting, showing major differences between the two groups. The self-employed reported earnings that were less than half that of their wage-and-salary counterparts at baseline, yet their total household wealth was more than three times that of wage-and-salary workers and their household income from all sources except individual earnings was more than 2.5 times that of wage-and-salary workers, revealing that the self-employed may have a stronger financial safety net, on average. Older self-employed Americans were much more likely to report receiving Social Security retirement benefits and slightly more likely to report receiving pension income than older wage-and-salary workers.

Considering workplace characteristics, self-employed respondents were more likely to report part-time work and had, on average, about two more years of tenure on the job than wage-and-salary workers. Self-employed respondents were also more likely to work at least 35 hours per week, less likely to be a part of a workplace pension plan, and more likely to be in a white collar (vs. blue collar) occupation and goods producing (vs. service producing) industry. While statistically significant, the difference between the level of stress on the job and having a job that requires good eyesight was low. There were no significant differences between the two groups regarding other job requirements (having a job that requires lots of physical effort, lifting heavy loads, or stopping, kneeling, or crouching).

As shown in Appendix D, nearly all tests were significant. This may often be due to meaningful differences between self-employment and wage-and-salary work; however, the large sample size in this study increases the chance of finding statistically-significant results. Further, many of these bivariate differences may be attributable to confounders. Age, for example, might explain the difference between the self-employed and wage-and-salary workers regrading average tenure on the job and being more likely to die or have their responses given by proxy. The next two sections, which reveal results for Questions 1 and 2, utilizes covariate control to reduce the effect of confounders. Question 2, additionally, uses IPTW to reduce problems that arise from self-selection into self-employment, creating a quasi-experimental study.

4.2 Question 1: Characteristics of Self-Employed Older Americans

Question 1 asked, "What are the characteristics of self-employed older adults, in comparison to those in wage-and-salary work, among older Americans working at baseline?" To answer this question, I considered sociodemographic variables; levels of human, social, and financial capital; and risk tolerance. I hypothesized that within this sample of working Americans aged 50 and older, human, social, and financial capital, as well as age and identifying as male and white, are positively associated with being self-employed. Given the mixed findings on risk tolerance among self-employed older adults, I provided no hypothesis for this attribute.

Table 2 lists the results from multinomial logistic regression using six biennial waves of the HRS, ranging from 2004 to 2014. The model was significant: $F(56, 3.24\ x\ 10^{6}) = 150.6$, $p <$

0.001. Sandwich estimates were included to control for serial correlation within households over time, which created the robust standard errors shown in the table. To answer Question 1, my focus will be to describe the relationship between the self-employed and wage-and-salary groups; however, corresponding to Strategy 1B, as outlined in Appendix A, respondents were allowed to leave the workforce after baseline. Therefore, Table 2 also includes results that compare those not working to the wage-and-salary reference group. These should be interpreted with caution, however, as this group includes respondents belonging to several categories, including retirees and those who reported being unemployed or disabled. For the purposes of this study and due to the small sample sizes of some of these groups (e.g., those who identify as disabled), I decided to group them together.

While controlling for the covariates listed in Table 2 and relative to wage-and-salary work, age (*RRR* = 1.02, $p < 0.006$) and being male (*RRR* = 0.33, $p < 0.001$) were positively associated with being self-employed, supporting my hypothesis. Although race was significant in the bivariate results, identifying as black (compared to those identifying as white) was not significant in the multivariate results (*RRR* = 0.77, $p = 0.088$), counter to my hypothesis that self-employed older adults were more likely to identify as white. Similarly, the positive relationship between veteran status and self-employment found in the bivariate results became nonsignificant in the multivariate results. Lastly, self-employed respondents had higher levels of risk tolerance than those in wage-and-salary work (*RRR* = 1.16, $p < 0.001$).

Regarding human capital, self-employment, relative to wage-and-salary work, was positively associated with self-rated health (*RRR* = 1.16, $p = 0.001$); it was also positively associated with having health problems that limit one's ability to work (*RRR* = 1.40, $p = 0.001$). Further, self-employed respondents were less likely to have health insurance from governmental (*RRR* = 0.71, *p* = 0.001), workplace (*RRR* = 0.26, *p* < 0.001), and spousal (*RRR* = 0.45, *p* < 0.001) sources. Educational attainment, which was slightly higher among the self-employed in the bivariate results, was nonsignificant in the multivariate results: (*RRR* = 1.04, *p* = 0.056). As such, my hypothesis that self-employment was positively associated with human capital was only partially supported. While increased self-rated health was associated with self-employment, educational attainment was nonsignificant and factors that could be considered to lead to lower human capital, such as health problems limiting work and being uninsured, were significant.

Regarding social capital, self-employed older adults were less likely to report being married or having a partner, compared to those with nonworking spouses (*RRR* = 2.31, *p* < 0.001); however, there was no significant relationship between those with working and nonworking spouses. While they were no more or less likely to report involvement in formal volunteer activities, the self-employed were more likely to report involvement in informal volunteer activities in both levels of time commitment tracked, compared to those who did not participant in informal volunteer activities (<100 hours: *RRR* = 1.25, *p* = 0.002; 100+ hours: *RRR* = 1.50, *p* < .001). Therefore, my hypothesis that self-employment was positively associated with social capital was only partially supported. While informal volunteering (compared to not being involved in informal volunteer activities) was associated with self-employment, there was no relationship between self-employment and formal volunteering, and being married was negatively associated with self-employment.

Regarding financial capital, self-employed respondents earned less than those in wage-and-salary work (*RRR* = 0.70, *p* < 0.001), yet household wealth (*RRR* = 1.04, *p* < 0.001) and household income (*RRR* = 2.22, *p* < 0.001), with individual earnings subtracted, were positively associated with self-employment. They were also less likely to be receiving Social Security retirement benefits ($RRR = 0.52$, $p < 0.001$) and pension income ($RRR = 0.49$, $p < 0.001$). Consequently, my hypothesis that financial capital was positively associated with self-employment was only partially supported. While total household wealth and total household income, minus individual earnings, were positively associated with self-employment, individual earnings and receiving Social Security retirement benefits and pension income were negatively associated with self-employment.

To summarize my findings from Question 1, my hypothesis that self-employment among Americans aged 50 and older is positively associated with human, social, and financial capital, as well as age and identifying as male and white, is partially supported. My finding on risk tolerance, which showed higher levels among the self-employed, will aid future theory and hypothesis development.

Table 2. Multinomial Logistic Regression of Work Status, Relative to Wage-and-Salary Employment

Variables	*Self-Employed*					*Not Working*				
	exp(b)	*Robust SE*[a]	*t*	*p*	*CI*	*exp(b)*	*Robust SE*[a]	*t*	*p*	*CI*
Age	1.02**	(0.01)	2.76	0.006	1.00 - 1.04	1.02**	(0.01)	3.85	0.000	1.01 - 1.04
Female (male)	0.33**	(0.03)	-10.55	0.000	0.25 - 0.43	0.70**	(0.05)	-4.99	0.000	0.58 - 0.84
Race (white)										
Black	0.77	(0.12)	-1.71	0.088	0.52 - 1.14	1.01	(0.09)	0.06	0.950	0.81 - 1.25
Other races	1.04	(0.25)	0.17	0.867	0.57 - 1.91	1.11	(0.15)	0.77	0.443	0.78 - 1.58
Hispanic (not)	0.92	(0.19)	-0.41	0.684	0.54 - 1.55	0.92	(0.12)	-0.63	0.526	0.65 - 1.30
Veteran (not)	0.94	(0.12)	-0.48	0.632	0.69 - 1.29	0.86	(0.08)	-1.76	0.079	0.68 - 1.07
Risk tolerance	1.16**	(0.04)	4.30	0.000	1.06 - 1.26	1.02	(0.02)	0.79	0.428	0.96 - 1.09
Education, in years	1.04	(0.02)	1.91	0.056	0.99 - 1.09	1.07**	(0.01)	5.36	0.000	1.03 - 1.10
Health, self-rated	1.16**	(0.05)	3.30	0.001	1.03 - 1.30	0.95	(0.03)	-1.59	0.111	0.88 - 1.03
Health problems limiting work (no)	1.40**	(0.14)	3.27	0.001	1.07 - 1.82	3.37**	(0.23)	18.02	0.000	2.83 - 4.01
Health insurance source										
Government (not)	0.71**	(0.08)	-3.19	0.001	0.54 - 0.94	0.90	(0.08)	-1.22	0.223	0.71 - 1.13
Work (not)	0.26**	(0.03)	-13.54	0.000	0.21 - 0.34	0.39**	(0.03)	-13.89	0.000	0.32 - 0.46
Spouse's work (not)	0.45**	(0.05)	-6.57	0.000	0.33 - 0.62	0.79**	(0.07)	-2.79	0.005	0.63 - 0.98
Spouse's work status (not working)										
Working	1.01	(0.10)	0.09	0.931	0.78 - 1.31	0.54**	(0.04)	-7.86	0.000	0.45 - 0.66
Not married	2.31**	(0.30)	6.45	0.000	1.65 - 3.23	0.94	(0.08)	-0.68	0.493	0.76 - 1.17
Household members	0.96	(0.04)	-0.96	0.336	0.86 - 1.07	0.94*	(0.02)	-2.17	0.030	0.88 - 1.01
Formal volunteering, past year (none)										
<100 hours	0.97	(0.08)	-0.36	0.720	0.78 - 1.21	0.82**	(0.05)	-3.11	0.002	0.69 - 0.97
100+ hours	0.93	(0.10)	-0.67	0.501	0.70 - 1.23	0.79**	(0.06)	-2.98	0.003	0.65 - 0.97
Informal volunteering, past year (none)										
<100 hours	1.25**	(0.09)	3.13	0.002	1.04 - 1.49	1.06	(0.06)	1.07	0.287	0.92 - 1.22
100+ hours	1.50**	(0.15)	4.20	0.000	1.17 - 1.93	1.21*	(0.09)	2.39	0.017	0.99 - 1.47
Individual earnings[b]	0.70**	(0.01)	-48.45	0.000	0.68 - 0.71	0.69**	(0.00)	-66.27	0.000	0.68 - 0.70
Household wealth[b]	1.04**	(0.01)	4.46	0.000	1.02 - 1.07	1.02**	(0.01)	2.76	0.006	1.00 - 1.03
Household income, less individual earnings[b]	2.22**	(0.13)	13.70	0.000	1.91 - 2.58	1.11**	(0.02)	7.27	0.000	1.07 - 1.16
Currently receiving:										
Social Security retirement benefits (no)	0.52**	(0.06)	-6.09	0.000	0.39 - 0.68	1.43**	(0.13)	3.88	0.000	1.13 - 1.81
Receiving pension income (no)	0.49**	(0.05)	-7.25	0.000	0.38 - 0.63	1.75**	(0.12)	8.08	0.000	1.46 - 2.09
Controls										
Dies during the study (no)	1.46**	(0.20)	2.74	0.006	1.02 - 2.08	0.77**	(0.08)	-2.59	0.010	0.60 - 1.00
Nonresponse during the study (no)	1.29*	(0.14)	2.26	0.024	0.96 - 1.72	0.96	(0.08)	-0.52	0.601	0.78 - 1.18
Proxy respondent (no)	1.34	(0.24)	1.61	0.107	0.84 - 2.13	0.80	(0.11)	-1.61	0.108	0.56 - 1.14
Intercept	0.00**	(0.00)	-11.35	0.000	0.00 - 0.00	0.39*	(0.17)	-2.19	0.028	0.13 - 1.18
F test: (56, 3.242e+06) = 150.6, $p < 0.001$										

Notes: Data from a combined 6 waves of the HRS that include 6,473 individuals (33,092 total observations) in 5,281 households. Individual (m=20) estimates combined using Rubin's combination rules. ** $p < 0.01$, * $p < 0.05$, two-tailed tests. **a.** Exponentiated robust standard errors are derived using the delta rule: exp(b)*se(b). **b.** Transformed using the inverse hyperbolic sine function.

4.3 Question 2: The Influence of Self-Employment in Later Life

Question 2 asked, "How does self-employment in later life influence financial well-being and personal health, in comparison to wage-and-salary work, among those working at baseline?" Financial well-being was operationalized as individual earnings through one's work and total household wealth, and personal health was operationalized as self-rated health and total number of depressive symptoms. Following Hamilton's (2000) findings among working adults throughout the lifespan, I hypothesized that within this sample of working Americans aged 50 and older, self-employment leads to reduced income, on average, compared to wage-and-salary employment. However, given this study's exploratory nature, I did not propose hypotheses for the remaining three outcomes. As Question 2 aims to identify the estimated treatment effect that self-employment has on the four outcome variables, I will focus on those results. Specifically, I will focus on the estimated average treatment effect (ATE) for the population overall, although the final two of the four alternative models for each outcome variable in Appendix F estimate the average treatment effect for the treated (ATT). Major discrepancies between the main models and the alternative models shown in Appendix F will be discussed. I will then cover notable findings from the covariates in the doubly-robust models. All models included data from the final five biennial waves of this study (2006 to 2014), as the baseline wave (2004) was used to create the inverse probability of treatment weights and the addition of lagged dependent variables prevented the use of the baseline wave. Further, all models included sandwich estimators to account for serial correlation within households over time, with the associated robust standard errors shown in the results tables.

4.3.1 Personal Health

Considering the IPTW-only estimation model, self-employment is estimated to have a positive influence on self-rated health while controlling for selection into self-employment at baseline ($OR = 1.19$, $p = 0.045$). However, once controlling for time-variant and -invariant covariates, including sociodemographic factors; measures of human, social, and financial capital; and workplace characteristics, the positive relationship becomes nonsignificant ($OR = 1.13$, $p = 0.076$). Naturally, the previous wave's self-rated health measure has a large magnitude ($OR = 4.93$, $p < 0.001$) which, as discussed in Chapter 3, might also have had the effect of reducing the magnitude of the estimated treatment effect and the remaining covariates in the model. The doubly-robust model was significant: $F(43, 189{,}157) = 76.26$, $p < 0.001$.

The supplemental models in Appendix F show similar results. While the models without incorporating IPTW report some of the largest odds ratios, those with and without covariates that incorporate IPTW reveal nonsignificant estimated effects. Considered together, these models suggest that while self-employment may lead to increased health, the magnitude of this increase becomes nonsignificant when using doubly-robust methods, suggesting that other factors—such as sociodemographic factors; measures of human, social, and financial capital; workplace characteristics; and the control variables—may play a greater role in self-reported health than self-employment itself.

The results are clearer when considering the number of depressive symptoms; namely, using negative binomial regression, self-employment was not found to have a significant effect on the number of reported depressive symptoms. The main doubly-robust model was significant: $F(42, 263{,}541) = 87.36$, $p < 0.001$. The supplemental, weighted-estimation only ATE model, however, suggested that self-employment may increase the number of depressive symptoms ($IRR = 1.15$,

$p < 0.05$), yet once controlling for potential confounders in the doubly-robust estimation, this effect became nonsignificant. The supplemental models that estimated the ATT found general agreement that self-employment leads to higher numbers of depressive symptoms.

To summarize, my main and supplemental models suggest that while self-employment may have a positive effect on self-rated health, it likely does not influence the number of depressive symptoms among the overall population. While the directions of these relationships remain the same in all but one of the self-rated health models and all the depressive symptom models, the lack of consistent significant or nonsignificant findings decreases my confidence in the findings.

