Wealth management and divorce: How stress adjustment affects the accumulation, management and distribution of wealth

by

Michael Gerard Kothakota

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Family Studies and Human Services
College of Health and Human Services

KANSAS STATE UNIVERSITY
Manhattan, Kansas

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Abstract

The dearth of research on short and long-term effects of divorce on financial behaviors warrants further investigation. This study investigates the effects of divorce on precautionary and retirement savings, proportion of assets in risk investments, and bequest intentions. Using data from the Panel Study on Income Dynamics from the University of Michigan Center for Social Research, exponential fractional regression models (EFRM) were specified to examine changes in savings behaviors and risky asset share post divorce. Binary logistic regressions were specified on bequest intentions for leaving assets to children, religious organizations, and non-religious charities. For all subgroups, precautionary savings behaviors and retirement savings intially decreased post-divorce, then stabilized and increased in later years. Similarly, for all subgroups risky asset share decreased over time. Sub-analyses also indicate differences between divorced individuals for single income versus double income households, as well as differences between the sexes. Divorced individuals were more likely to hold bequest intentions for children and less likely to bequest to religious and non-religious organizations than married individuals. Practical implications are discussed and recommendations for future research are provided.

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Approved by:

Major Professor
Stuart J. Heckman, Ph.D.

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Table of Contents

List of Figures

List of Tables

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Dedication

This dissertation is dedicated to the financial professionals working with people going through divorce.

Chapter 1 - Introduction

Introduction and statement of the problem

Financial planning is a general term for the process of gathering and analyzing financial personal in order to meet short-term and long-term goals (www.cfp.net). Financial plans are not meant to be static documents (*CFP Board*, 2015) and are subject to change as circumstances change. These adjustments are usually minor provided there are no major inputs to the plan that change (Van Rooij, Lusardi, & Alessie, 2012). A change such as a divorce provides a major disruption to a financial plan, forcing short-term and long-term ramifications (Kothakota & Heckman, 2017). An important area of financial planning that may be altered substantially is wealth management.

While there are many definitions of wealth management, the term has been described as:

> *"…the utilization of processes, services and products designed to grow, protect, utilize and disseminate one's wealth"* (Chamberlain, 2018).

For purposes of this study, wealth management is further narrowly defined as the accumulation, management and distribution of wealth. Within financial planning this often corresponds to savings, investment allocation of savings and the distribution of savings. Savings involves the tradeoff between current discretionary spending and the future non-discretionary and discretionary spending. The amount an individual or household chooses to save has a large impact on their ability to consume resources over time (Meghir & Pistaferri, 2011). Investment allocation of savings is a strategic decision process that separates long-term and short-term savings by use of risky and non-risky assets in a manner that aligns with the wealth management goals (Duchin, Gilbert, Harford, & Hrdlicka, 2017). The distribution of savings involves the

1

spending of those monies when an individual or household no longer has wage or business income (Medina, 2016) in addition to how accumulated savings will be distributed upon the death of an individual.

Divorce is an event that can drastically alter a financial plan (Morgan & Kothakota, 2012). This disruption can turn a single, two-person household operating under a specific income into two, one-person households operating under a reduced income (Kothakota & Heckman, 2018). While there is a legal process for getting a divorce where rights and entitlements matter, law is driving the outcome and not the plan. Therefore, when a divorce occurs new plans must be examined. A couple operates under a joint utility paradigm (Browning, Chiappori, & Lewbel, 2013), while individual households may often share little in regards to the same utility (Lim, 2013). Priority of saving versus discretionary spending, along with the allocation of that savings may be adjusted to account for the new paradigm (Light & Ahn, 2010). Further, the disruption to the family dynamic may cause individual former spouses to re-examine how they will distribute their wealth upon their death.

In short, divorce causes trauma to both finances and emotions (Amato, 2000). This trauma may cause a temporary or prolonged change involving prioritization of financial goals and execution of a plan to reach those goals. Thus, in a post-divorce paradigm, individuals are constrained both financially and by the emotional toll taken by the divorce process.

Purpose and justification of the study

The purpose of this study is to examine the effects of divorce on wealth management as defined above over time. First, it is important to determine if there are significant changes to wealth management behaviors following a divorce. After determining if a change to wealth management behaviors occurs, it is then necessary to determine whether these effects persist over time, or if they are temporary. Identifying aspects of wealth management more prone to chronic adjustment (i.e., behaviors that persist and become the "new normal") and aspects more likely to be temporary (i.e., behavior is short-term and situational) will allow practitioners to better assist individuals in planning during and after their divorce.

Background

The majority of work related to divorce has focused on family effects. Psychology, social work and sociology has done a good deal of work in the area related to trauma to both the divorced individuals and children of divorce. Some of these studies (Amato, 2000; Amato, 2010; Amato, Kane, & James, 2011; Carbone, 1994; Hetherington & Blechman, 2014; Jordan, 2016; Symoens, Bastaits, Mortelmans, & Bracke, 2013; Symoens, Colman, & Bracke, 2014) have dealt with longer-term consequences associated with divorce, especially as it relates to children. However, few studies focus on the long-term financial outcomes related to divorce.

Financial planning as a discipline has many sub-disciplines. Financial planning for divorcing or divorced individuals is one of them. The Institute for Divorced Financial Analysts is the most widely recognized certifying body for financial planners assisting clients before and after divorce. They sanction and allow members who have passed their exams to use the Certified Divorce Financial Analyst™ or CDFA™ marks. The Association of Divorce Financial Planners (ADFP) is a body that puts out informational and best practice information for those financial planners specializing in divorce. Divorce and finance is ubiquitous as it relates to financial planning that the American Institute of Certified Public Accountants puts on an annual conference to discuss financial issues surrounding divorce.

Need for the study

For financial planners, the need for someone versed in the intricacies of divorce and finance is clear. This niche has attracted many practitioners over the years who have followed best practices. Unfortunately, in a legal-driven process, academic research surrounding financial best practices in divorce has been lacking (Kothakota, 2018).

Most research has focused on the economic or mental health consequences of divorce. Financial planning and wealth management are action-oriented processes in a profession requiring skilled decision-making (Lurtz, Kothakota & MacDonald, 2017). The idea is to process information and use it to map resources to short- and long-term financial goals. By understanding the financial behaviors of individuals post-divorce, best practices can be developed to assist those individuals in their wealth management needs. Meeting these needs may assist in divorced individuals having better outcomes.

As of this writing, no research has been found examining wealth management of divorced households longitudinally. Previous research has outlined the immediate economic consequences of divorce. Knowing which aspects of wealth management are affected, the magnitude of the effect and the persistence of the effect can help individuals and the planners assisting them to recognize, adjust for and reduce any negative structural or behavioral financial issues associated with their plan. Given this gap in the literature, this study sought to examine the following research question.

Research question

Given the broad nature of financial planning, it is important to narrowly define the scope of research. Since financial planning is a collection of various concepts and is made of many parts, this study examines some of the more common inputs within a financial plan, specifically wealth management. The overarching research question is: What effect does divorce have on wealth management?

Additionally, in order to narrow the scope of the study, only certain aspects of wealth management were examined. The study plan is to examine the following areas: 1) savings rates, 2) riskiness of investment portfolio and 3) bequest intentions. Of note, there was no examination of insurance (i.e., protection of wealth), retirement income adequacy, college planning or tax planning as those planning techniques are beyond the scope of this study.

Theoretical framework

Stress adjustment has been used to describe many phenomena in psychology, social work and sociology (Ross, Coltrain, Duffy, & Buriel, 2004; Papp, Cummings & Schermerhorn, 2004; Scott & Spivey, 2010). Further, stress adjustment has been used to describe aspects of consumer science (Lim, Heckman, Letkiewicz, & Montalto, 2014). While stress may be an obvious part of a trauma such as divorce, empirical research has confirmed the stress on both individual and their families can cause adjustments to behavior.