Table 3. Estimated Effect of Self-Employment on Personal Health

Variables	*Self-Rated Health: Ordered Logistic Regression*					*Depressive Symptoms: Negative Binomial Regression*				
	exp(b)	*Robust SE*[b]	*t*	*p*	*CI*	*exp(b)*	*Robust SE*[b]	*t*	*p*	*CI*
IPTW estimation only (ATE)[a]										
Self-employment (wage-and-salary)	1.19*	(0.10)	2.01	0.045	1.00 - 1.40	1.04	(0.07)	0.63	0.529	0.92 - 1.18
Doubly-robust estimation (ATE)[a]										
Self-employment (wage-and-salary)	1.13	(0.08)	1.78	0.076	0.99 - 1.30	1.01	(0.04)	0.13	0.899	0.93 - 1.09
Age	0.98**	(0.00)	-4.26	0.000	0.97 - 0.99	0.99**	(0.00)	-3.10	0.002	0.98 - 1.00
Female (male)	1.24**	(0.08)	3.51	0.000	1.10 - 1.40	1.15**	(0.05)	3.58	0.000	1.07 - 1.24
Race (white)										
Black	0.72**	(0.05)	-5.16	0.000	0.64 - 0.82	0.97	(0.04)	-0.80	0.424	0.89 - 1.05
Other races	1.15	(0.19)	0.84	0.399	0.83 - 1.57	1.06	(0.08)	0.72	0.470	0.91 - 1.24
Hispanic	0.69**	(0.10)	-2.67	0.008	0.53 - 0.91	0.99	(0.06)	-0.16	0.874	0.87 - 1.13
Veteran	1.10	(0.07)	1.39	0.164	0.96 - 1.24	0.93	(0.05)	-1.37	0.170	0.84 - 1.03
Risk tolerance	1.01	(0.02)	0.39	0.697	0.98 - 1.04	1.02	(0.01)	1.73	0.084	1.00 - 1.04
Health, self-rated										
Concurrent						0.72**	(0.02)	-15.13	0.000	0.69 - 0.75
Lagged, *t-1*	4.93**	(0.27)	29.47	0.000	4.43 - 5.48					
Depressive symptoms										
Concurrent	0.81**	(0.01)	-13.16	0.000	0.78 - 0.83					
Lagged, *t-1*						1.28**	(0.01)	29.17	0.000	1.26 - 1.30
Education, in years	1.07**	(0.01)	6.50	0.000	1.05 - 1.09	0.99	(0.01)	-1.35	0.178	0.98 - 1.00
Health problems limiting work	0.32**	(0.02)	-17.35	0.000	0.28 - 0.36	1.39**	(0.06)	7.18	0.000	1.27 - 1.52
Has health insurance (does not)	0.92	(0.08)	-0.93	0.352	0.78 - 1.09	0.90	(0.05)	-1.79	0.073	0.81 - 1.01
Spouse's work status (not working)										
Working	1.01	(0.06)	0.12	0.904	0.89 - 1.13	0.94	(0.04)	-1.33	0.183	0.87 - 1.03
Not married	0.97	(0.06)	-0.50	0.616	0.85 - 1.10	1.15**	(0.05)	3.25	0.001	1.06 - 1.25
Household members	0.94**	(0.02)	-2.90	0.004	0.90 - 0.98	1.01	(0.01)	0.81	0.420	0.98 - 1.04
Formal volunteering, past year (none)										
<100 hours	1.10	(0.06)	1.77	0.077	0.99 - 1.22	0.91*	(0.04)	-2.51	0.012	0.84 - 0.98
100+ hours	1.22**	(0.09)	2.83	0.005	1.06 - 1.40	0.98	(0.05)	-0.42	0.675	0.88 - 1.09
Informal volunteering, past year (none)										
<100 hours	1.14**	(0.06)	2.61	0.009	1.03 - 1.27	0.98	(0.03)	-0.69	0.487	0.91 - 1.04
100+ hours	1.24**	(0.09)	2.90	0.004	1.07 - 1.44	1.01	(0.05)	0.10	0.917	0.91 - 1.11
Individual earnings[c]	1.00	(0.01)	0.08	0.937	0.99 - 1.01	0.99	(0.00)	-1.45	0.146	0.98 - 1.00
Household wealth[c]	1.01	(0.01)	1.36	0.173	0.99 - 1.04	0.98*	(0.01)	-2.50	0.013	0.97 - 1.00
Household income, less individual earnings[c]	1.01**	(0.00)	2.76	0.006	1.00 - 1.02	1.00	(0.00)	-1.81	0.070	0.99 - 1.00
Currently receiving:										
Social Security retirement benefits	1.10	(0.08)	1.37	0.171	0.96 - 1.26	1.06	(0.05)	1.19	0.232	0.97 - 1.15
Receiving pension income	1.04	(0.05)	0.94	0.345	0.95 - 1.14	0.98	(0.04)	-0.45	0.655	0.91 - 1.06

Variables	*Self-Rated Health: Ordered Logistic Regression*					*Depressive Symptoms: Negative Binomial Regression*				
	exp(b)	*Robust SE*[b]	*t*	*p*	*CI*	*exp(b)*	*Robust SE*[b]	*t*	*p*	*CI*
Labor force status (full-time)										
Part-time or partly retired	0.90	(0.12)	-0.82	0.412	0.70 - 1.16	1.19	(0.12)	1.72	0.085	0.98 - 1.44
Fully retired	0.52*	(0.13)	-2.57	0.010	0.31 - 0.85	1.02	(0.24)	0.09	0.925	0.65 - 1.61
Unemployed or otherwise not working	0.52*	(0.14)	-2.38	0.017	0.31 - 0.89	1.28	(0.31)	1.00	0.317	0.79 - 2.07
Job requires…										
lots of physical effort	0.99	(0.05)	-0.30	0.767	0.90 - 1.08	1.06	(0.04)	1.62	0.105	0.99 - 1.13
lifting heavy loads	1.08	(0.05)	1.64	0.101	0.98 - 1.19	1.00	(0.04)	-0.06	0.948	0.92 - 1.08
stooping, kneeling, crouching	0.97	(0.04)	-0.84	0.403	0.89 - 1.05	1.00	(0.03)	0.16	0.874	0.95 - 1.06
good eyesight	1.03	(0.04)	0.74	0.457	0.96 - 1.10	0.93*	(0.03)	-2.44	0.015	0.88 - 0.99
Job involves lots of stress	0.95	(0.03)	-1.47	0.141	0.89 - 1.02	1.26**	(0.04)	7.57	0.000	1.18 - 1.33
Years at current job	1.00	(0.00)	-0.17	0.861	0.99 - 1.00	1.00	(0.00)	-0.34	0.733	0.99 - 1.00
Number of employees (more than one)										
Work alone	1.04	(0.11)	0.35	0.723	0.84 - 1.29	0.96	(0.07)	-0.51	0.607	0.83 - 1.12
Not working	1.72	(0.48)	1.95	0.051	1.00 - 2.97	1.68*	(0.42)	2.04	0.042	1.02 - 2.75
35+ hours worked per week (<35 hours)	0.90	(0.11)	-0.82	0.411	0.70 - 1.15	1.11	(0.11)	1.05	0.292	0.92 - 1.34
Pension from current job	1.07	(0.08)	1.00	0.316	0.94 - 1.23	0.95	(0.05)	-0.83	0.405	0.85 - 1.07
Blue collar occupation (white collar)	1.02	(0.06)	0.31	0.753	0.91 - 1.15	0.96	(0.06)	-0.66	0.509	0.85 - 1.08
Goods producing industry (service producing)	0.98	(0.08)	-0.21	0.836	0.85 - 1.15	1.01	(0.06)	0.14	0.891	0.89 - 1.14
Controls										
Dies during the study	0.59**	(0.06)	-5.55	0.000	0.49 - 0.71	1.19**	(0.07)	3.07	0.002	1.07 - 1.33
Nonresponse during the study	0.99	(0.07)	-0.13	0.893	0.86 - 1.14	1.03	(0.06)	0.51	0.613	0.92 - 1.14
Proxy respondent[d]	0.79	(0.10)	-1.91	0.057	0.61 - 1.01					
Thresholds:										
Fair/poor to ≥ good	2.80*	(1.13)	2.55	0.011	1.27 - 6.19					
≤ Good to ≥ very good	39.77**	(16.47)	8.89	0.000	17.66 - 89.53					
≤ Very good to excellent	716.09**	(301.59)	15.61	0.000	313.67 - 1,634.79					
Intercept						1.96*	(0.63)	2.07	0.038	1.04 - 3.69
F test	(43, 189157) = 76.26, *p* < 0.001					(42, 263541) = 87.36, *p* < 0.001				
N	26,502[e]					25,435[f]				

Notes: Data from a combined 6 waves of the HRS that include 6,473 individuals. Individual (*m*=20) estimates combined using Rubin's combination rules. ** $p < 0.01$, * $p < 0.05$, two-tailed tests. **a.** ATE = average treatment effect where weight is $1/P$ for a "treated" case and $1/(1 - P)$ for a comparison case, where P is predicted using generalized boosted modeling from the RAND *twang* Stata macro; **b.** Exponentiated robust standard errors are derived using the delta rule: exp(b)*se(b); **c.** Transformed using the inverse hyperbolic sine function; **d.** By design, proxy respondents did not answer the depressive symptom questions; Within **e.** 5,045 and **f.** 4,974 households.

4.3.2 Financial Well-Being

Considering individual earnings from work, the IPTW-only estimation model in Table 4 estimates a strong and negative relationship with self-employment (b = -5.56, $p < 0.001$). This relationship, while reduced in magnitude, continued to hold in the doubly-robust model (b = -2.99, $p < 0.001$). The main doubly robust model was significant: $F(43, 4{,}949) = 475.2$, $p < 0.001$). All supplemental models show similar results, estimating self-employment's negative effects on individual earnings with a slightly reduced magnitude once accounting for potential confounders. Therefore, my hypothesis that self-employment leads to reduced individual earnings, compared to wage-and-salary employment, was supported.

Considering total household wealth, the IPTW-only (b = 0.41, p = 0.037) and doubly-robust (b = 0.30, p = 0.019) estimation models in Table 4 estimated a slight positive relationship with self-employment. While the sample-weight only models in Appendix F show stronger positive relationships, self-employment was not found to have an effect in most of the IPTW-adjusted models. Interestingly, the IPTW-only ATT model estimated that self-employment leads to less wealth among the self-employed than if they had worked in wage-and-salary employment (b = -0.80, $p < 0.05$); however, this relationship switched directions and become nonsignificant once doubly-robust estimation was performed.

To summarize, the agreement between the main and supplemental models regarding the negative effect of self-employment on income increases my confidence in the findings. However, while the main model shows a slight positive relationship between self-employment and total household wealth, the supplemental models that incorporate propensity score techniques, while mostly displaying the same direction of the relationship, are nonsignificant.

Table 4. Estimated Effect of Self-Employment on Financial Health

Variables	***Individual Earnings, Transformed***[b]					***Total Household Wealth, Transformed***[b]				
	b	*SE*	*t*	*p*	*CI*	*b*	*SE*	*t*	*p*	*CI*
IPTW estimation only (ATE)[a]										
Self-employment (wage-and-salary)	-5.56**	(0.14)	-39.32	0.000	-5.83 - -5.28	0.41*	(0.20)	2.09	0.037	0.03 - 0.80
Doubly-robust estimation (ATE)[a]										
Self-employment (wage-and-salary)	-2.99**	(0.15)	-20.25	0.000	-3.28 - -2.70	0.30*	(0.13)	2.35	0.019	0.05 - 0.54
Age	0.00	(0.01)	0.33	0.740	-0.01 - 0.02	-0.00	(0.01)	-0.45	0.654	-0.02 - 0.01
Female (male)	-0.14	(0.12)	-1.22	0.222	-0.37 - 0.09	0.03	(0.12)	0.22	0.827	-0.21 - 0.26
Race (white)										
Black	0.06	(0.14)	0.45	0.654	-0.22 - 0.34	-1.10**	(0.23)	-4.90	0.000	-1.54 - -0.66
Other races	0.30	(0.20)	1.46	0.144	-0.10 - 0.70	-0.35	(0.21)	-1.64	0.101	-0.77 - 0.07
Hispanic	-0.46**	(0.17)	-2.73	0.006	-0.79 - -0.13	-0.01	(0.19)	-0.07	0.946	-0.39 - 0.37
Veteran	0.03	(0.13)	0.25	0.806	-0.22 - 0.28	-0.05	(0.15)	-0.33	0.745	-0.35 - 0.25
Risk tolerance	-0.02	(0.03)	-0.81	0.420	-0.08 - 0.03	-0.03	(0.04)	-0.70	0.486	-0.12 - 0.06
Health, self-rated	0.01	(0.05)	0.13	0.898	-0.09 - 0.11	0.19**	(0.05)	4.10	0.000	0.10 - 0.29
Depressive symptoms	-0.02	(0.03)	-0.74	0.457	-0.07 - 0.03	-0.08**	(0.03)	-2.75	0.006	-0.13 - -0.02
Education, in years	0.03	(0.02)	1.88	0.061	-0.00 - 0.07	0.12**	(0.02)	6.32	0.000	0.08 - 0.15
Health problems limiting work	-0.37**	(0.11)	-3.28	0.001	-0.59 - -0.15	-0.16	(0.14)	-1.11	0.266	-0.43 - 0.12
Has health insurance (does not)	0.51*	(0.22)	2.35	0.019	0.08 - 0.93	0.36	(0.20)	1.76	0.079	-0.04 - 0.76
Spouse’s work status (not working)										
Working	0.22	(0.12)	1.83	0.067	-0.02 - 0.46	-0.42**	(0.10)	-4.24	0.000	-0.61 - -0.22
Not married	0.07	(0.13)	0.52	0.605	-0.18 - 0.31	-0.80**	(0.11)	-7.09	0.000	-1.03 - -0.58
Household members	0.02	(0.04)	0.39	0.700	-0.07 - 0.10	-0.22**	(0.05)	-4.01	0.000	-0.33 - -0.11
Formal volunteering, past year (none)										
<100 hours	-0.01	(0.13)	-0.04	0.967	-0.25 - 0.24	-0.05	(0.12)	-0.46	0.649	-0.29 - 0.18
100+ hours	-0.36**	(0.12)	-3.00	0.003	-0.60 - -0.13	0.09	(0.11)	0.79	0.427	-0.13 - 0.30
Informal volunteering, past year (none)										
<100 hours	0.14	(0.09)	1.44	0.149	-0.05 - 0.32	0.02	(0.10)	0.18	0.861	-0.18 - 0.22
100+ hours	-0.03	(0.15)	-0.20	0.844	-0.33 - 0.27	0.13	(0.13)	1.05	0.295	-0.12 - 0.38
Individual earnings[b]										
Concurrent						0.03*	(0.01)	2.34	0.019	0.00 - 0.05
Lagged, *t-1*	0.28**	(0.02)	16.55	0.000	0.25 - 0.32					
Household wealth[b]										
Concurrent	0.02*	(0.01)	2.21	0.027	0.00 - 0.03					
Lagged, *t-1*						0.51**	(0.03)	18.90	0.000	0.46 - 0.57
Household income, less individual earnings[b]	-0.10**	(0.02)	-5.11	0.000	-0.14 - -0.06	0.13**	(0.02)	5.90	0.000	0.08 - 0.17
Currently receiving:										
Social Security retirement benefits	-0.40**	(0.15)	-2.62	0.009	-0.70 - -0.10	0.17	(0.13)	1.34	0.179	-0.08 - 0.42
Receiving pension income	-0.49**	(0.13)	-3.88	0.000	-0.73 - -0.24	0.11	(0.07)	1.42	0.155	-0.04 - 0.25

Variables	*Individual Earnings, Transformed*[b]					*Total Household Wealth, Transformed*[b]				
	b	*SE*	*t*	*p*	*CI*	*b*	*SE*	*t*	*p*	*CI*
Labor force status (full-time)										
Part-time or partly retired	-0.66	(0.37)	-1.76	0.078	-1.39 - 0.07	0.27	(0.20)	1.37	0.171	-0.12 - 0.65
Fully retired	-4.14*	(1.97)	-2.10	0.035	-8.00 - -0.28	-0.38	(0.32)	-1.19	0.234	-1.02 - 0.25
Unemployed or otherwise not working	-2.40	(1.97)	-1.22	0.223	-6.25 - 1.46	-1.28**	(0.36)	-3.51	0.000	-1.99 - -0.57
Job requires…										
lots of physical effort	-0.07	(0.08)	-0.86	0.391	-0.23 - 0.09	-0.08	(0.09)	-0.96	0.339	-0.25 - 0.09
lifting heavy loads	-0.08	(0.11)	-0.74	0.462	-0.29 - 0.13	-0.13	(0.10)	-1.29	0.198	-0.32 - 0.07
stooping, kneeling, crouching	0.02	(0.07)	0.27	0.788	-0.12 - 0.16	0.09	(0.07)	1.29	0.198	-0.05 - 0.24
good eyesight	-0.01	(0.11)	-0.05	0.957	-0.21 - 0.20	-0.10	(0.07)	-1.41	0.160	-0.25 - 0.04
Job involves lots of stress	0.22**	(0.07)	3.00	0.003	0.08 - 0.37	0.00	(0.09)	0.02	0.985	-0.17 - 0.17
Years at current job	-0.01	(0.01)	-1.73	0.084	-0.02 - 0.00	0.02**	(0.00)	3.05	0.002	0.01 - 0.02
Number of employees (more than one)										
Work alone	-1.31**	(0.21)	-6.33	0.000	-1.72 - -0.91	-0.31	(0.18)	-1.71	0.087	-0.66 - 0.04
Not working	-0.19	(1.98)	-0.10	0.922	-4.07 - 3.69	0.22	(0.41)	0.54	0.593	-0.59 - 1.03
35+ hours worked per week (<35 hours)	-0.78*	(0.35)	-2.23	0.026	-1.47 - -0.10	-0.10	(0.19)	-0.52	0.604	-0.48 - 0.28
Pension from current job	1.51**	(0.16)	9.49	0.000	1.20 - 1.82	0.32**	(0.10)	3.13	0.002	0.12 - 0.52
Blue collar occupation (white collar)	0.22	(0.14)	1.62	0.106	-0.05 - 0.49	-0.09	(0.14)	-0.65	0.517	-0.37 - 0.19
Goods producing industry (service producing)	-0.04	(0.17)	-0.22	0.822	-0.36 - 0.29	-0.01	(0.18)	-0.05	0.956	-0.36 - 0.34
Controls										
Dies during the study	0.05	(0.19)	0.28	0.778	-0.32 - 0.42	0.01	(0.17)	0.08	0.936	-0.33 - 0.35
Nonresponse during the study	-0.08	(0.13)	-0.64	0.523	-0.34 - 0.17	-0.07	(0.21)	-0.36	0.721	-0.48 - 0.33
Proxy respondent	-0.01	(0.24)	-0.04	0.964	-0.48 - 0.46	0.22	(0.26)	0.86	0.392	-0.28 - 0.72
Intercept	6.54**	(0.87)	7.51	0.000	4.83 - 8.24	3.27**	(0.75)	4.37	0.000	1.80 - 4.73
F test	(43, 4,949) = 475.2, $p < 0.001$					(43, 4,943) = 79.29, $p < 0.001$				
N	26,521					26,521				

Notes: Data from a combined 6 waves of the HRS that include 6,473 individuals with 5,046 households. Individual (m=20) estimates combined using Rubin's combination rules. ** $p < 0.01$, * $p < 0.05$, two-tailed tests. **a.** ATE = average treatment effect where weight is $1/P$ for a "treated" case and $1/(1 – P)$ for a comparison case, where P is predicted using generalized boosted modeling from the RAND *twang* Stata macro; **b.** Transformed using the inverse hyperbolic sine function.