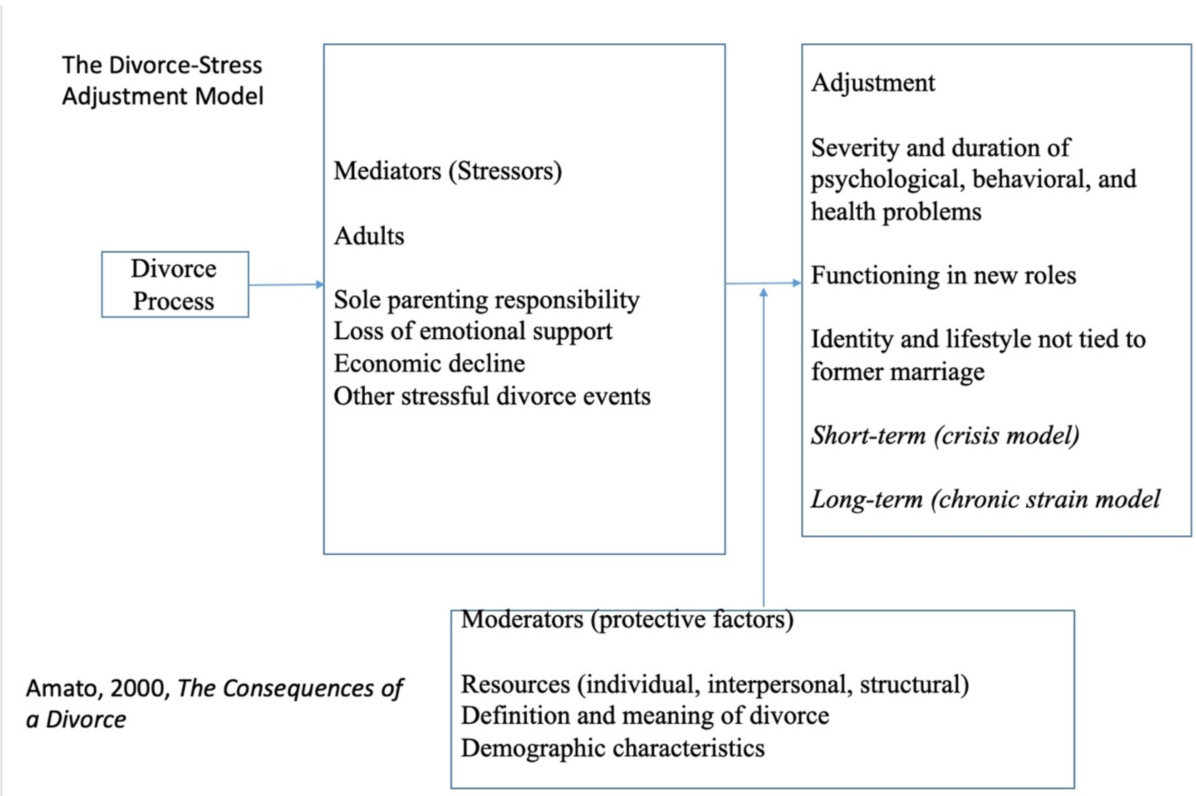
These psychological impacts can inhibit the ability of an individual who has gone through divorce to complete many tasks. Over the course of years, many theories have been used to explain the effects of divorce in various domains. Feminist theory (Carbone, 1994), attachment theory (McMullen, 2011), attribution theory (Votruba, Braver, Ellman, & Fabricius, 2014) and systems theory have all been used to explain economic and psychological effects. However, the majority of research used to describe the effects of divorce have been stress models (Pearlin & Bierman, 2013; Hetherington & Blechman, 2014; Symoens et al., 2013; Symoens et al., 2014).

In financial planning, the stress adjustment model has been used to describe the effects of factors related to financial stress in college students (e.g., Lim, Heckman, Letkiewicz, & Montalto, 2014). Stress adjustment models where finances are affected are particularly important for divorce, as financial aspects are at the core of divorces. Thus, a stress adjustment perspective can be useful in examining how divorced individuals accomplish various day to day and lifelong tasks.

General conceptualization of the theory

One model of examining how a stress adjustment model may work comes from sociological research (Amato, 2000). Amato's meta-analysis of divorce literature from a divorce stress adjustment perspective allows for a generalization of how the divorce process affects certain domains. The model in Figure 1 is adapted from the Divorce-Stress Adjustment Model. The divorce process instigates stressors such as: sole parenting responsibility, loss of emotional support from a partner, negative economic effects and other stress events related to divorce (Amato, 2010). Divorce can cause a lack of focus (Starnes, 2011), which may make it more difficult to complete wealth management tasks. This may in turn lead to more stress.