4.3.3 Covariates of Note

While not the focus of the study, the doubly-robust models found that females working at baseline experienced better health (*OR* = 1.24, $p < 0.001$) yet more depressive symptoms (*IRR* = 1.15, $p < 0.001$) than males, while controlling for all other variables in the models. Those who identified as black or African American experienced worse health (*OR* = 0.72, $p < 0.001$) and lower household wealth ($b = -1.10$, $p < 0.001$) in comparison to those who identified as white, and those who identified as Hispanic experienced worse health (*OR* = 0.69, $p = 0.008$) and lower individual earnings ($b = -0.46$, $p = 0.006$) than those who did not. Self-rated health and number of depression symptoms were negatively associated with one another (ordered logistic regression on self-rated health: *OR* = 0.81, $p < 0.001$; negative binomial regression on depressive symptoms: *IRR* = 0.72, $p < 0.001$), and having died during the study time frame was negatively associated with self-rated health (*OR* = 0.59, $p < 0.001$) and positively associated with depressive symptoms (*IRR* = 1.19, $p = 0.002$). Volunteering, overall, was associated with better health (formal volunteering at 100+ hours: *OR* = 1.22, $p = 0.005$; informal volunteering at <100 hours: *OR* = 1.14, $p = 0.009$; informal volunteer at 100+ hours: *OR* = 1.24, $p = 0.004$), and having a stressful job was predictive of reporting more depressive symptoms (*IRR* = 1.26, $p < 0.001$) yet higher earnings ($b = 0.22$, $p = 0.003$). Further, reporting health problems that limit one's ability to work ($b = -0.37$, $p = 0.001$), in addition to working alone, in comparison to working with others ($b = -1.31$, $p < 0.001$), was associated with decreased individual earnings.

4.3.4 Summary of Results

Among Americans aged 50 and older, the results strongly indicate that self-employment negatively influences individual earnings. There is some evidence that self-employment leads to better self-rated health and increased total household wealth, although the supplemental models show nonsignificant relationships. Finally, there is little evidence that self-employment influences the number of depressive symptoms experienced by older adults.

Chapter 5: Discussion and Implications

Results from Question 1 in Chapter 4 revealed that those who are older, identify as male, have higher levels of risk tolerance, and better overall health—yet more health problems that limit one's ability to work—are all predictive of being self-employed past the age of 50, while controlling for all other variables in the model. The results also revealed that older self-employed Americans are less likely to receive health insurance from any source, less likely to be married, and more likely to informally volunteer. They also took home less in individual earnings from work, yet had higher levels household wealth and income from all sources (with individual earnings removed).

Regarding the analysis from the quasi-experimental portion of this study, results from Question 2 strongly indicate that self-employment leads to reduced earnings from work. The main models, shown in Tables 3 and 4, used inverse probability of treatment weights created through a form of machine learning called generalized boosted modeling that has been shown to outperform other IPTW-creation methods, such as logistic regression (Lee et al., 2009; McCaffrey et al., 2004). They indicate that self-employment may lead to better health and increased wealth, although they do not indicate that self-employment influences depressive symptoms. The supplementary models, provided in Appendix F, find results that are most generally in the same direction as the main models, but not always statistically significant, especially when doubly-robust methods are incorporated.

These results paint a complex picture about self-employment in an aging America, both supporting and raising questions about the excitement that has been shown for this type of work in the media, by policymakers, and by program operators. Further, the results from this study show how complex the concepts of human, social, and financial capital are, providing an explanation for why my hypothesis that these concepts are positively related to self-employment was only partially supported. For example, in this study, social capital was operationalized as being married or having a partner and the labor force status of their spouses or partners, the number of household members, and the amount of both formal and informal volunteering undertaken by respondents. Indeed, only two measures of social capital—not being married or partnered and engaging in informal volunteer activities—were associated with self-employment. Future research should seek to understand the complexities of these relationships, focusing on hypotheses related to specific variables that might explain why certain relationships exist.

In this chapter, I will discuss some of the implications, limitations, and contributions from this study. Instead of dividing this chapter by research question, I will instead divide it by the key concepts in the conceptual model that framed this dissertation: sociodemographic characteristics and risk tolerance; separate sections for human, social, and financial capital; and the nature of the work. I will then conclude with a discussion of this dissertation's limitations and contributions, covering its potential impact on the knowledge base regarding later-life self-employment, as well as research methodologies.

5.1 Results from Questions 1 and 2

5.1.1 Sociodemographic Characteristics and Risk Tolerance

This study found that age was positively associated with being self-employed. This might be explained by previous scholarship that posits as people age, they want to exert a greater deal of control over their work (Ng & Feldman, 2013). Further, they may be experiencing higher levels of real or perceived age discrimination, pushing them into self-employment (Hytti, 2005; Neumark, Burn, & Button, 2015). This trend has also been documented in previous descriptive and bivariate research that use both the HRS and the Current Population Survey (Pitt-Catsouphes et al., 2017; Zissimopoulos & Karoly, 2007b).

Considering gender, females were less likely to be self-employed than males, relative to wage-and-salary work. Using an older sample, this replicates a long-running and documented trend using data from the Current Population Survey, where self-employment rates for females between the ages of 20 and 64 are just less than half that of males (Ewing Marion Kauffman Foundation, 2017). In this study's sample, this difference may be partially explained by labor force trends, as men are more likely to be working past the age of 55 than women (U.S. Bureau of Labor Statistics, U.S. Department of Labor, 2015). However, there are likely larger cultural issues at play, as females have also been shown to have lower levels of "entrepreneurial self-efficacy," or self-confidence in one's ability to pursue self-employment, which could lead to one being less likely to pursue this type of work (Wilson, Kickul, Marlino, Barbosa, & Griffiths, 2009). The authors discussed the importance of engaging women in entrepreneurship education programming in MBA and undergraduate coursework while highlighting the need to expand the universe that is targeted by this programming to include women of diverse socioeconomic, racial, and ethnic backgrounds. Expanding upon this, I would argue that it is important to reach women from diverse backgrounds *and* ages with programming aimed not only to encourage self-employment, but to increase success in self-employment, given previous scholarship that shows that women are more likely to enter this form of work past the age of 50 than before (Zissimopoulos & Karoly, 2007b) and my own findings that self-employed older adults make less than those who work for someone else.

Considering race, this study's bivariate findings suggest that older African Americans are less likely to be self-employed than white Americans (13.1% vs. 23.1%), echoing a trend documented in younger national samples (Ewing Marion Kauffman Foundation, 2017). This might point to the lack of opportunity to pursue self-employment, given the economic disparities and systemic racism that exists within the American context. This relationship, however, became nonsignificant in the multivariate model, with the loss of this significant relationship being explained by the model's additional covariates. For example, older African Americans in this sample, in comparison to older whites, were younger (64.3 years vs. 65.4 years) with fewer years of formal education (12.7 years vs. 13.4 years), more likely to be female (62.2% vs. 51.3%), and less likely to be veterans (15.1% vs. 23.4%), among other differences.

Interestingly, this study's bivariate results indicate that older Hispanic adults were less likely to be self-employed, although no relationship was found in the multivariate analysis. This is contrary to what has been documented in younger national samples using the Current Population Survey, with nearly one-quarter of newly self-employed adults aged 20 to 64 identifying as Latino and whose self-employment rate was nearly twice that of white, non-Latino Americans in 2016 (Ewing Marion Kauffman Foundation, 2017). While documenting these trends is important, future research should look at different racial and ethnic groups to understand why individuals are interested in self-employment, what factors lead individuals within these groups to make the transition, what unique barriers and facilitators exist during the decision-making process and transition, and what programs and policies can increase opportunities to pursue self-employment for those who choose to.

While the concept of risk tolerance and its relationship with self-employment or entrepreneurship has been covered in the literature, its relationship with age has had less consideration. As such, this study contributes to the field by documenting that older self-employed Americans have higher levels of risk tolerance, on average, relative to older wage-and-salary employees. Previous research has shown that age is negatively associated with risk tolerance (Xu & Ruef, 2004), yet when considering only older adults, this study shows that those who decide to work for themselves are willing to take on more financial risk than those who do not. Including the risk tolerance variable, given its higher level of missing data in comparison to the other variables in the model, was a methodological risk that I determined was merited to explore its relationship with self-employment in later life. Moving forward and with new sources of data, I plan to consider new ways to measure risk tolerance. Further, given my findings on the relationship between self-employment and gender, race, and ethnicity, future research might look at how risk tolerance moderates these relationships and how various forms of economic opportunity—wealth or access to lines of credit, for example—influence these relationships.

Nearly three in 10 veterans in this sample reported being self-employed compared to about two in 10 non-veterans, resulting in a significant bivariate test. However, this relationship became nonsignificant in the multinomial logistic regression model. Veterans have historically had high rates of self-employment (Ewing Marion Kauffman Foundation, 2017), yet this loss of significance in the multivariate model can be explained by several covariates. For example, older veterans, compared to older non-veterans, are higher in age (67.9 years to 64.3 years) and more likely to be male (97.9% vs. 33.4%), white (86.4% vs. 77.9%), partly retired (21.4% vs. 14.4%), fully retired (31.4% vs. 28.3%), and to die during the study (12.9% vs. 6.0%).

5.1.2 Human Capital

Regarding human capital, the finding that self-employment is associated with both self-rated health and having health problems that limit one's ability to work is perplexing. Self-rated health—shown to be a good and consistent predictor of objective health (Miilunpalo et al., 1997; Schnittker & Bacak, 2014)—and reporting whether health problems limit one's ability to work are both arguably subjective. Older self-employed adults may, in fact, *feel* healthier, on average, yet also might seek the flexibility provided by self-employment to work around existing health conditions. To mitigate the negative effects of health problems that limit their ability to work, acting as their own boss through self-employment may create more aging-friendly work environments than working in wage-and-salary employment (Appannah & Biggs, 2015). This may or may not be seen in positive light by self-employed respondents, who might have transitioned into this type of work out of necessity. Future research could aim to investigate the role of self-employment in mitigating the effects of health problems, such as chronic diseases, that tend to increase with chronological age.

Education appears not to be a significant factor ($RRR = 1.04$, $p = 0.056$), as shown in Table 2. This is counter to previous research on the individual attributes of self-employed older adults. For example, Zissimopolous and Karoly (2007b), using earlier waves of the HRS and cross-tabulations, found that older self-employed adults were more likely to have a bachelor's degree and a doctorate, law, or medical degree than those in wage-and-salary work. Using a continuous measure of educational attainment in this study, I also found in my bivariate analysis that years of education were positively associated with self-employment, although the magnitude of this relationship was small. Interestingly, scholars—using a sample of Americans aged 20 to 64—have documented the long-running trend of high rates of self-employment among those with less than a high school degree (Ewing Marion Kauffman Foundation, 2017). While education might make it easier to pursue self-employment, the lack of economic opportunities that come with lower levels of educational attainment might push others into self-employment.

It is also evident that regardless of source, self-employed older adults are less likely to have health insurance, raising serious concerns about how to promote health equity among older

Americans—especially those who are pre-Medicare eligible—when health insurance is so often tied to our employers in the U.S. It is important that we consider how to de-link health insurance from the workplace, or at least to provide more accessible and affordable alternatives for self-employed adults to become insured. These findings have been replicated by Zissimopolous and Karoly (2007b) and may be unique to the U.S. among the most economically developed countries, where we have a tradition of linking health and pension benefits to our place of employment. In fact, scholars have proposed that our health insurance distribution system creates an environment that discourages entrepreneurship. Fairlie and colleagues (2011), for example, found that those in jobs with health insurance but without access to spousal health insurance are less likely to transition to self-employment. They also found that rates of self-employment increase once Americans turn age 65 and become eligible for Medicare, although this contrasts with a more recent study that found no such association (Ramnath, Shoven, & Slavov, 2017). The potential negative association between health insurance and self-employment may not just be an American phenomenon, with a recent German study suggesting that the decision to move into self-employment is negatively associated with the cost of health insurance for the self-employed (Fossen & König, 2017).

As a scholar, I take a more neutral stance on whether we, as a country, should promote self-employment in later life—at least until we know more about the causes and consequences of this form of work. However, it is clear that policies that would increase one's access to affordable health insurance until the Medicare-eligible age of 65, might create a more equitable field for those with and without personal safety nets.

To answer Question 2, this dissertation also investigated how self-employment influences personal health, as measured by self-rated health and the number of depressive symptoms, a proxy for mental health. While inconclusive, the findings indicate that self-employment may have a small-but-positive influence on self-rated health, but that other variables may play a larger role, as shown by the reduction in magnitude and the transition from significance to non-significance in the doubly-robust estimation of the main model in Table 3. If this result can be replicated, it might be explained by the fact that older adults, through being their own bosses, have a great deal of autonomy over their work, creating environments that promote well-being and are aging-friendly (Appannah & Biggs, 2015; Ng & Feldman, 2013). Further, self-employed older adults may be working in roles that they are passionate about, bring a sense of accomplishment, and provide flexibility, all aspects of work that have been shown to be important to those over the age of 50 who are interested in starting new organizations (Penn Schoen Berland & Civic Ventures, 2011). While not considered for this dissertation, future research should seek to understand if aspects of autonomy, passion, accomplishment, and flexibility influence the relationship between self-employment and health.

Self-employment was not found to influence the number of depressive symptoms experienced by respondents. However, in the IPTW-only estimation in the supplemental models, it was estimated to have a positive effect. Similar to my findings for self-rated health, once controlling for additional variables through the doubly-robust estimation procedures, this relationship vanishes. It is possible, for example, that working alone might lead to increases in depressive symptoms; indeed, my bivariate results show that working alone is very common among older self-employed adults. As such, the finding that self-employment increases depressive symptoms in my IPTW-only models might be explained by working alone, perhaps a proxy for social isolation, which has been shown to be predictive of depressive symptoms among older adults (Steptoe, Shankar, Demakakos, & Wardle, 2013). As such, the nonsignificant finding for self-employment may be explained by the addition of the working alone control (in addition to other variables) in my doubly-robust analysis. Future research might include hierarchical regression procedures to identify key concepts or variables that explain this change.

Finally, the personal health variables used in this dissertation—self-rated health and number of depressive symptoms—are subjective. While still good indicators of overall health, future research should look to expand our knowledge on the influence of self-employment on health. For example, the HRS has objective data on biomarkers and diabetes, among other topics, that might be considered for future research. Studies could also look at the role self-employment plays in physical activity.

5.1.3 Social Capital

Regarding social capital, although previous research found that later-life entrepreneurs were more likely to be married (Weller et al., 2015), this study's multivariate analysis found the opposite result. This might be explained by different samples being considered for analysis. For example, Weller and colleagues (2015) operationalized entrepreneurs as those whose businesses were worth at least $5,000, whereas this study's operationalization of self-employment did not, given the limitations of the HRS dataset. While easy to understand, they also used cross-tabulations, which do not control for confounding variables. Indeed, my bivariate analysis also found that the self-employed were more likely to be married, with this relationship reversed once I used a multivariate model. As such, this might indicate that many of those who pursue self-employment in later life are pursuing "necessity" entrepreneurship, instead of "opportunity" entrepreneurship (Ewing Marion Kauffman Foundation, 2017), given that they do not have a spouse or partner to rely on for financial or other forms of support.

Volunteering was also considered as an aspect of social capital in later life, an argument previously made by Gonzales and Nowell (2016). While previous research has shown that older adults who work part-time have higher numbers of volunteer hours than those not in the workforce (Choi, 2003), the relationship between volunteer engagement and work is complicated. For example, volunteering in later life has been shown to be both a destination and a means to another form of engagement through paid work, new volunteer roles, and social activities (Nancy Morrow-Howell, Lee, McCrary, & McBride, 2014). This dissertation found that while formal and informal volunteering were positively associated with self-employment in bivariate analyses, only informal volunteering maintained this association in multivariate analysis. Further, the likelihood of being self-employed increased with higher amounts of informal volunteering, when compared to those who reported no informal volunteer activities. Again, this might be explained through the flexibility afforded through being one's own boss; however, it might also be a consequence of working alone and seeking more social interaction, given that the bivariate results showed that more than four in five of the self-employed respondents in this study worked alone.

5.1.4 Financial Capital

To answer Question 1, I found that self-employed older adults earned less income, on average, relative to those in wage-and-salary work, when controlling for all other variables in the model. Interestingly, they also reported having higher levels of household income from all sources (less individual earnings) and slightly higher levels of household wealth. These findings held true in both the bivariate and multivariate models. The bivariate models in Appendix D, for example, show that older self-employed adults earned less than half that of those in wage-and-salary work at baseline, on average, while also reporting about three times more household wealth and nearly four times more in household income, less individual earnings. In the multivariate model, self-employed older adults were also less likely to be drawing upon Social Security retirement benefits and to be receiving pension income, relative to wage-and-salary employment, although this relationship was reversed in the bivariate results.

Question 2, while controlling for selection into self-employment through propensity score analysis, found that self-employment is not just associated with lower income, but may actually reduce one's earnings. In other words, the results from this quasi-experimental analysis indicate that older adults would have earned more if they had worked for someone else. This finding remained true in each of the IPTW-only and doubly-robust estimation models conducted through sensitivity analysis. Interestingly, self-employment was also shown to slightly increase one's wealth, in comparison to wage-and-salary work, in the main model. These counterintuitive findings—self-employment both decreases earnings while increasing wealth among older adults—are, at first, difficult to explain. Using sensitivity analysis, which allows me to look for trends using different models, I found that while the estimated effect on individual earnings remained negative and significant in each of my models, the positive effect on wealth become nonsignificant in my doubly-robust sensitivity analysis. As such, my findings related to wealth, while suggestive of a positive association through my main model, are not persuasive. One possible explanation is that by this point in their lives, respondents may have built up most of their wealth and would see little relative change in it, compared to individual earnings, which could dramatically change from year to year. Assuming that self-employment does increase wealth, it is possible that for many, self-employment is seen as a wealth builder and less as a source of immediate income. Business owners may invest their revenues back into the business while growing their asset base, at the cost of taking home a smaller paycheck. Others may simply see their self-employment as a source of continued income but not as a business from which to build wealth.