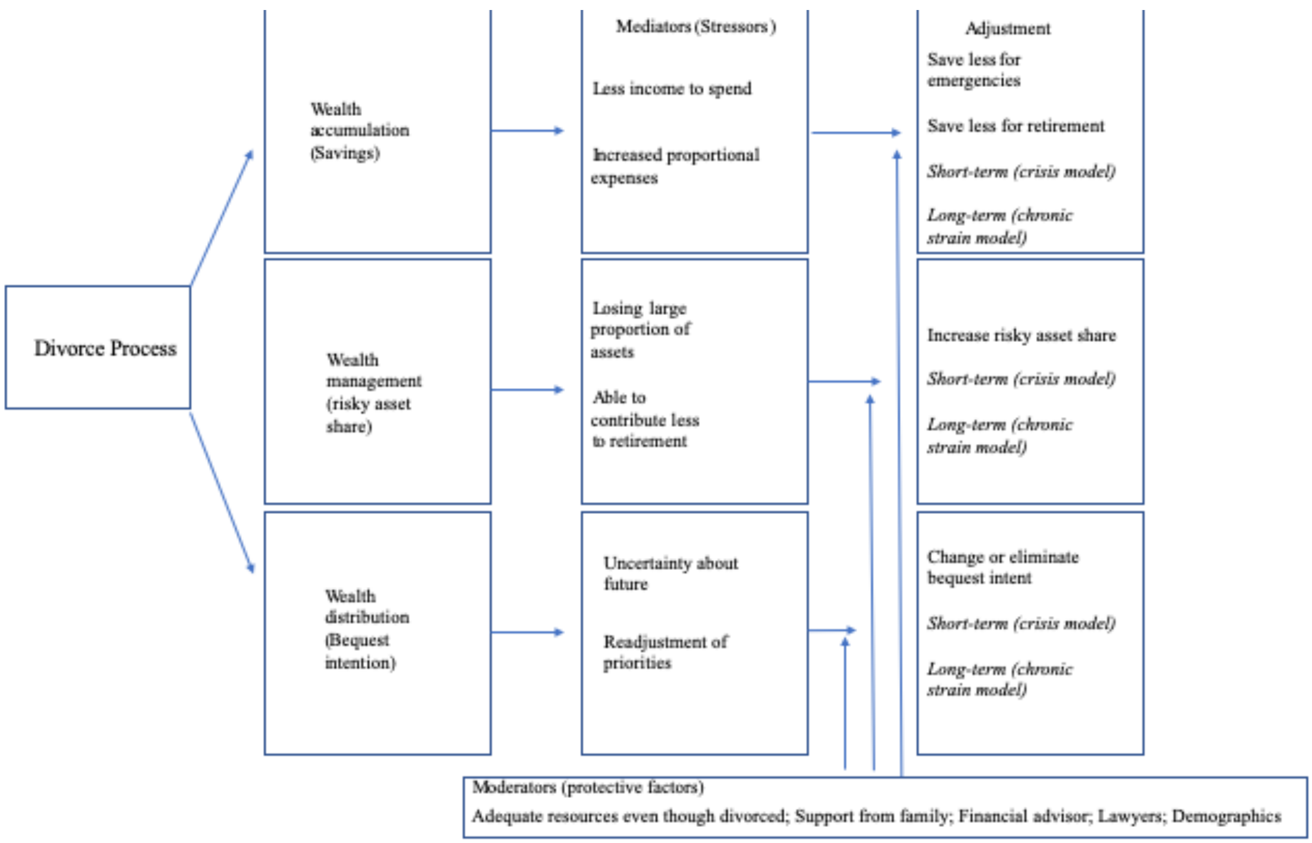
Figure 1 Divorce-Stress Adjustment Model



These stressors create an adjustment in the psychological, behavioral and health domains within an individual. Short-term and long-term behavioral effects related to wealth management as a result of divorce are differentiated as some behavioral effects may dissipate over time. Both short-term and long-term behavioral effects are moderated by certain protective factors that can include demographics, what divorce means to an individual, and the resources an individual may have. Despite pushes for access to justice in divorce (Starnes, 2012) divorced individuals often need the professional help of attorneys in order to complete the dissolution of their marriage. This proximity to attorneys may place those individuals in the frame of mind to reach out to professionals for wealth management. In particular, divorced individuals often need to adjust estate plans following a divorce.