It should be stressed that the individual earnings variable used in the analysis is from self-reported data. As such, it is possible that this study's self-employed respondents underreported their income or reduced their income by subtracting business expenses, such as home offices. Previous scholarship has shown that underreporting of income among the self-employed in household surveys is an ongoing issue (Engström & Hagen, 2017; Hurst, Li, & Pugsley, 2014).

Nevertheless, these findings raise serious concerns regarding the mechanisms that lead one to pursue self-employment in later life and the outcomes from this work. For example, if older adults have a built-in safety net at home, perhaps through spousal income or high mutual fund balances, then pursuing one's passion or higher levels of autonomy through self-employment might be prominent goals, with earned income as a less important goal. This is an example of what has been called the non-pecuniary motivations for entrepreneurship in a study that found similar results while controlling for selection into self-employment using Heckman's sample selection framework (Hamilton, 2000; Heckman, 1979). In fact, a recent study using data from the Federal Reserve's Survey of Consumer Finances highlighted the positive association between diversified sources of wealth and entrepreneurship in older households, with the likelihood of being an entrepreneur—defined here as owning and managing a business worth more than $5,000—increasing when dividend and interest income made up at least one fifth of total income (Weller et al., 2018). In a major sense, those with higher levels of wealth can more afford to take the risk of moving into self-employment.

Using American tax return data, a recent study found that the drop in income associated with switching from wage-and-salary work to self-employment is larger for older workers than younger ones. Among those who transitioned to self-employment, younger workers' incomes increased during the tenure of their self-employment while it declined for older workers (Ramnath et al., 2017). The authors suggest that this result supports the idea that self-employment in later life can be a bridge to retirement. Future research should aim to understand if the relationship between self-employment and income remains negative for those from diverse socioeconomic, gender, racial, and ethnic backgrounds, among other characteristics. These findings could inform the development of targeted programs and policies to increase self-employment success, however that is measured.

The finding that self-employed older adults are less likely to participate in workplace pension programs foretells a financially-insecure future for many, highlighting a major issue regarding the tradeoffs between self-employment and wage-and-salary employment throughout the life course. Just like policymakers should consider how to de-link health insurance from the workplace to increase insurance uptake among the self-employed so, too, should they consider new ways to de-link retirement savings vehicles from the workplace to promote more universal retirement savings. Earlier research showed that older Americans in self-employment between 1992 to 2004 were less likely to participate in retirement savings plans (Zissimopoulos & Karoly, 2007a), with this dissertation finding a similar result for older self-employed Americans when considering the years 2004 through 2014. Further, the difficulty in preparing for a financially-secure retirement is not just an American issue, with a recent Australian study highlighting the low levels of retirement savings among self-employed females (Redmond, Walker, & Hutchinson, 2017). Research that analyzed data from both the HRS and administrative tax returns found that receiving Social Security retirement benefits increased the probability of transitioning from wage-and-salary work to self-employment. This association held for those who signed up for benefits at both early and full retirement ages, yet receiving private pensions had no association (Ramnath et al., 2017).

As new businesses have been shown to be important to the growth of our economy (Haltiwanger, Jarmin, & Miranda, 2013), advocates for entrepreneurship may want to focus on building a stronger social safety net for would-be entrepreneurs. Indeed, the Kauffman Foundation, one of the largest funders of entrepreneurship research, has advocated for such policies to make it easier for potential entrepreneurs to transition into this type of work (Ewing Marion Kauffman Foundation, 2016). Increased safety net programs, such as universal health insurance and enhanced food and nutrition programs, might prevent the potentially negative consequences of reduced earnings from self-employment while improving upon a variety of other metrics. Put simply, increasing our social safety net programs would help to even the playing field, thereby closing the self-employment "opportunity gap" between those with and without the means to pursue this work or to protect themselves from financial duress (Halvorsen & Morrow-Howell, 2017). This would increase the number and diversity of individuals who have the opportunity experience the potential benefits of self-employment.

5.1.5 Nature of the Work

The conceptual framework that guided this dissertation's design stressed the importance of work and workplace characteristics in shaping personal health and financial well-being outcomes. This makes conceptual sense, as the nature of the work—such as full- or part-time employment, physical effort required and stress involved, hours worked, and occupation and industry, among others—could all be argued to predict various outcomes. Some of these attributes, which were included in the doubly-robust estimation models for Question 2, were found to do so. For example, moving into full retirement, unemployment, or otherwise not working (while having been working at baseline) were associated with worse self-rated health, and having a job with a lot of stress predicted more symptoms of depression yet higher individual earnings. With these and a few other exceptions, however, the work-related variables were not heavily indicative of personal or financial health outcomes. Yet their inclusion, along with the individual-level characteristics in the doubly-robust models, added important contextual information to help estimate the influence of self-employment on personal and financial health outcomes while reducing bias from potentially misspecified propensity score models.

Why was this study unable to identify key workplace characteristics that predict individual-level outcomes? This may, in large part, be due to the large amount of variation within the workplace among those both in self-employment and wage-and-salary work. In other words, while this study attempted to estimate the overall effects of self-employment on financial well-being and personal health, it did not look at the great deal of variation *within* self-employment, my area of interest. As such, I plan to look at similar workplace characteristics in future research that considers only older self-employed adults and not those in wage-and-salary positions, asking, "What workplace characteristics lead to more positive personal and financial outcomes among self-employed older adults?" This would allow me to isolate these factors within one type of work and, as a result, aid discussions on creating better workplaces for an aging workforce.

5.2 Limitations and Contributions

This study contributes substantively to the literature on self-employment in later life. With any study, however, there are limitations that must be taken into consideration. In this section, I outline key limitations and contributions from this dissertation, while providing thoughts on how to move forward with future scholarship.

5.2.1 Variation in Work

Imagine the work environments for an automotive plant technician, a teacher, a restaurant owner, and a human resources consultant working from home. Within these professions there is certainly a great deal of variation, and between these professions there is certainly even more. This dissertation, which dichotomizes self-employment and wage-and-salary work, treats them as two distinct types of work. This is true to a large extent, as those who are self-employed are generally in charge of their own work. However, self-employment incorporates several types of work, including independent contracting, consulting, small business ownership, entrepreneurship, and social entrepreneurship (Pitt-Catsouphes et al., 2017). A limitation to the HRS dataset is that it asks only one question—whether respondents work for themselves—to determine self-employment status. This does not account for the variation in industries, occupations, and work environments within self-employment and wage-and-salary work. To address this limitation, this study included several covariates that attempt to assess different types of self-employment and wage-and-salary work (e.g., occupation and industry codes, working alone or with others, and hours worked per week), offering further descriptions of a diverse set of work experiences. As described previously, while variables related to the nature of the work were largely unpredictive of the outcomes measured, they did help to account for the variation within the workplace, lending greater credibility to the estimated treatment effects of self-employment.

5.2.2 Consideration of Work Motivations

This study also had a limited ability to explore the motivations for pursuing self-employment, such as job autonomy (Ng & Feldman, 2013) and the level of choice one perceived as having when pursuing self-employment. It is possible that among the older self-employed, these motivations are more salient than among older wage-and-salary workers. As such, after controlling for several important variables, differences in outcomes between older self-employed adults and those who work in wage-and-salary positions may be explained by these concepts.

Regarding the concept of choice when transition to self-employment, and as outlined in Halvorsen and Morrow-Howell's (2017) review article, scholars have theorized about the level of choice older adults perceive in their self-employment. Kautonen (2008), for example, described how older entrepreneurs can be "pushed" or "pulled" into their work, suggesting that pull motivations, such as "I wanted to earn more money" and "I wanted to carry out my own ideas," carried more weight than push motivations, such as "Unemployment or threat of redundancy" and "I wanted a less stressful job," in a study of older Finnish entrepreneurs (p. 9). The concept of choice in self-employment has been described in similar ways, as well. Singh and DeNobel (2003) identified three archetypes of older entrepreneurs—constrained, rational, and reluctant—in their scholarship. Constrained older entrepreneurs were described as those who want to become entrepreneurs but have not yet done so due to perceived or real constraints; rational older entrepreneurs are those who decide to become self-employed by rational choice, such as seeking continued income; and reluctant older entrepreneurs, or those who feel they lack other options, such as those undertaking entrepreneurship due to unemployment. While one can speculate about the reasoning behind this study's results, I was unable to directly measure the level of choice self-employed older Americans felt when pursuing their work, leaving this area ripe for future qualitative and quantitative work.

A major push into self-employment might be unemployment. While this dissertation did not consider the recession that began in 2008 in final analyses due to the small-but-present increase in unemployment among older workers (see Appendix B), other scholars have examined this relationship. Also using data from the HRS, researchers found the recession that began in 2008 predicted a higher likelihood of entering into self-employment from unemployment among older adults, but the recession that began in 2001 predicted a lower likelihood of entering into self-employment from unemployment (Biehl, Gurley-Calvez, & Hill, 2014). The authors cited the different length of the recessions, the industries affected, and the number of layoffs as potential explanations for this difference. Using the Survey of Income and Program Participation and considering Americans aged 16 and older, those who transitioned into self-employment during the recession were older, on average, as were those who remained self-employed (Beckhusen, 2014).

5.2.3 Examining the Aging Context

Most quantitative (Bönte, Falck, & Heblich, 2009; Weller et al., 2015; Xu & Ruef, 2004; Zissimopoulos & Karoly, 2009) and qualitative (Lewis & Walker, 2013; Maâlaoui et al., 2013; Platman, 2003) publications consider chronological age when discussing self-employment in later life. That is also true of this dissertation. However, it is likely that other concepts related to chronological age, such as perceived future time, are more predictive of self-employment motivations, experiences, and outcomes than chronological age itself (Halvorsen & Morrow-Howell, 2017). For example, Gielnik, Zacher, & Frese (2012) found that while chronological age was negatively associated with venture growth, a focus on opportunities in one's future work—a form of perceived future time—mediated this relationship.

Further, using "older adult" to constitute individuals aged 50 and older is incredibly broad. Even within cultures, this is a heterogeneous group of individuals who come from different generations and belong to different subgroups. It is important to understand the historical time from when individuals were born (e.g., birth cohorts, such as the baby boom generation) and enter into key moments (e.g., graduation, marriage, or having a child), as well as the changing age norms (Elder, 1975, 1994). For example, it is possible that women in the "younger old" category—those closer to 50—may be more likely to become self-employed than women of earlier generations when they were around 50, reflecting changes in culture and the workforce. Thus, new and sustained efforts that incorporate the life-span (Kanfer & Ackerman, 2004) and life course (Elder, 1975, 1994) perspectives, which are grounded in the fields of psychology and sociology, respectively, are needed to understand the heterogeneity of self-employed older adults and their trajectories. While this dissertation does not consider birth cohort, it does consider work and retirement status (an example of life stage).

5.2.4 Advances in Methodologies

Question 1 used multinomial logistic regression, with sandwich estimators to account for serial clustering, to estimate relations between individual characteristics and being self-employed, in wage-and-salary work, and not working at all. Currently, most published work uses descriptive statistics, such as cross-tabulations, to describe self-employment in an aging America and does not directly compare self-employed older workers to those who are in wage-and-salary work.

A major contribution of this study is its incorporation of inverse probability of treatment weighting—a form of propensity score analysis—to account for selection into self-employment for Question 2. This technique, along with its use of longitudinal data spanning six waves and 10 years, creates a quasi-experimental study. While many researchers have used results that include propensity score analysis to show causal relations, this family of methods controls only for *identified* and *measured* predictors of selection into a “treatment,” whereas a well-designed randomized control trial would theoretically control for *all* predictors of selection. Of course, it would not be ethical, nor plausible, to conduct such a study to estimate the overall treatment effects of self-employment in the general older population. Given the previous scholarship on self-employment in later life (e.g., Zissimopoulos & Karoly, 2007b, 2009), key predictors of movement into self-employment in older adults have been established that were used when estimating propensity scores. However, hidden selection bias likely remains an issue due to the omission of key variables that may be associated with becoming self-employed. For example, variables that measure the motivation to work, which may be different for older self-employed respondents compared to older wage-and-salary respondents, were not available in the dataset to be included in this study. Further, the variables included when creating the propensity score weights were from baseline in 2004; however, it is possible that measures of these variable prior to 2004 had a meaningful effect on self-employment. Given my use of doubly-robust estimation procedures and machine-learning techniques to create the propensity scores, which have both been shown to decrease bias in the estimation of treatment effects (Bang & Robins, 2005; Li et al., 2016; McCaffrey et al., 2004), my confidence in this study’s findings is increased.

This study estimates the effect of self-employment on personal health and physical well-being using a time-invariant treatment variable. To accomplish this, I excluded about 10% (*N*=734) of the sample working at baseline who transitioned from self-employment to wage-and-salary work, or vice versa, during the study’s time period. As such, the analyses in this dissertation consider only those who worked in one form of work at baseline and beyond, while allowing them to leave the workforce. However, there are methods that estimate treatment effects using time-varying treatment variables, which would have allowed me to keep these respondents in the analysis (e.g., Brand & Xie, 2006; Robins, Hernán, & Brumback, 2000). I aim to incorporate these methods in future work.

The incorporation of multiple imputation in this dissertation is an additional advancement to the field. Studies that use data from the HRS commonly use list-wise deletion or do not mention their handling of missing data at all. For example, in a search through the past two years in one of the highest-regarded academic journals in gerontology, *The Gerontologist*, I found that most studies using the HRS employed list-wise deletion, while many others did not discuss missing data or how they handled it at all. While list-wise deletion may not bias the results for certain research questions due to the high-response rate in the HRS, the high number of variables used in my models, combined with the higher amount of missing data for key work-related variables, might lead to heavily biased results. Therefore, the use of multiple imputation in this dissertation should increase one's confidence in the findings, especially when incorporating the work-related variables from Question 2.

Overall, this dissertation will build upon previous work, most notably Zissimopoulos and Karoly's (2007b, 2007a, 2009) publications, while contributing to discussions about the causal effects of later-life self-employment and program and policy developments to support longer working lives. Because of this study's large sample size, I was able to incorporate several methodologies that increase one's confidence in the results: sandwich estimators to account for serial correlation that require a large number of clusters (Angrist & Pischke, 2009), categorical variables during multiple imputation that can cause models to fail to converge from empty cells when there are not enough observations, and large, conceptually-driven models that include individual- and work-related variables to answer my research questions.

5.2.5 Examining the American Context

This dissertation also advances our knowledge of self-employment in later life in the American context. Although scholarship on this topic has benefited from detailed accounts of self-employment motivations through in-depth interviews, many of these studies were based in other highly-developed regions, including central Europe (e.g., Harms et al., 2014; Maâlaoui et al., 2013), the United Kingdom (e.g., Platman, 2003, 2004), Scandinavia (e.g., Kautonen, 2008), and New Zealand (e.g., Lewis & Walker, 2013). As such, this dissertation adds to the literature through its consideration of self-employment in the American context. In addition to further quantitative research using the HRS and other U.S.-based secondary datasets, such as the Current Population Survey, the Kauffman Firm Survey, and the Survey of Consumer Finances, future research should look to expand upon the rich qualitative evidence from Europe in the American context, covering the antecedents, experiences, and outcomes of this work.

5.3 Moving Forward

This dissertation provides direction for program developers and policymakers to create an environment that supports self-employment in later life, often promoted as a solution to financial insecurity in older adults. In short, the predictors of and outcomes from self-employment in later life paint a complicated picture, and program developers and advocates for self-employment in later life should pause after reading this dissertation's results. Yes, self-employment may increase an older adult's self-rated health, yet it is also clearly linked to reduced individual earnings and a lack of health insurance. Just who, then, are advocates advocating for? This dissertation shows that those who many benefit the most—or, perhaps, harmed the least—from self-employment in later life are those with stronger social and financial safety nets. Until more is known about the effects of later-life self-employment and how to increase positive outcomes, we, as a society, should be very careful in how and to whom we encourage this risky form of work. In short, it is not always a “step up” from working for someone else.

This dissertation sets the stage for my future research agenda. Already, I, along with Nancy Morrow-Howell, proposed several research propositions regarding the antecedents to, experiences during, and outcomes from self-employment in later life (Halvorsen & Morrow-Howell, 2017), with the conceptual framework proposed in that publication guiding this dissertation. Areas of interest include exploring later-life self-employment in relation to concepts like socioemotional selectivity theory and perceived future time (see Carstensen, 1995; Gielnik et al., 2012), generativity and legacy motivations (see Erikson, 1963), and the Big Five personality traits (see Brandstätter, 2011). These remain interesting to me and are areas where I would like to devote a portion of my future work.

Research that evaluates entrepreneurship training programs that are open to or designed for older adults is also of interest. There is a need to understand how these programs operate, if they serve clients better when they include age-specific or age-diverse cohorts, and ways they could encourage optimal financial, physical, and mental outcomes. Further, this dissertation showed that risk tolerant older adults are more likely to be self-employed and that risk tolerance had no relationship with the four outcome variables among older workers overall; however, future research might examine how risk tolerance moderates the relationship between antecedents and outcomes. If that is known and if the effect is strong, then program developers could implement screening questions to identify individuals who exhibit traits that have been shown to be more or less successful in self-employment and provide targeted information and assistance to suit their unique needs. A study of Americans aged 18 and older, for example, found that adults who were more risk tolerant benefitted more from an entrepreneurship training program, in terms of operating a business or having started a business in future points in time (Fairlie & Holleran, 2012). Depending on the motivations for moving into self-employment (e.g., business growth vs. continued income), programs might also highlight a different set of resources to meet their needs.