In order to adapt this model to wealth management, an action step is added (Figure 2). In addition, this model outlines the lack of an ability to focus on the long term and may include items such as identity changes and priority shifts (e.g., “not my responsibility to leave a bequest”). A moderator in this case would include professionals involved in the divorce process that can help facilitate a smoother and more informed process (e.g., having a lawyer, accountant or financial planner involved). Other mediators include the type of divorce (i.e., pro se, mediated, collaborative, negotiated or litigated) (Morgan & Kothakota, 2012), the level of self-efficacy of the individual (Warrener, Koivenun & Postmus, 2013), and demographic characteristics (i.e., income, net worth, supporting or dependent household role, etc.).

Figure 2 Adapted Divorce-Stress Adjustment Model for Financial Behaviors



It is appropriate to use a model that describes both a crisis moment (short-term) and chronic strain (long-term) effect of divorce on aspects of financial planning. The goal of this study is to describe changes that occur post-divorce and how long those changes persist. Divorce is a stressful event (Amato et al., 2011) and the subsequent trauma to both the financial and emotional aspects of an individual life are likely to cause a need for adjustments.

Each aspect of the wealth management process may fit appropriately in this model, which is simple and falsifiable. A reduction or increase in savings may be the result of information gained in the divorce process, such as finding out they were not saving as much as they thought, or a reduced ability to meet expenses resulting from the division of households. This may cause the individual to “panic save” or alternatively to disregard the importance of saving in lieu of meeting lifestyle needs.

Replacing retirement savings may matter less to an individual in the moment of divorce, as more immediate needs may take priority. As the individual gets closer to retirement however, living in retirement may become more salient and the ability to afford retirement may be more concerning. In that situation the individual would need to save as much as they could.

While there may be a *prima facie* concern for the well-being of children post-divorce, many individuals may be more concerned with their own future. They may also abrogate some of their responsibility to their former spouse as it relates to the welfare of the children. Thus, if there were a joint intention to leave a bequest, there may be a need to not have such an intention post-divorce as the individual may wish to ensure their resources are available for their later years. As the individual gets closer to retirement however, this may again shift. Evidence suggests that the leaving of a bequest is less of a priority for individuals post-divorce (Hendricks, 2001).

Risky assets are needed for portfolio growth absent saving (Blanchett, Finke, & Pfau, 2017). A reduction in saving may increase the perception that more risk needs to be taken.

However, as a portfolio grows, this need may be reduced by actual growth or a change in the savings rate.

Limitations

This study is exploratory in nature. To date, no comprehensive review of the effects of divorce on wealth management has been conducted. However, the design of the study is around an existing data set not created specifically for this study. Thus, proxies will need to be used and may not be exact representations of the concepts being measured. Every effort is made to approximate these concepts.

In addition, because the PSID is nationally representative and covers all age demographics, there may not be much data on risky asset share as many younger people do not have assets. This also may affect bequest intentions, as younger individuals may not be thinking about leaving money they do not possess to a next generation. Further, many poorer households find it difficult to save in the best of circumstances (Karlan, Ratan, & Zinman, 2014), and poorer households are more likely to divorce than wealthier ones.

Wealth management is a dynamic and complex process, where one aspect of a plan influences another. This can result in interactions between various aspects of a financial plan. For example, an increase in insurance premiums may reduce the ability to save. Further, individuals may share household expenses in the future with someone they do not marry, or they may become married again.

Importantly, this study does not examine financial planning as defined by the CFP Board of Standards and is focused instead on the narrow definition of wealth management outlined previously. Examining financial planning would require an experiment examining actual financial plans and the effect on the plans post-divorce.

For purposes of this study, divorce is assumed to cause some sort of financial trauma. It is further assumed that household expenditures are higher due to household size post-divorce. Savings is assumed to be proportional to income before and after divorce. That is, if household income is higher prior to divorce and the savings rate is a specific percentage of that income, it is assumed that proportion should be close to the same after divorce, *ceteris paribus.* This study does not account for income specific savings proportions. As an example, someone who earns a high income may need to save a lower proportion of their income for precautionary reasons but may need to save a higher proportion for retirement needs. Conversely, an individual earning lower income will not need to save as much for retirement due to entitlement programs but may need a higher percentage of their income saved as a precaution.

The population of interest is divorced individuals. The study only includes divorced individuals only in the precauationary savings, retirement savings and risky asset share analyses. It includes divorced and married individuals for the bequest intention analysis. Results are not generalizable to the overall population. The study does not examine the financial effect on retirement planning, tax planning and college planning, which are three aspects of wealth management and financial planning. Retirement planning includes pensions and Social Security, which are not presently examined in this study. Further, not knowing what the proper savings ratio is for each individual circumstance limits the power of any finding as it relates to retirement. Ignoring taxes can also have an impact as taxes are payable and good plans can prevent overpayment of taxes, which can increase the ability of someone to save. College planning in particular has an impact in this study as there are measurements of money an individual spends on college for children, which may have an effect on savings and risky asset share. There is no examination of life insurance or disability insurance or other sub-categories of wealth, such as business planning or advanced income planning techniques. Not including life insurance does not help with any sort of catastrophic loss, and not looking at disability insurance does not help with a job loss. Businesses are often the largest asset people have (Juster, Smith & Stafford, 1999) and not accounting for them may bias risky asset share higher. Advanced income planning techniques can be useful in multiple life stages and not knowing if these techniques are being used, there are variables not being examined. Financial planning and wealth management have many moving parts and one aspect of a plan may influence another. By not examining these other aspects, financial behaviors may be getting missed.

Summary and potential implications

This study seeks to help individuals and financial planning practitioners understand the needs of a divorced population as it relates to wealth management. Currently, financial planners and wealth managers working with divorced individuals only have anecdotes and personal experience to operate off of as it relates to how individuals behave with their savings post-divorce. Knowing what may happen post-divorce can assist financial planners and wealth managers in advising their clients and also helping them make new plans to meet their new goals. Going from a joint utility, single household paradigm to individual utilities as separate households is a reality professionals in the field will have to navigate.

Chapter 2 - Review of the literature

Historical context discussion

Empirical research on divorce and various aspects of financial planning and wealth management is thin (Kothakota & Heckman, 2018). Divorce has been a part of human life for a long period of time. The Code of Hammurabi discusses divorce in detail as it relates to how economic resources are shared or not post-divorce. There are passages related to the reasons behind the re-allocation of resources that have to do with future care and responsibility for children, relevant to financial planning.

> "If a man wish to separate from a woman who has borne him children, or from his wife who has borne him children: then he shall give that wife her dowry, and a part of the usufruct of field, garden, and property so that she can rear her children. When she has brought up her children, a portion of all that is given to the children, equal as that of one son, shall be given to her. She may then marry the man of her heart" (Harper, 1904).

More relevant to the present day in the United States is the English version. Women prior to the year 1857 could not own property and any property inherited passed to her husband who would then control any assets (McCoy, 2005). This stemmed from the laws of coverture wherein a woman who married become part of the single unit. In return for ceding control of financial assets, women were supposed to be supported by their husbands for the rest of their lives.

The early system of alimony was predicated upon this marital arrangement. The Ecclesiastical system could not grant absolute divorces. They would not technically be divorced, as only Parliament could grant an absolute divorce (Oldham, 2008), and only rarely did so, typically when the couple was wealthy. Married couples could be divorced "from bed and board." The couple could live separate and apart, and the husband was required to continue paying for the wife's expenses. Divorce from bed and board is still used in some states in abuse situations.

Law and divorce

Divorce is a legal process (Starnes, 2012) with household dynamic consequences as well as economic and psychological effects. The law outlines parameters for the distribution of property, income allocation and child custody arrangements post-divorce (Morgan & Kothakota, 2014). Among the economic consequences for divorce are the increase of household expenses due to the need for two households (Kothakota & Heckman, 2018; Stevenson & Wolfers, 2007). In the past, this has been ameliorated through transfer payments in the form of tax-transferrable spousal support (Wery, Kothakota, & Morgan, 2017). However, changes to the tax code surrounding this tax-advantaged status have eliminated this (Tax Cuts and Jobs Act of 2017) for 2018 and the years following. This creates larger issues surrounding household finances after divorce, as there is even less income to cover more expenses (Kothakota, 2018).