An immediate priority, however, is to examine the potential profiles of self-employed older adults and to document workplace-related characteristics that lead to better personal and financial outcomes among self-employed older adults. The development and success of programs and policies to increase positive outcomes from self-employment in later life may depend on having a good understanding of these profiles. For example, using the push/pull framework of self-employment motivations (Kautonen, 2008; Weller et al., 2018), the antecedents, experiences, and outcomes of those who feel pushed and pulled into this work may differ. To illustrate this concept, those with lower levels of socioeconomic status may be more likely to pursue self-employment as a means to continued income, whereas those with higher levels of socioeconomic status may be more likely to pursue self-employment to follow their passions.

More recent research has considered the role of self-employment as a bridge to retirement, where this form of work may provide supplemental or continued income and social engagement (Ramnath et al., 2017; Von Bonsdorff, Zhan, Song, & Wang, 2017). In a study using the HRS that included Americans who started receiving pension income as a proxy for retirement, income was negatively associated with moving into wage-and-salary work as a bridge relative to full retirement, and income was positively associated with moving into self-employment as a bridge relative to full retirement. Further, income was positively associated with moving into self-employment as a bridge relative to moving into wage-and-salary work as a bridge (Von

Bonsdorff et al., 2017). Research using the HRS has also documented that older adults who moved into self-employment as a bridge job during the recession were healthier, on average, than those who did not (Cahill et al., 2013). To illustrate this concept, those who pursue self-employment as a bridge to retirement may see it as a way to earn supplemental income, perhaps in combination with existing retirement benefits, while opening new time to pursue family and leisure time outside of work.

Some combination of the push/pull factors and whether the self-employment is acting as a bridge to retirement, along with individual characteristics like sociodemographic factors, risk tolerance, and human, social, and financial capital, may relate to key subgroups of self-employed older adults. So, too, may the duration of the self-employment and the stability of that duration. For example, a recent study using Current Population Survey data found that artists are not only more likely to move into self-employment, but they are also more likely to quickly move out of self-employment, than non-artist professionals (Woronkowicz & Noonan, 2017). The authors called this type of movement *churning*.

Moving forward, I will also explore different ways to operationalize key concepts used in this research. Social capital, for example, has generally been operationalized as individual-level factors, such as being married or volunteering, in the literature on productive engagement in later life (Gonzales & Nowell, 2016; McNamara & Gonzales, 2011). This differs from more community-driven factors that were long established in the sociological literature, such as trust and social structures (Coleman, 1988; N. Morrow-Howell & Greenfield, 2016). Depending on my data source, I also plan become more discerning in how self-employment is operationalized. In this dissertation, for example, it includes older adults who say they work for themselves. However, self-employment can be defined in a variety of ways and, in major sense, may be too broad of a category. My future work might consider occupation, industry, revenues, number of employees, incorporation status of the businesses, and preceding labor force status as just a few ways that the broad category of self-employment could be divided into narrower groups. Or, through primary data collection, I might group the self-employed by how they see their work: as a business with wealth accumulation as the primary goal, as a job with continued income as the primary goal, or something else entirely. Key outcomes of interest may differ as a result.

Future research should also take into consideration important contextual factors, such as family, community, societal, and economic characteristics. Two individuals who otherwise share identical characteristics might be driven into different forms of work and experience different outcomes due to these factors (Halvorsen & Morrow-Howell, 2017). Indeed, the effects of business cycles; governmental policies toward pensions, health care, and other safety net programs; tax policies; and access to information and assistance—including lines of credit, should be considered when assessing movement into, experiences in, and outcomes from self-employment in later life. These are areas not deeply considered for this dissertation study but that are still important.

As a social work scholar, however, I remain committed to scholarship that promotes a more equitable society. As such, I seek to undertake work that not only makes it easier for older adults with fewer resources to pursue self-employment if and when they choose, but also to improve outcomes—whether they be financial, social, or physical—from this work. It is imperative that my future work combines analysis of the strong secondary datasets that already exist with mixed-methods primary studies that include both self-employed older adults and those who have chosen not to pursue self-employment by choice or a perceived or real lack of opportunity. Through this scholarship, my long-term scholarly agenda aims to reduce disparities by increasing economic and social engagement opportunities in later life, especially for those who need them the most.

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Appendix A: “Treatment” Condition Options

The inverse probability of treatment weighting used to answer Question 2 requires a binary and time-invariant “treatment” variable. Six possible sampling strategies to create this variable are outlined below. As described in Section 3.1.2, I employed Strategy 1B, which maximizes the amount of information used in the study while taking a conservative stance by not allowing the type of work (i.e., self-employed or wage-and-salary) to vary over time.

Strategy 1. Include those who were *either* self-employed *or* in wage-and-salary work 100% of the time:

- **A)** During *each* of the six waves. Respondents who switched to the other category of work (i.e., self-employed to wage-and-salary, or vice versa), retired or stopped working for other reasons, died or moved to an institutional setting, or did not respond to a subsequent wave(s) would be excluded. This most-conservative sampling strategy would utilize data from approximately 21% of respondents (5% self-employed and 16% wage-and-salary).
- **B)** **CHOSEN STRATEGY**. During all waves *with reported work*. Respondents who reported working during three waves, for example, would be included in this variable if they were in the same type of work all three times. This would also be true for those reporting working during only one wave (baseline) or up to the six maximum waves. This sampling strategy would utilize 90% of respondents (19% self-employed and 71% wage-and-salary).

Strategy 2. Include those who were in one form of work at least 80% of the time:

- **A)** Working in one type of work for *at least five out of the six waves*. This sampling strategy would utilize 34% of respondents (8% self-employed and 26% wage-and-salary).
- **B)** During all waves *with reported work*. This would include those who were in one type of work at least five out of six waves of reported work, four out of five waves, or in all waves if three or fewer were completed. This sampling strategy would utilize 92% of respondents (20% self-employed and 72% wage-and-salary).

Strategy 3. Include those who were in one form of work at least 60% of the time:

- **A)** Working in one type of work for *at least four out of the six waves*. This sampling strategy would utilize 46% of respondents (11% self-employed and 36% wage-and-salary).
- **B)** During all waves *with reported work*. This would include those who were in one type of work at least four out of six waves of reported work, three out of four or five waves, two out of three waves, or 100% of the time if work was reported for only one or two waves. This least-conservative sampling strategy would utilize 98% of respondents (23% self-employed and 75% wage-and-salary).

Appendix B: Descriptive Statistics

Table 5. Descriptive Statistics by Wave, 2004 to 2014

Variable	**2004**	**2006**	**2008**	**2010**	**2012**	**2014**	**% Missing**[a]
	M (SD) or *%* *N*=6,473[b]	*M (SD)* or *%* *N*=5,913[b]	*M (SD)* or *%* *N*=5,703[b]	*M (SD)* or *%* *N*=5,431[b]	*M (SD)* or *%* *N*=5,159[b]	*M (SD)* or *%* *N*=4,820[b]	*Baseline (Max)*
Demographics							
Age	60.51 (7.67)	62.57 (7.63)	64.45 (7.58)	66.57 (7.51)	68.22 (7.30)	69.83 (7.08)	0.0% (9.2%)
Age, by group							
50-59	50.2%	42.0%	33.2%	20.4%	9.3%	0.5%	
60-69	36.8%	39.4%	42.2%	45.5%	49.7%	52.4%	
70-79	11.3%	15.9%	20.6%	28.2%	33.5%	37.2%	
80+	1.7%	2.7%	4.0%	5.9%	7.5%	10.0%	
Female	51.7%	51.9%	52.2%	52.7%	53.5%	54.1%	0.0%
Race							0.0%
White	79.7%	79.8%	79.8%	79.8%	79.7%	79.4%	
Black	14.2%	14.2%	14.2%	14.2%	14.1%	14.2%	
Another race	6.1%	6.1%	6.1%	6.1%	6.2%	6.4%	
Hispanic	8.8%	8.8%	8.8%	8.9%	9.0%	9.2%	0.0%
Veteran	22.4%	22.2%	22.0%	21.6%	20.9%	20.3%	0.2%
Human capital							
Education	13.20 (2.96)	13.20 (2.95)	13.22 (2.94)	13.24 (2.92)	13.25 (2.92)	13.26 (2.93)	0.3%
Self-reported health[c]	2.52 (0.96)	2.48 (0.95)	2.37 (0.94)	2.40 (0.92)	2.35 (0.92)	2.28 (0.91)	0.0% (9.2%)
Depression (CESD score)	1.09 (1.68)	1.20 (1.80)	1.14 (1.77)	1.11 (1.74)	1.13 (1.75)	1.14 (1.79)	7.6% (12.8%)
Health problem limiting work	14.5%	15.1%	18.3%	23.5%	26.4%	30.5%	0.5% (11.3%)
Health insurance from…							
federal government	30.6%	39.0%	47.5%	56.4%	63.2%	73.0%	0.3% (9.6%)
employer	55.9%	50.7%	44.8%	39.3%	34.2%	29.6%	0.5% (10.3%)
spouse's employer	17.1%	15.6%	14.6%	12.8%	11.8%	11.5%	0.4% (10.2%)
Social capital							
Married/partnered	74.1%	73.0%	71.5%	69.6%	67.6%	65.8%	0.1% (9.2%)
Spouse in paid work[d]	63.6%	58.4%	53.4%	46.1%	41.7%	36.9%	2.5% (11.7%)
People living in household	2.39 (1.19)	2.31 (1.18)	2.25 (1.11)	2.23 (1.15)	2.18 (1.16)	2.14 (1.12)	0.0% (9.2%)

Variable	2004	2006	2008	2010	2012	2014	% Missing[a]
	M (SD) or *%* *N*=6,473[b]	*M (SD)* or *%* *N*=5,913[b]	*M (SD)* or *%* *N*=5,703[b]	*M (SD)* or *%* *N*=5,431[b]	*M (SD)* or *%* *N*=5,159[b]	*M (SD)* or *%* *N*=4,820[b]	*Baseline (Max)*
Formal volunteering							0.2% (9.3%)
None	62.3%	61.5%	62.7%	59.6%	62.1%	62.0%	
<100 hours/year	21.4%	21.8%	22.1%	24.9%	23.1%	21.8%	
100+ hours/year	16.3%	16.7%	15.3%	15.5%	14.9%	16.2%	
Informal volunteering							0.4% (9.4%)
None	38.9%	39.0%	41.5%	40.6%	44.5%	46.6%	
<100 hours/year	43.8%	42.4%	43.7%	44.6%	42.8%	40.8%	
100+ hours/year	17.3%	18.6%	14.9%	14.9%	12.8%	12.7%	
Financial capital							
Individual earnings[e]	$32,575 (49,844)	$31,697 (95,762)	$28,514 (51,518)	$23,499 (41,056)	$20,527 (45,341)	$18,277 (41,521)	0.0% (9.2%)
Total household income[f]	$89,081 (130,686)	$96,070 (405,314)	$87,430 (129,988)	$78,828 (102,240)	$79,776 (124,140)	$83,551 (153,497)	0.0% (9.2%)
Total household wealth[g]	$483,083 (1,268,024)	$576,207 (1,289,771)	$579,923 (1,376,257)	$533,884 (1,322,156)	$538,261 (1,331,160)	$585,814 (1,285,124)	0.0% (9.2%)
Receiving Social Security	30.8%	39.6%	47.4%	55.9%	62.9%	71.3%	0.0% (9.2%)
Receiving any pension income	15.1%	17.7%	20.5%	20.8%	29.6%	33.3%	1.1% (10.4%)
Work characteristics							
Working	100%	79.1%	68.5%	56.0%	48.0%	40.5%	0.0% (9.2%)
Self-employed[h]	21.4%	20.0%	20.5%	21.7%	21.7%	22.9%	0.0% (9.2%)
Labor force status							0.0% (9.2%)
Full-time work	65.0%	52.8%	45.4%	34.6%	28.7%	22.5%	
Part-time work	13.8%	10.2%	8.5%	7.1%	5.7%	4.7%	
Partly retired	21.3%	16.6%	14.7%	14.4%	13.7%	13.3%	
Fully retired	0.0%	16.5%	26.3%	37.8%	47.6%	56.5%	
Unemployed	0.0%	1.7%	2.4%	4.0%	2.4%	1.5%	
Disabled	0.0%	0.7%	0.9%	0.8%	0.6%	0.5%	
Otherwise not in labor force	0.0%	1.5%	1.8%	1.3%	1.4%	1.0%	
Years at current job[h]	12.2 (11.9)	13.8 (12.1)	14.4 (12.3)	15.2 (12.5)	15.5 (12.9)	15.9 (13.2)	2.3% (9.7%)
Blue collar occupation[h,i]	43.0%	40.5%	40.7%	40.1%	38.4%	36.9%	37.8% (37.8%)
Goods producing industry[h,j]	22.5%	21.5%	18.5%	17.5%	16.9%	16.3%	41.7% (41.7%)
Work alone[g,k]	12.4%	10.0%	9.4%	9.4%	8.5%	8.4%	14.6% (17.7%)
35+ hours worked per week[h]	61.6%	62.5%	61.5%	57.4%	56.5%	52.7%	4.00% (11.1%)

Variable	2004	2006	2008	2010	2012	2014	% Missing[a]
	M (SD) or *%* *N*=6,473[b]	*M (SD)* or *%* *N*=5,913[b]	*M (SD)* or *%* *N*=5,703[b]	*M (SD)* or *%* *N*=5,431[b]	*M (SD)* or *%* *N*=5,159[b]	*M (SD)* or *%* *N*=4,820[b]	*Baseline (Max)*
Job requires…[h]							
lots of physical effort	2.17 (1.12)	2.14 (1.10)	2.13 (1.09)	2.10 (1.08)	2.08 (1.07)	2.07 (1.07)	5.2% (10.4%)
lifting heavy loads	1.61 (0.93)	1.60 (0.92)	1.61 (0.91)	1.60 (0.89)	1.56 (0.86)	1.54 (0.84)	5.2% (11.8%)
stooping, kneeling, crouching	2.01 (1.07)	2.00 (1.06)	2.00 (1.05)	1.96 (1.03)	1.93 (1.02)	1.94 (1.02)	5.2% (11.0%)
good eyesight	3.51 (0.80)	3.55 (0.76)	3.56 (0.76)	3.54 (0.76)	3.54 (0.75)	3.55 (0.76)	5.2% (10.2%)
Job involves lots of stress[h]	2.65 (0.85)	2.67 (0.85)	2.67 (0.84)	2.59 (0.86)	2.59 (0.85)	2.56 (0.83)	4.8% (10.0%)
Risk tolerance[l]	2.30 (1.48)	2.30 (1.48)	2.30 (1.48)	2.30 (1.48)	2.29 (1.48)	2.29 (1.48)	44.1%
Pension from current job[h]	47.7%	49.5%	50.5%	47.0%	51.3%	49.8%	0.7% (9.7%)
Respondent status							
Proxy response	7.4%	4.9%	4.2%	4.8%	4.0%	3.9%	0.0% (9.2%)
Respondent status (all N=6,473)							
Responded to survey	100.0% (6,473)	91.4% (5,913)	88.1% (5,701)	83.9% (5,432)	79.7% (5,159)	74.5% (4,820)	
Nonresponsive, presumed alive[m]	0.0%	7.0% (455)	8.0% (518)	8.7% (564)	8.7% (566)	9.2% (595)	
Died since last wave	0.0%	1.5% (99)	2.0% (130)	3.2% (209)	2.8% (180)	3.2% (203)	
Total attrition since 2004[n]	0.0%	1.6% (105)	3.9% (252)	7.4% (478)	11.6% (748)	16.3% (1,058)	

Notes: See Appendix A for how this final sample was created, and Appendix C for details on each variable.

[a] Baseline percentages are out of the original sample (*N*=6,473), with maximum percent missing in any of the six waves considering those who were still alive or presumed alive during that wave. Time-invariant variables list only baseline percent missing.

[b] Sample size each wave includes the original sample (*N*=6,473) minus individuals who did not respond to that wave or were otherwise dropped from the sample due to death, by request, or other reasons.

[c] Ranging from 1 (poor/fair health) to 4 (excellent health).

[d] Asked only of those who were married.

[e] Includes individual income from wages/salary, bonuses/overtime pay/commissions/tips, second job, military reserve earnings, professional practice, or trade income.

[f] Includes all income from respondents and spouses, if applicable, but no one else living in the household.

[g] Includes the net value of total wealth (assets minus debts), including a second home, for the household.

[h] Asked only of those in the labor force.

[i] Occupation categories are white collar and blue collar.

[j] Industry categories are service producing and goods producing.

[k] Self-employed were asked how many people work for their business, including themselves. Wage-and-salary employees were asked how many people work at their work location.

[l] Asked only of those younger than 65 with 10 exceptions. Range of 1 (least risk tolerant) to 6 (most risk tolerant).

[m] Includes those who did not respond to the survey, as well as those who did not report a working status.

[n] Cumulative total of all deaths and respondents dropped from the sample by request or other reasons since 2004. This does not necessarily include all those who were nonresponsive in each wave—only those who were dropped from the sample altogether due to death, by request, or other reasons.

Appendix C: Variable Descriptions

All data from this dissertation were derived from the RAND HRS (v.P) data file and the RAND Enhanced HRS Fat Files, with the sample consisting of respondents who were working for pay in 2004 in wage-and-salary work or self-employment. Variables from six consecutive waves of the HRS were used, from 2004 to 2014 (waves 7 through 12). Not all variables listed here were used in final analysis; however, they were used during sample creation or multiple imputation, or to gain a better understanding the sample.

Table 6. Variable Names and Descriptions

Variable name	Time variant	Notes
		Sample characteristics
rahhidpn		Individual identifier
hhid		Household identifier
riwstat	X	Response and mortality status
rfamr	X	Primary respondent for family-related questions
rfinr	X	Primary respondent for financial-related questions
rwtresp	X	Person-level weight, structured to match the makeup of the older American population as found by the Current Population Survey
wave	X	Wave number (7-12)
		Outcome variables
rwork	X	Question 1: Three-category variable that includes those who are self-employed, in wage-and-salary work, and not working
rshltRC	X	Question 2: Self-rated health, ordinal, also a covariate
rcesd	X	Question 2: Depressive symptoms, count, also a covariate (CESD-8 score)
riearntrans	X	Question 2: Individual earnings, including wage/salary income, bonuses/overtime pay/commissions/tips, second job or military reserve earnings, and professional practice or trade income; continuous, inverse hyperbolic sine (IHS) transformation, also a covariate
hatotbtrans	X	Question 2: Total household wealth, including housing wealth, minus all debts; continuous, IHS transformation, also a covariate
		Control variables
radeath		Death during the study's timeframe
raattrition		Non-response at some point during the study's timeframe
rproxy	X	Interview conducted by proxy
		Demographics
ragey_b	X	Age at interview in years
ragender		Gender, binary
raracem		Race, categorical (white/Caucasian, black/African American, another race)
rahispan		Hispanic, binary
ravetrn		Veteran status, binary
rariskT		Risk tolerance, ordinal (1=least risk tolerant, 6=most risk tolerant)
		Human capital
raedyrs		Education (in years), continuous
rshltRC	X	Self-rated health, ordinal, also an outcome variable
rhlthlm	X	Health problem limited kind or amount of paid work, binary
rhigov	X	Health insurance from federal government, including Medicare, Medicaid, VA, etc.; binary
rcovr	X	Health insurance from current or former employer, binary
rcovs	X	Health insurance from spouse's employer, binary
rinsured	X	Combined indicator for having health insurance; binary

Variable name	Time variant	Notes
		Social capital
rmarried	X	Married or partnered, binary
hhhres	X	Number of people living in household, count
swork	X	Spouse in paid work, binary
rfvol	X	Formal volunteering in past year, categorical (none, <100 hours, 100+ hours)
rivol	X	Informal volunteering in past year, categorical (none, <100 hours, 100+ hours)
		Financial capital
riearntrans	X	Individual earnings, including wage/salary income, bonuses/overtime pay/commissions/tips, second job or military reserve earnings, and professional practice or trade income; continuous, IHS transformation, also an outcome variable
hitotrtrans	X	Total income from respondent and spouse, minus individual earnings from work from respondent; continuous, IHS transformation
hatotbtrans	X	Total household wealth, including housing wealth, minus all debts; continuous, IHS transformation, also an outcome variable
rss	X	Receiving Social Security retirement benefits, binary
rpeninc	X	Receiving pension income but not considering spousal pensions, binary
		Work characteristics
rlaborR	X	Labor force status, categorical (full-time, part-time or partly retired, fully retired, unemployed or otherwise not working)
rhours	X	Hours worked/week/year, categorical (<35/week, 35+/week, not working)
rjcten	X	Years of tenure in current job, continuous (not working = 0)
rfsizeC	X	Number of employees at work location, including self, categorical (1, 2 or more, not working = 0)
rjcpen	X	Pension plan from current job, categorical (no, yes, not working)
rjphys	X	Current job requires lots of physical effort, ordinal (none/almost none of the time = 1, all/almost all the time = 4, not working = 0)
rjlift	X	Current job requires lifting heavy loads, ordinal (none/almost none of the time = 1, all/almost all the time = 4, not working = 0)
rjstoop	X	Current job requires stooping, kneeling, or crouching; ordinal (none/almost none of the time = 1, all/almost all the time = 4, not working = 0)
rjsight	X	Current job requires good eyesight, ordinal (none/almost none of the time = 1, all/almost all the time = 4, not working = 0)
rjstres	X	Current job involves lots of stress, ordinal (strongly agree = 1, strongly disagree = 4, not working = 0)
rbluecollar	X	Occupation, categorical (blue collar, white collar, and not working); reduced from 25 codes following Cahill, Giandrea, & Quinn (2011)
rgoodsindustry	X	Industry, categorical (goods producing, service producing, not working); reduced from 19 codes following Kail & Warner (2013) and Bureau of labor Statistics (2016)

Appendix D: Bivariate Statistics

Table 7. Baseline Associations Between Type of Work and Outcome Variables

Variables	***Wage-and-Salary*** *M(SD) or row %*	***Self-Employed*** *M(SD) or row %*	***p***
At baseline:	78.6% *n* = 5,090	21.4% *n* = 1,383	
Age	59.70 (7.22)	63.49 (8.51)	<0.001
Gender			
Female	84.70%	15.30%	
Male	72.15%	27.85%	<0.001
Race			
White	76.90%	23.10%	
Black	86.91%	13.09%	
Other races	81.98%	18.02%	<0.001
Ethnicity			
Hispanic	82.63%	17.37%	
Not Hispanic	78.24%	21.76%	0.015
Veteran status			
Veteran	70.76%	29.24%	
Not a veteran	80.91%	19.09%	<0.001
Risk tolerance	2.23 (1.43)	2.69 (1.70)	<0.001
Health, self-reported	2.50 (0.96)	2.58 (0.98)	0.006
Depressive symptoms	1.11 (1.71)	1.02 (1.58)	0.071
Education, in years	13.14 (2.93)	13.42 (3.06)	0.002
Health problems limiting work			
Yes	80.79%	19.21%	
No	62.62%	37.38%	<0.001
Has health insurance from any source			
Yes	80.79%	19.21%	
No	62.62%	37.38%	<0.001
… from the government (e.g., Medicare)			
Yes	68.14%	31.86%	
No	83.35%	16.65%	<0.001
…from workplace			
Yes	89.02%	10.98%	
No	65.54%	34.46%	<0.001
…from spouse			
Yes	73.25%	26.75%	
No (including not married)	79.75%	20.25%	<0.001
Spouse's work status (not working)			
Not working for pay	77.15%	22.85%	
Working for pay	76.79%	23.21%	
Not married	83.21%	16.79%	<0.001
Household members	2.43 (1.23)	2.27 (1.00)	<0.001
Formal volunteering, past year			
None	80.54%	19.46%	
<100 hours	78.02%	21.98%	
100+ hours	72.58%	27.42%	<0.001
Informal volunteering, past year			
None	81.84%	18.16%	
<100 hours	76.75%	23.25%	
100+ hours	76.63%	23.37%	<0.001
Individual earnings	$37,039 (41,550)	$ 16,147 (70,242)	<0.001
Household wealth	$337,151 (681,353)	$1,020,173 (2,335,214)	<0.001
Household income, less individual earnings	$41,732 (73,249)	$110,879 (201,091)	<0.001

Variables	*Wage-and-Salary* M(SD) or row %	*Self-Employed* M(SD) or row %	*p*
Currently receiving			
…Social Security retirement benefits			
Yes	67.29%	32.71%	
No	83.68%	16.32%	<0.001
…pension income			
Yes	75.58%	24.15%	
No	79.07%	20.93%	<0.001
Labor force status[a]			
Full-time	83.94%	16.06%	
Part-time or partly retired	68.80%	31.20%	<0.001
Job requires…			
lots of physical effort	2.16 (1.12)	2.19 (1.14)	0.453
lifting heavy loads	1.61 (0.94)	1.62 (0.93)	0.790
stooping, kneeling, crouching	2.01 (1.07)	2.00 (1.08)	0.744
good eyesight	3.54 (0.78)	3.41 (0.87)	<0.001
Job involves lots of stress	2.68 (0.84)	2.51 (0.84)	<0.001
Years at current job	11.86 (11.09)	13.59 (14.28)	<0.001
Work colleagues/employees			
Work alone[b]	15.11%	84.89%	
Work with others	85.57%	14.43%	<0.001
Hours worked per week			
35+	70.49%	29.51%	
<35	84.68%	15.32%	<0.001
Pension plan in current job			
Yes	95.54%	4.46%	
No	63.14%	36.86%	<0.001
Occupation			
Blue collar	69.40%	30.60%	
White collar	63.21%	36.79%	<0.001
Industry			
Goods producing	60.07%	39.93%	
Service producing	64.83%	35.17%	0.011
Dies during the study			
Yes	70.28%	29.72%	
No	79.85%	20.15%	<0.001
Nonresponse during the study			
Yes	76.74%	23.26%	
No	79.16%	20.84%	0.050
Proxy respondent			
Yes	70.65%	29.35%	
No	79.27%	20.73%	<0.001

Notes: N=6,473, not accounting for missing data. Row percentages shown. *t* tests were run for continuous dependent variables and χ^2 tests were run for nominal dependent variables.
a. Because this sample only includes respondents working at baseline, respondents did not report being unemployed, disabled, or otherwise not working; however, some moved into these categories in future waves. See Appendix B for those descriptive statistics. **b.** Respondents were asked how many people worked at their organization's location, not at the entire company.

Appendix E: Propensity Score Balancing Check

Table 5, below, lists results from a set of bivariate models between each covariate used to create the inverse probability of treatment weights and the "treatment" indicator (i.e., wage-and-salary work or self-employment). The pre-IPTW column is unbalanced; that is, it includes only the sampling weights provided by the HRS. The remaining models consider "grand" weights that are a product of the sampling weights and inverse probability of treatment weights created to analyze the average treatment effect (ATE) using generalized boosted modeling and logistic regression, respectively; and the average treatment effect for the treated (ATT) using generalized boosted modeling and logistic regression, respectively. Results are discussed in Chapter 3.

Table 8. Covariate Imbalance Before and After Inverse Probability of Treatment Weighting

	Pre-IPTW		*GBM ATE[a]*		*Logit ATE[b]*		*GBM ATT[a]*		*Logit ATT[b]*	
	b (Robust SE)		*b (Robust SE)*		*b (Robust SE)*		*b (Robust SE)*		*b (Robust SE)*	
Age	3.19***	(0.27)	0.59*	(0.29)	-0.25	(0.36)	-0.42	(0.38)	-0.45	(0.73)
Female (male)	-0.69***	(0.07)	-0.09	(0.10)	0.18	(0.11)	-0.15	(0.08)	0.37	(0.20)
Race (white)										
Black	-0.75***	(0.13)	-0.24	(0.17)	-0.29	(0.24)	-0.22	(0.15)	-0.71	(0.69)
Other races	-0.21	(0.16)	0.03	(0.23)	0.35	(0.24)	-0.05	(0.19)	0.37	(0.23)
Hispanic (not)	-0.21	(0.14)	-0.02	(0.17)	0.33	(0.17)	-0.09	(0.15)	0.32	(0.21)
Veteran (not)	0.37***	(0.08)	0.06	(0.12)	-0.09	(0.15)	-0.07	(0.10)	-0.22	(0.32)
Risk tolerance	0.41***	(0.08)	0.08	(0.07)	-0.03	(0.11)	0.11	(0.09)	-0.11	(0.30)
Self-reported health	0.09*	(0.04)	0.07	(0.05)	-0.04	(0.06)	0.02	(0.04)	-0.05	(0.10)
4+ depressive symptoms (<4)	-0.28*	(0.14)	-0.39*	(0.17)	-0.12	(0.17)	-0.04	(0.16)	0.15	(0.31)
Education, in years	0.28**	(0.10)	0.01	(0.12)	-0.41*	(0.16)	-0.03	(0.12)	-0.76**	(0.26)
Has health insurance (does not)	-1.11***	(0.10)	-0.25*	(0.12)	-0.13	(0.12)	-0.24*	(0.12)	-0.41*	(0.20)
Married or partnered (not)	0.31***	(0.09)	0.20	(0.13)	-0.01	(0.13)	0.00	(0.11)	-0.36	(0.21)
Household income[d]	0.22***	(0.05)	0.03	(0.04)	-0.23*	(0.09)	0.05	(0.07)	-0.43	(0.22)
Household wealth[d]	1.39***	(0.16)	0.56***	(0.15)	0.15	(0.26)	0.09	(0.17)	-0.84	(0.43)
Part-time worker (full-time)	0.91***	(0.07)	0.28**	(0.09)	0.21	(0.12)	-0.06	(0.09)	0.17	(0.26)
Proxy respondent (not)	0.45***	(0.13)	0.21	(0.18)	0.14	(0.17)	0.26	(0.14)	0.40	(0.22)
N	6,391		6,391		6,391		6,391		6,391	

Notes: OLS, logistic, and multinomial logistic regression analyses were used, depending on the outcome variable. Data are from the 2004 (baseline) wave of the HRS. ATE = average treatment effect where weight is $1/P$ for a "treated" case and $1/(1 - P)$ for a comparison case. ATT = average treatment effect for the treated where weight is 1 for a "treated" case and $P(1 - P)$ for a comparison case. P is predicted using **a.** generalized boosted modeling from the RAND *twang* Stata macro, and **b.** logistic regression; **d.** Transformed using the inverse hyperbolic sine function. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, two-tailed tests.

Appendix F: Alternative Outcome Models

The following pages contain a set of models that act as a form of sensitivity analysis for Question 2. Within each table, the first model considers the sampling weights provided by the HRS, while the final three models consider "grand" weights that are a product of the sampling weights and inverse probability of treatment weights created to analyze the average treatment effect (ATE) using logistic regression, the average treatment effect for the treated (ATT) using generalized boosted modeling, and the ATT using logistic regression, respectively. Differences in key findings are discussed in Chapter 4.

Table 9. Estimated Effect of Self-Employment on Self-Rated Health, Supplemental Models

	Sample Weights Only			*Logit ATE Estimation[a]*			*GBM ATT Estimation[b]*			*Logit ATT Estimation[a]*		
	exp(b)	*Robust SE[c]*	*t*	*exp(b)*	*Robust SE[c]*	*t*	*exp(b)*	*Robust SE[c]*	*t*	*exp(b)*	*Robust SE[c]*	*t*
Weighted estimation only												
Self-employment (wage-and-salary)	1.22**	(0.08)	3.24	1.09	(0.11)	0.84	1.07	(0.08)	0.87	1.02	(0.23)	0.09
Doubly-robust estimation												
Self-employment (wage-and-salary)	1.12*	(0.05)	2.45	1.11	(0.09)	1.30	1.00	(0.06)	-0.06	0.97	(0.11)	-0.27
Age	0.99**	(0.00)	-4.99	0.98**	(0.00)	-4.80	0.98**	(0.01)	-3.17	0.97**	(0.01)	-3.17
Female (male)	1.19**	(0.05)	4.37	1.27**	(0.10)	3.05	1.25**	(0.07)	3.75	1.30*	(0.14)	2.37
Race (white)												
Black	0.76**	(0.03)	-6.03	0.69**	(0.06)	-4.02	0.77**	(0.05)	-3.95	0.54**	(0.11)	-3.02
Other races	0.88	(0.07)	-1.68	1.27	(0.22)	1.35	1.04	(0.12)	0.31	1.08	(0.13)	0.66
Hispanic	0.84*	(0.06)	-2.54	0.67**	(0.10)	-2.71	0.70**	(0.07)	-3.51	0.59**	(0.08)	-4.09
Veteran	1.09	(0.05)	1.85	1.11	(0.08)	1.33	1.22**	(0.08)	3.24	1.11	(0.12)	0.97
Risk tolerance	1.01	(0.01)	0.92	0.98	(0.02)	-0.88	1.01	(0.02)	0.58	0.96	(0.03)	-1.17
Self-rated health, lagged	5.14**	(0.16)	54.07	5.21**	(0.30)	28.30	4.78**	(0.21)	35.87	5.28**	(0.50)	17.72
Depressive symptoms	0.81**	(0.01)	-19.18	0.80**	(0.02)	-11.04	0.80**	(0.01)	-12.76	0.74**	(0.04)	-5.12
Education, in years	1.07**	(0.01)	9.84	1.07**	(0.01)	5.69	1.06**	(0.01)	6.05	1.06**	(0.02)	4.15
Health problems limiting work	0.34**	(0.01)	-24.88	0.31**	(0.02)	-16.59	0.29**	(0.02)	-18.71	0.30**	(0.04)	-9.71
Has health insurance (does not)	0.97	(0.05)	-0.58	0.97	(0.09)	-0.35	0.96	(0.08)	-0.44	1.14	(0.14)	1.02
Spouse's work status (not working)												
Working	1.04	(0.04)	1.14	0.98	(0.07)	-0.28	0.97	(0.05)	-0.57	0.84	(0.11)	-1.32
Not married	1.01	(0.04)	0.23	0.89	(0.06)	-1.63	0.88*	(0.06)	-1.99	0.81	(0.09)	-1.86
Household members	0.95**	(0.01)	-3.49	0.92**	(0.02)	-3.70	0.93**	(0.02)	-3.15	0.90**	(0.04)	-2.62
Formal volunteering, past year (none)												
<100 hours	1.13**	(0.04)	3.48	1.04	(0.06)	0.56	1.10	(0.06)	1.76	0.91	(0.12)	-0.76
100+ hours	1.19**	(0.05)	3.97	1.09	(0.09)	1.12	1.20**	(0.08)	2.74	0.98	(0.11)	-0.20
Informal volunteering, past year (none)												
<100 hours	1.12**	(0.04)	3.26	1.07	(0.06)	1.12	1.10	(0.05)	1.86	0.98	(0.11)	-0.15
100+ hours	1.21**	(0.06)	4.18	1.21*	(0.09)	2.51	1.19*	(0.08)	2.57	1.31	(0.20)	1.78
Individual earnings[d]	1.00	(0.00)	0.05	1.00	(0.01)	0.21	0.99	(0.01)	-1.42	1.01	(0.01)	0.90
Household wealth[d]	1.01	(0.01)	1.44	1.01	(0.01)	0.90	1.01	(0.01)	0.88	1.01	(0.02)	0.57
Household income, less individual earnings[d]	1.01**	(0.00)	4.13	1.01**	(0.00)	2.93	1.01*	(0.00)	2.26	1.01	(0.01)	1.94
Currently receiving:												
Social Security retirement benefits	1.08	(0.05)	1.78	1.03	(0.08)	0.41	1.08	(0.08)	1.00	0.83	(0.12)	-1.32
Receiving pension income	1.05	(0.04)	1.47	1.08	(0.06)	1.27	1.04	(0.05)	0.70	1.20	(0.15)	1.43
Labor force status (full-time)												
Part-time or partly retired	0.86	(0.08)	-1.74	0.89	(0.12)	-0.84	0.73*	(0.10)	-2.24	0.68*	(0.10)	-2.53
Fully retired	0.67	(0.21)	-1.29	0.46*	(0.15)	-2.35	0.44**	(0.13)	-2.70	0.43*	(0.15)	-2.38
Unemployed or otherwise not working	0.67	(0.22)	-1.22	0.47*	(0.16)	-2.23	0.45*	(0.15)	-2.46	0.37*	(0.16)	-2.28

	Sample Weights Only			***Logit ATE Estimation***[a]			***GBM ATT Estimation***[b]			***Logit ATT Estimation***[a]		
	exp(b)	*Robust SE*[c]	*t*	*exp(b)*	*Robust SE*[c]	*t*	*exp(b)*	*Robust SE*[c]	*t*	*exp(b)*	*Robust SE*[c]	*t*
Job requires…												
lots of physical effort	0.99	(0.03)	-0.43	0.96	(0.04)	-1.05	0.99	(0.04)	-0.29	0.90*	(0.05)	-1.97
lifting heavy loads	1.05	(0.03)	1.57	1.11*	(0.05)	2.25	1.08	(0.05)	1.66	1.12*	(0.06)	2.02
stooping, kneeling, crouching	1.00	(0.03)	0.15	0.97	(0.04)	-0.81	1.02	(0.04)	0.55	1.02	(0.05)	0.32
good eyesight	1.03	(0.03)	1.23	0.99	(0.06)	-0.14	1.02	(0.04)	0.51	0.88	(0.12)	-0.95
Job involves lots of stress	0.92**	(0.02)	-3.48	0.93	(0.04)	-1.89	0.95	(0.03)	-1.39	0.86**	(0.05)	-2.63
Years at current job	1.00	(0.00)	0.24	1.00	(0.00)	-0.09	1.00	(0.00)	1.15	1.00	(0.00)	0.33
Number of employees (more than one)												
Work alone	1.03	(0.07)	0.42	1.15	(0.18)	0.88	1.04	(0.08)	0.46	1.61	(0.46)	1.69
Not working	1.28	(0.42)	0.76	1.62	(0.59)	1.33	1.78	(0.57)	1.80	0.77	(0.40)	-0.51
35+ hours worked per week (<35 hours)	0.92	(0.08)	-1.00	0.98	(0.14)	-0.14	0.78	(0.10)	-1.85	0.91	(0.15)	-0.54
Pension from current job	1.01	(0.05)	0.22	1.00	(0.10)	0.02	1.03	(0.07)	0.39	0.80	(0.22)	-0.81
Blue collar occupation (white collar)	1.01	(0.05)	0.21	0.99	(0.07)	-0.15	0.96	(0.06)	-0.55	0.95	(0.09)	-0.54
Goods producing industry (service producing)	1.00	(0.05)	-0.03	0.89	(0.09)	-1.20	0.93	(0.07)	-0.92	0.72*	(0.11)	-2.10
Controls												
Dies during the study	0.54**	(0.04)	-9.04	0.60**	(0.06)	-5.25	0.56**	(0.06)	-5.57	0.59**	(0.08)	-4.15
Nonresponse during the study	1.01	(0.05)	0.30	0.96	(0.07)	-0.56	0.98	(0.06)	-0.31	0.90	(0.09)	-1.11
Proxy respondent	0.80*	(0.07)	-2.53	0.77	(0.11)	-1.93	0.79*	(0.09)	-1.99	0.71*	(0.11)	-2.29
Thresholds:												
Fair/poor to ≥ good	3.86**	(1.10)	4.71	1.48	(0.73)	0.80	1.77	(0.89)	1.15	0.24	(0.24)	-1.41
≤ Good to ≥ very good	54.06**	(15.66)	13.78	22.76**	(10.83)	6.57	23.92**	(12.03)	6.31	4.73	(4.18)	1.76
≤ Very good to excellent	1,004.45**	(296.47)	23.42	417.30**	(201.40)	12.50	423.97**	(213.38)	12.02	90.54**	(79.76)	5.11
Intercept												
F test	(43, 860397) = 143.5, $p < 0.001$			(43, 160227) = 65.86, $p < 0.001$			(43, 309048) = 69.45, $p < 0.001$			(43, 26106) = 36.62, $p < 0.001$		
N[e]	26,696[f]			26,696[f]			26,502[g]			26,696[f]		

Notes: Data from a combined 6 waves of the HRS that include 6,473 individuals. Individual (m=20) estimates combined using Rubin's combination rules. ** $p < 0.01$, * $p < 0.05$, two-tailed tests. ATE = average treatment effect where weight is $1/P$ for a "treated" case and $1/(1 – P)$ for a comparison case. ATT = average treatment effect for the treated where weight is 1 for a "treated" case and $P(1 – P)$ for a comparison case. P is predicted using **a.** logistic regression, and **b.** generalized boosted modeling from the RAND *twang* Stata macro; **c.** Exponentiated robust standard errors are derived using the delta rule: exp(b)*se(b); **d.** Transformed using the inverse hyperbolic sine function; **e.** Sample sizes vary due to weighting differences; Within **f.** 5,027 and **g.** 5,045 households.

Table 10. Estimated Effect of Self-Employment on Depressive Symptoms, Supplemental Models

	Sample Weights Only			***Logit ATE Estimation[a]***			***GBM ATT Estimation[b]***			***Logit ATT Estimation[a]***		
	exp(b)	*Robust SE[c]*	*t*	*exp(b)*	*Robust SE[c]*	*t*	*exp(b)*	*Robust SE[c]*	*t*	*exp(b)*	*Robust SE[c]*	*t*
Weighted estimation only												
Self-employment (wage-and-salary)	1.00	(0.05)	0.02	1.15*	(0.08)	2.07	1.17**	(0.07)	2.67	1.28*	(0.16)	2.01
Doubly-robust estimation												
Self-employment (wage-and-salary)	1.05	(0.04)	1.41	1.07	(0.05)	1.43	1.04	(0.05)	0.79	1.19*	(0.09)	2.22
Age	0.99**	(0.00)	-3.36	0.99**	(0.00)	-3.19	0.99	(0.00)	-1.94	0.99	(0.01)	-1.80
Female (male)	1.15**	(0.04)	4.32	1.19**	(0.05)	3.88	1.16**	(0.05)	3.20	1.30**	(0.10)	3.40
Race (white)												
Black	0.97	(0.03)	-0.81	0.88	(0.07)	-1.54	0.97	(0.05)	-0.49	0.62	(0.16)	-1.90
Other races	1.05	(0.05)	0.96	1.02	(0.10)	0.26	1.16	(0.09)	1.94	1.21*	(0.10)	2.24
Hispanic	1.05	(0.05)	0.95	0.97	(0.07)	-0.49	0.92	(0.06)	-1.15	0.88	(0.07)	-1.56
Veteran	0.98	(0.04)	-0.41	0.97	(0.06)	-0.51	0.96	(0.05)	-0.75	0.99	(0.09)	-0.14
Risk tolerance	1.02	(0.01)	1.66	1.02	(0.02)	1.39	1.02	(0.01)	1.43	1.03	(0.02)	1.23
Self-rated health	0.73**	(0.01)	-20.24	0.71**	(0.02)	-12.01	0.71**	(0.02)	-14.70	0.64**	(0.04)	-6.75
Depressive symptoms, lagged	1.28**	(0.01)	38.18	1.28**	(0.01)	26.87	1.29**	(0.01)	26.69	1.27**	(0.03)	11.25
Education, in years	0.99	(0.01)	-1.79	0.99	(0.01)	-1.02	0.99	(0.01)	-1.55	0.99	(0.01)	-0.81
Health problems limiting work	1.36**	(0.04)	11.35	1.30**	(0.08)	4.17	1.32**	(0.06)	6.56	1.12	(0.19)	0.70
Has health insurance (does not)	0.92*	(0.03)	-2.24	0.89	(0.06)	-1.81	0.87*	(0.05)	-2.44	0.82**	(0.05)	-3.32
Spouse's work status (not working)												
Working	0.99	(0.03)	-0.27	0.93	(0.05)	-1.24	1.01	(0.05)	0.18	0.91	(0.07)	-1.22
Not married	1.20**	(0.04)	5.72	1.08	(0.06)	1.30	1.22**	(0.06)	4.09	1.14	(0.09)	1.58
Household members	1.01	(0.01)	1.31	1.00	(0.02)	-0.22	1.01	(0.02)	0.66	0.97	(0.04)	-0.68
Formal volunteering, past year (none)												
<100 hours	0.92**	(0.03)	-2.81	1.01	(0.07)	0.10	0.90*	(0.04)	-2.28	1.22	(0.20)	1.19
100+ hours	0.90**	(0.03)	-2.76	1.02	(0.07)	0.26	0.97	(0.05)	-0.62	1.12	(0.11)	1.17
Informal volunteering, past year (none)												
<100 hours	0.98	(0.02)	-0.90	0.98	(0.04)	-0.53	0.95	(0.03)	-1.53	1.00	(0.07)	-0.01
100+ hours	0.98	(0.03)	-0.56	0.95	(0.05)	-1.01	0.91	(0.05)	-1.83	0.84*	(0.06)	-2.42
Individual earnings[d]	1.00	(0.00)	-0.86	1.00	(0.01)	-0.52	1.00	(0.00)	-0.23	1.01	(0.01)	1.07
Household wealth[d]	0.99*	(0.00)	-2.40	0.98**	(0.01)	-2.91	0.98*	(0.01)	-2.21	0.98	(0.01)	-1.67
Household income, less individual earnings[d]	0.99**	(0.00)	-3.23	1.00	(0.00)	-1.45	1.00	(0.00)	-1.18	0.99	(0.00)	-1.69
Currently receiving:												
Social Security retirement benefits	1.04	(0.04)	1.25	1.16*	(0.07)	2.26	1.00	(0.05)	-0.07	1.28*	(0.15)	2.07
Receiving pension income	0.96	(0.03)	-1.50	1.03	(0.05)	0.55	1.02	(0.04)	0.51	1.08	(0.07)	1.20
Labor force status (full-time)												
Part-time or partly retired	1.12	(0.09)	1.39	1.11	(0.12)	1.00	1.03	(0.12)	0.30	0.99	(0.16)	-0.05
Fully retired	1.29	(0.29)	1.12	0.99	(0.24)	-0.05	1.35	(0.39)	1.03	1.08	(0.30)	0.28
Unemployed or otherwise not working	1.57*	(0.36)	1.98	1.30	(0.32)	1.04	1.62	(0.49)	1.60	1.44	(0.40)	1.31

	Sample Weights Only			***Logit ATE Estimation*** [a]			***GBM ATT Estimation*** [b]			***Logit ATT Estimation*** [a]		
	exp(b)	*Robust SE* [c]	*t*	*exp(b)*	*Robust SE* [c]	*t*	*exp(b)*	*Robust SE* [c]	*t*	*exp(b)*	*Robust SE* [c]	*t*
Job requires…												
lots of physical effort	1.07**	(0.02)	3.25	1.04	(0.04)	1.02	1.07*	(0.03)	2.21	0.99	(0.04)	-0.38
lifting heavy loads	0.97	(0.02)	-1.22	0.99	(0.04)	-0.27	0.96	(0.03)	-1.05	0.98	(0.04)	-0.48
stooping, kneeling, crouching	1.01	(0.02)	0.40	0.99	(0.03)	-0.32	1.02	(0.03)	0.50	1.04	(0.04)	1.04
good eyesight	0.94**	(0.02)	-3.09	0.88*	(0.05)	-2.20	0.96	(0.03)	-1.28	0.81**	(0.06)	-2.93
Job involves lots of stress	1.24**	(0.02)	10.72	1.23**	(0.04)	5.82	1.26**	(0.04)	6.90	1.22*	(0.11)	2.11
Years at current job	1.00	(0.00)	-1.56	1.00	(0.00)	-1.02	1.00	(0.00)	-1.32	0.99*	(0.00)	-2.38
Number of employees (more than one)												
Work alone	1.00	(0.05)	0.05	0.89	(0.07)	-1.49	1.03	(0.06)	0.54	0.89	(0.11)	-0.93
Not working	1.30	(0.30)	1.12	1.21	(0.37)	0.62	1.27	(0.40)	0.75	0.74	(0.23)	-0.98
35+ hours worked per week (<35 hours)	1.09	(0.08)	1.10	1.05	(0.11)	0.51	0.95	(0.11)	-0.45	0.95	(0.15)	-0.33
Pension from current job	0.95	(0.03)	-1.41	0.96	(0.06)	-0.66	0.90	(0.05)	-1.80	0.94	(0.07)	-0.78
Blue collar occupation (white collar)	0.99	(0.04)	-0.17	1.03	(0.07)	0.39	0.92	(0.05)	-1.47	1.12	(0.08)	1.57
Goods producing industry (service producing)	1.05	(0.04)	1.05	1.14	(0.08)	1.71	1.01	(0.07)	0.11	1.25*	(0.12)	2.35
Controls												
Dies during the study	1.13**	(0.04)	3.02	1.18*	(0.08)	2.42	1.14*	(0.07)	2.05	1.18*	(0.09)	2.20
Nonresponse during the study	1.06	(0.04)	1.36	1.01	(0.06)	0.16	1.09	(0.06)	1.47	0.96	(0.09)	-0.38
Intercept	1.65*	(0.36)	2.27	3.61**	(1.64)	2.83	1.71	(0.53)	1.71	6.82*	(5.54)	2.36
F test	$(42, 1.02x10^6) = 121.4$, $p < 0.001$			$(42, 244039) = 65.59$, $p < 0.001$			$(42, 309314) = 66.22$, $p < 0.001$			$(42, 134729) = 42.99$, $p < 0.001$		
N [e]	25,620[f]			25,620[f]			26,435[g]			25,620[f]		

Notes: Data from a combined 6 waves of the HRS that include 6,473 individuals. Individual (m=20) estimates combined using Rubin's combination rules. ** $p < 0.01$, * $p < 0.05$, two-tailed tests. ATE = average treatment effect where weight is $1/P$ for a "treated" case and $1/(1 – P)$ for a comparison case. ATT = average treatment effect for the treated where weight is 1 for a "treated" case and $P(1 – P)$ for a comparison case. P is predicted using **a.** logistic regression, and **b.** generalized boosted modeling from the RAND *twang* Stata macro; **c.** Exponentiated robust standard errors are derived using the delta rule: exp(b)*se(b); **d.** Transformed using the inverse hyperbolic sine function; **e.** Sample sizes vary due to weighting differences; Within **f.** 5,001 and **g.** 4,974 households.

Table 11. Estimated Effect of Self-Employment on IHS-Transformed Individual Earnings, Supplemental Models

	Sample Weights Only			*Logit ATE Estimation[a]*			*GBM ATT Estimation[b]*			*Logit ATT Estimation[a]*		
	b	*Robust SE*	*t*	*b*	*Robust SE*	*t*	*b*	*Robust SE*	*t*	*b*	*Robust SE*	*t*
Weighted estimation only												
Self-employment (wage-and-salary)	-5.62**	(0.12)	-46.86	-5.74**	(0.25)	-23.15	-4.78**	(0.20)	-23.88	-6.02**	(0.68)	-8.79
Doubly-robust estimation												
Self-employment (wage-and-salary)	-2.80**	(0.11)	-26.55	-3.03**	(0.17)	-18.00	-2.63**	(0.14)	-18.26	-2.77**	(0.19)	-14.90
Age	0.01	(0.00)	1.38	0.00	(0.01)	0.15	-0.01	(0.01)	-1.06	-0.01	(0.01)	-0.58
Female (male)	-0.12*	(0.06)	-2.18	-0.27*	(0.13)	-2.06	-0.09	(0.11)	-0.80	-0.34*	(0.14)	-2.39
Race (white)												
Black	-0.10	(0.06)	-1.51	0.22	(0.18)	1.20	0.13	(0.13)	0.96	0.53**	(0.20)	2.58
Other races	0.00	(0.10)	0.05	0.27	(0.24)	1.13	-0.04	(0.19)	-0.19	-0.01	(0.19)	-0.04
Hispanic	-0.34**	(0.11)	-3.11	-0.36*	(0.19)	-1.96	-0.19	(0.23)	-0.81	-0.14	(0.21)	-0.67
Veteran	0.08	(0.07)	1.13	0.08	(0.16)	0.49	0.09	(0.13)	0.63	0.08	(0.17)	0.46
Risk tolerance	-0.02	(0.02)	-1.06	-0.02	(0.05)	-0.49	0.00	(0.04)	0.10	-0.01	(0.06)	-0.23
Self-rated health	0.03	(0.03)	1.18	-0.01	(0.06)	-0.09	-0.05	(0.06)	-0.90	0.03	(0.07)	0.38
Depressive symptoms	-0.01	(0.01)	-0.47	0.01	(0.03)	0.20	-0.00	(0.03)	-0.15	0.07	(0.04)	1.83
Education, in years	0.05**	(0.01)	4.70	0.04*	(0.02)	2.15	0.04*	(0.02)	2.06	0.04	(0.02)	1.93
Health problems limiting work	-0.39**	(0.07)	-5.85	-0.40**	(0.12)	-3.45	-0.39**	(0.12)	-3.36	-0.23	(0.14)	-1.66
Has health insurance (does not)	0.47**	(0.11)	4.20	0.57**	(0.20)	2.87	0.37	(0.19)	1.94	0.38*	(0.19)	2.06
Spouse's work status (not working)												
Working	0.21**	(0.06)	3.33	-0.05	(0.15)	-0.35	0.12	(0.13)	0.95	-0.40**	(0.14)	-2.79
Not married	0.11	(0.07)	1.56	-0.00	(0.15)	-0.03	0.02	(0.14)	0.12	-0.07	(0.18)	-0.38
Household members	0.01	(0.02)	0.50	-0.02	(0.04)	-0.52	0.01	(0.05)	0.23	0.01	(0.05)	0.19
Formal volunteering, past year (none)												
<100 hours	-0.00	(0.06)	-0.03	-0.07	(0.12)	-0.55	-0.01	(0.13)	-0.04	-0.19	(0.16)	-1.19
100+ hours	-0.27**	(0.07)	-3.92	-0.32	(0.18)	-1.79	-0.26	(0.14)	-1.81	-0.18	(0.20)	-0.93
Informal volunteering, past year (none)												
<100 hours	0.02	(0.05)	0.33	0.17	(0.10)	1.68	0.12	(0.10)	1.13	0.32	(0.16)	1.96
100+ hours	-0.03	(0.07)	-0.44	0.02	(0.17)	0.09	-0.12	(0.15)	-0.84	0.01	(0.19)	0.05
Individual earnings, lagged[c]	0.33**	(0.01)	39.11	0.29**	(0.02)	15.26	0.30**	(0.01)	20.66	0.34**	(0.02)	18.59
Household wealth[c]	-0.06**	(0.01)	-5.54	-0.07**	(0.02)	-2.85	-0.10**	(0.03)	-3.86	-0.04	(0.03)	-1.13
Household income, less individual earnings[c]	0.01**	(0.00)	3.14	0.01	(0.01)	1.72	0.01	(0.01)	1.36	0.03**	(0.01)	2.81
Currently receiving:												
Social Security retirement benefits	-0.64**	(0.09)	-7.23	-0.41**	(0.15)	-2.70	-0.19	(0.16)	-1.16	-0.27	(0.21)	-1.29
Receiving pension income	-0.23**	(0.06)	-3.61	-0.51**	(0.12)	-4.32	-0.33**	(0.11)	-3.04	-0.31*	(0.16)	-2.00
Labor force status (full-time)												
Part-time or partly retired	-0.35*	(0.14)	-2.57	-0.53	(0.35)	-1.52	-0.41	(0.32)	-1.28	-0.29	(0.29)	-0.99
Fully retired	-4.55**	(1.10)	-4.12	-5.11**	(1.85)	-2.76	-3.14*	(1.52)	-2.07	-4.13**	(1.35)	-3.06
Unemployed or otherwise not working	-2.58*	(1.11)	-2.31	-3.38	(1.86)	-1.82	-1.42	(1.55)	-0.92	-2.46	(1.38)	-1.78

	Sample Weights Only			*Logit ATE Estimation*[a]			*GBM ATT Estimation*[b]			*Logit ATT Estimation*[a]		
	b	*Robust SE*	*t*	*b*	*Robust SE*	*t*	*b*	*Robust SE*	*t*	*b*	*Robust SE*	*t*
Job requires…												
lots of physical effort	-0.01	(0.04)	-0.34	-0.06	(0.08)	-0.76	-0.01	(0.08)	-0.18	-0.06	(0.09)	-0.73
lifting heavy loads	-0.03	(0.05)	-0.75	-0.09	(0.10)	-0.93	-0.14	(0.11)	-1.29	-0.13	(0.10)	-1.24
stooping, kneeling, crouching	-0.02	(0.03)	-0.51	-0.08	(0.08)	-1.05	-0.04	(0.08)	-0.47	-0.18*	(0.08)	-2.09
good eyesight	0.06	(0.04)	1.45	0.06	(0.11)	0.52	-0.01	(0.09)	-0.15	0.11	(0.08)	1.40
Job involves lots of stress	0.10**	(0.03)	2.87	0.12	(0.09)	1.36	0.14	(0.08)	1.69	-0.01	(0.08)	-0.13
Years at current job	-0.01*	(0.00)	-2.56	-0.01	(0.01)	-1.88	-0.01	(0.01)	-1.12	-0.02**	(0.01)	-2.86
Number of employees (more than one)												
Work alone	-1.13**	(0.13)	-8.95	-1.15**	(0.25)	-4.57	-1.17**	(0.17)	-6.92	-0.88**	(0.26)	-3.33
Not working	-0.09	(1.10)	-0.08	0.64	(1.88)	0.34	-0.93	(1.53)	-0.61	-0.56	(1.36)	-0.42
35+ hours worked per week (<35 hours)	-0.03	(0.12)	-0.27	-0.64	(0.33)	-1.91	-0.32	(0.32)	-1.01	-0.13	(0.30)	-0.44
Pension from current job	1.03**	(0.07)	13.76	1.59**	(0.16)	9.87	1.69**	(0.17)	9.90	1.60**	(0.24)	6.68
Blue collar occupation (white collar)	0.14*	(0.06)	2.23	0.22	(0.15)	1.54	0.32*	(0.14)	2.24	0.19	(0.15)	1.32
Goods producing industry (service producing)	-0.07	(0.08)	-0.92	0.16	(0.26)	0.63	-0.03	(0.20)	-0.15	0.36	(0.26)	1.37
Controls												
Dies during the study	0.01	(0.10)	0.12	-0.10	(0.18)	-0.59	-0.11	(0.17)	-0.66	-0.34	(0.18)	-1.88
Nonresponse during the study	-0.13	(0.07)	-1.76	-0.12	(0.14)	-0.84	-0.20	(0.13)	-1.53	-0.41**	(0.15)	-2.68
Proxy respondent	-0.08	(0.13)	-0.60	-0.06	(0.22)	-0.29	0.03	(0.21)	0.16	-0.01	(0.20)	-0.06
Intercept	5.29**	(0.43)	12.36	6.49**	(0.96)	6.73	6.88**	(0.90)	7.63	6.20**	(1.24)	5.01
F test	(43, 5035) = 1270, $p < 0.001$			(43, 4996) = 383.2, $p < 0.001$			(43, 4966) = 324.8, $p < 0.001$			(43, 4709) = 345.4, $p < 0.001$		
N[d]	26,715[e]			26,715[e]			26,521[f]			26,715[e]		

Notes: Data from a combined 6 waves of the HRS that include 6,473 individuals. Individual (m=20) estimates combined using Rubin's combination rules. ** $p < 0.01$, * $p < 0.05$, two-tailed tests. ATE = average treatment effect where weight is $1/P$ for a "treated" case and $1/(1 – P)$ for a comparison case. ATT = average treatment effect for the treated where weight is 1 for a "treated" case and $P(1 – P)$ for a comparison case. P is predicted using **a.** logistic regression, and **b.** generalized boosted modeling from the RAND *twang* Stata macro; **c.** Transformed using the inverse hyperbolic sine function; **d.** Sample sizes vary due to weighting differences; Within **e.** 5,073 and **f.** 5,046 households.

Table 12. Estimated Effect of Self-Employment on IHS-Transformed Household Wealth, Supplemental Models

	Sample Weights Only			*Logit ATE Estimation[a]*			*GBM ATT Estimation[b]*			*Logit ATT Estimation[a]*		
	b	*Robust SE*	*t*	*b*	*Robust SE*	*t*	*b*	*Robust SE*	*t*	*b*	*Robust SE*	*t*
Weighted estimation only												
Self-employment (wage-and-salary)	1.33**	(0.14)	9.25	0.15	(0.25)	0.63	0.05	(0.16)	0.30	-0.80*	(0.40)	-2.00
Doubly-robust estimation												
Self-employment (wage-and-salary)	0.64**	(0.10)	6.24	0.23	(0.14)	1.61	0.08	(0.10)	0.78	0.10	(0.11)	0.87
Age	0.01	(0.01)	0.86	-0.00	(0.01)	-0.11	-0.00	(0.01)	-0.28	-0.00	(0.01)	-0.31
Female (male)	0.00	(0.08)	0.06	-0.06	(0.12)	-0.48	-0.12	(0.10)	-1.30	-0.17	(0.10)	-1.80
Race (white)												
Black	-0.90**	(0.14)	-6.44	-1.00**	(0.21)	-4.81	-1.22**	(0.22)	-5.58	-0.86**	(0.20)	-4.32
Other races	-0.43	(0.22)	-1.96	-0.38	(0.25)	-1.53	-0.36	(0.21)	-1.72	-0.24	(0.20)	-1.20
Hispanic	0.00	(0.19)	0.00	-0.21	(0.22)	-0.95	-0.18	(0.18)	-1.04	-0.18	(0.20)	-0.86
Veteran	-0.10	(0.09)	-1.08	-0.09	(0.14)	-0.64	-0.23*	(0.11)	-2.20	-0.13	(0.12)	-1.09
Risk tolerance	0.03	(0.03)	1.16	0.00	(0.04)	0.06	0.01	(0.03)	0.32	-0.01	(0.03)	-0.35
Self-rated health	0.19**	(0.04)	4.96	0.17**	(0.06)	3.02	0.10*	(0.04)	2.22	0.12*	(0.05)	2.35
Depressive symptoms	-0.12**	(0.03)	-4.44	-0.06	(0.03)	-1.66	-0.07*	(0.03)	-2.41	-0.04	(0.03)	-1.11
Education, in years	0.10**	(0.02)	6.17	0.11**	(0.02)	5.81	0.09**	(0.01)	5.87	0.13**	(0.02)	7.33
Health problems limiting work	-0.23*	(0.10)	-2.24	-0.23	(0.14)	-1.69	-0.14	(0.11)	-1.30	-0.19	(0.11)	-1.85
Has health insurance (does not)	0.53**	(0.16)	3.30	0.22	(0.20)	1.08	0.26	(0.20)	1.32	0.37	(0.20)	1.84
Spouse's work status (not working)												
Working	-0.32**	(0.08)	-3.90	-0.42**	(0.10)	-4.20	-0.31**	(0.09)	-3.33	-0.32**	(0.10)	-3.34
Not married	-0.90**	(0.10)	-8.80	-0.86**	(0.13)	-6.61	-0.69**	(0.11)	-6.49	-0.78**	(0.12)	-6.25
Household members	-0.24**	(0.05)	-5.02	-0.25**	(0.06)	-4.05	-0.25**	(0.06)	-4.24	-0.27**	(0.06)	-4.49
Formal volunteering, past year (none)												
<100 hours	0.09	(0.09)	1.00	-0.08	(0.12)	-0.66	0.06	(0.10)	0.65	0.06	(0.10)	0.58
100+ hours	0.18	(0.09)	1.90	0.12	(0.12)	0.99	0.12	(0.09)	1.44	0.15	(0.09)	1.73
Informal volunteering, past year (none)												
<100 hours	0.00	(0.08)	0.05	0.02	(0.11)	0.20	0.02	(0.09)	0.24	0.04	(0.09)	0.46
100+ hours	0.06	(0.10)	0.63	0.16	(0.13)	1.23	0.14	(0.11)	1.22	0.05	(0.11)	0.44
Individual earnings[c]	0.03**	(0.01)	3.50	0.02	(0.01)	1.52	0.02	(0.01)	1.71	0.03*	(0.01)	2.58
Household wealth, lagged[c]	0.11**	(0.02)	6.10	0.15**	(0.02)	7.11	0.19**	(0.03)	7.04	0.20**	(0.03)	7.96
Household income, less individual earnings[c]	0.47**	(0.02)	25.44	0.51**	(0.03)	20.19	0.51**	(0.03)	18.36	0.52**	(0.03)	19.66
Currently receiving:												
Social Security retirement benefits	0.04	(0.10)	0.44	0.22	(0.12)	1.85	0.21	(0.11)	1.85	0.21	(0.12)	1.76
Receiving pension income	0.08	(0.08)	0.99	-0.10	(0.11)	-0.86	0.01	(0.07)	0.20	-0.24**	(0.09)	-2.58
Labor force status (full-time)												
Part-time or partly retired	0.26	(0.20)	1.32	0.18	(0.19)	0.93	0.09	(0.16)	0.56	0.19	(0.17)	1.15
Fully retired	-0.25	(0.32)	-0.77	-0.36	(0.30)	-1.20	-0.08	(0.26)	-0.31	-0.06	(0.29)	-0.21
Unemployed or otherwise not working	-1.15**	(0.38)	-3.02	-1.47**	(0.41)	-3.59	-1.10**	(0.35)	-3.13	-1.01**	(0.37)	-2.73

	Sample Weights Only			*Logit ATE Estimation*[a]			*GBM ATT Estimation*[b]			*Logit ATT Estimation*[a]		
	b	*Robust SE*	*t*	*b*	*Robust SE*	*t*	*b*	*Robust SE*	*t*	*b*	*Robust SE*	*t*
Job requires…												
lots of physical effort	-0.07	(0.06)	-1.28	-0.11	(0.08)	-1.37	-0.03	(0.07)	-0.46	-0.06	(0.07)	-0.84
lifting heavy loads	-0.10	(0.08)	-1.23	-0.05	(0.09)	-0.58	-0.09	(0.09)	-0.95	-0.09	(0.10)	-0.89
stooping, kneeling, crouching	0.01	(0.06)	0.10	0.09	(0.07)	1.27	0.14	(0.07)	1.87	0.07	(0.07)	1.03
good eyesight	-0.11*	(0.05)	-2.06	-0.09	(0.07)	-1.27	-0.10*	(0.05)	-1.96	-0.07	(0.04)	-1.50
Job involves lots of stress	-0.06	(0.06)	-1.00	-0.03	(0.08)	-0.43	-0.00	(0.07)	-0.02	-0.06	(0.07)	-0.82
Years at current job	0.01**	(0.00)	4.38	0.01**	(0.00)	2.99	0.01**	(0.00)	2.76	0.01**	(0.00)	3.18
Number of employees (more than one)												
Work alone	-0.22	(0.15)	-1.49	-0.26	(0.16)	-1.66	-0.43**	(0.14)	-3.02	-0.30*	(0.15)	-2.00
Not working	0.02	(0.36)	0.06	-0.02	(0.40)	-0.05	-0.16	(0.35)	-0.48	-0.15	(0.33)	-0.44
35+ hours worked per week (<35 hours)	0.01	(0.20)	0.05	-0.08	(0.18)	-0.42	-0.15	(0.16)	-0.97	-0.04	(0.16)	-0.28
Pension from current job	0.31**	(0.09)	3.30	0.30**	(0.11)	2.84	0.20*	(0.09)	2.25	0.25*	(0.13)	2.01
Blue collar occupation (white collar)	-0.08	(0.10)	-0.72	-0.04	(0.13)	-0.30	-0.16	(0.13)	-1.20	0.00	(0.14)	0.03
Goods producing industry (service producing)	0.13	(0.12)	1.16	-0.02	(0.15)	-0.14	0.08	(0.12)	0.64	0.02	(0.13)	0.13
Controls												
Dies during the study	-0.18	(0.15)	-1.21	-0.08	(0.21)	-0.37	-0.03	(0.17)	-0.17	-0.06	(0.18)	-0.34
Nonresponse during the study	0.04	(0.12)	0.31	0.07	(0.15)	0.46	0.06	(0.15)	0.43	0.07	(0.13)	0.56
Proxy respondent	0.15	(0.16)	0.93	0.20	(0.22)	0.92	0.22	(0.15)	1.43	-0.03	(0.24)	-0.11
Intercept	3.44**	(0.67)	5.15	3.44**	(0.88)	3.89	3.63**	(0.70)	5.21	2.76**	(0.78)	3.54
F test	(43, 5046) = 83.29, $p < 0.001$			(43, 5031) = 78.90, $p < 0.001$			(43, 4974) = 66.73, $p < 0.001$			(43, 4960) = 111.6, $p < 0.001$		
N[d]	26,715[e]			26,715[e]			26,521[f]			26,715[e]		

Notes: Data from a combined 6 waves of the HRS that include 6,473 individuals. Individual (*m*=20) estimates combined using Rubin's combination rules.
** $p < 0.01$, * $p < 0.05$, two-tailed tests. ATE = average treatment effect where weight is $1/P$ for a "treated" case and $1/(1 – P)$ for a comparison case. ATT = average treatment effect for the treated where weight is 1 for a "treated" case and $P(1 – P)$ for a comparison case. *P* is predicted using **a.** logistic regression, and **b.** generalized boosted modeling from the RAND *twang* Stata macro; **c.** Transformed using the inverse hyperbolic sine function; **d.** Sample sizes vary due to weighting differences; Within **e.** 5,073 and **f.** 5,046 households.