State laws do not specifically mandate individuals should save at their previous rate. However, many legal disputes involve a "standard of living" argument wherein an individual may argue they are entitled to live at their previous standard of living. This often includes both precautionary and retirement savings. This argument is used to negotiate for more household assets or income redistribution (i.e., alimony). Whether a divorced individual saves at the rate claimed during court proceedings is unknown.

State laws also do not mandate a specific investment allocation for long-term savings either. Experts may be used in a court situation to describe how a given allocation of assets will help an individual spouse meet certain goals (e.g., current income, retirement, etc.). The individual is not beholden to this recommended allocation however.

Individual states and courts may have influence on when an individual retires however (Kindregan, 2013). An individual may be required to continue working in order to meet spousal support or child support obligations beyond when they would have wished to retire (Hebenstreit, 2014). Courts may also order individuals to secure obligations from their death with their assets (Miller, 2015). In addition, the state of Illinois can legally obligate an individual to pay for their children's post-secondary education (Hinckey, 2017).

Psychological research in divorce

Divorce is described as a traumatic event (Rosenfeld, Thomas, & Falcon, 2015). Trauma can cause individuals to change previous behavior and creates tunnel vision (Furnham, 2014), often excluding what may be termed "non-essential" tasks by the individual. Divorced individuals are often diagnosed with adjustment disorder (Brinig & Crafton, 1994; Strain & Friedman, 2011). Often this is used as a catch-all for a traumatic event so mental health professionals can bill care for a divorced individual through health insurance (Jordan, 2016).

Both the financial and the emotional strain caused by divorce may interfere with the ability to accomplish tasks (Amato, 2000). Individuals who have experienced divorce may often lose part of their identity (Kisthardt, 2008), which has been shown to be particularly true for dependent spouses (e.g., stay-at-home spouses). This typically will mean self-efficacy plays a large role in how a divorced individual adapts to their lives post-divorce (Warrener, Koivunen, & Postmus, 2013).

Wealth management, financial planning, estate planning or even general life planning may take a back seat to more immediate concerns. This could include employment changes, taking on more childcare responsibility or individual financial degradation (Amato, 2000; Carbone, 1994). The psychological impact of divorce can have a great influence on how these individuals think about whether or not they leave a will or other estate planning instrument behind.

Wealth management

Savings behavior

Fisher and Montalto (2011) discuss savings asymmetry as a function of reference group. This study asks how earnings in relation to the household's reference group affect savings behavior. The authors present evidence of asymmetry in savings and also indicated that those who divorce are less likely to save. The asymmetry found by Fisher and Montalto (2011) may be from a reduction in economies of scale and misallocation of resources via support.

Evidence from Sweden indicates that savings post-divorce varies depending upon gender makeup and power differential as a function of income (Zetterdahl, 2015). In practice, a lower wage-earning spouse will likely spend above their current income because prior existing expenses still occur. A higher wage-earning spouse not paying domestic support will be more likely to save. A higher wage-earning spouse paying domestic support may not have enough to support themselves and a possible new spouse. Controlling for income, divorced/separate individuals may be less likely to save and adjust to a lower standard of living (Amato, 2010). For both a paying and receiving spouse, particularly in non-remarried households, there may be a loss in economies of scale. There is possible asymmetry in this re-allocation of income, as one spouse may have spent more than the other during the marriage.

Research in marriage dynamics suggests that when U.S. laws changed to force equal division of property that household savings rates increased, suggesting women influence a household to save more (Voena, 2015). However, evidence that women save less post-divorce and men save more post-divorce suggests that divorce may have at least a temporary effect on savings (Grossbard & Pereira, 2010).

There is evidence to suggest women tend to spend more on the household, implying that post-divorce their income is directed at consumption for child well-being (Eastman, 1992). Conversely, men are more likely to direct their attention to future consumption post-divorce and as such have been shown as more likely to save (Grossbard & Pereira, 2010).

In Italy, increased precautionary savings is associated with a higher risk of divorce (Pericoli & Ventura, 2011). However, estimation of both precautionary and durable savings post-divorce has not been researched. Further, whether there is a directional effect that persists post-divorce has not been assessed either.

Risky asset share

Investigations in risk tolerance (Light & Ahn, 2010) play a role in divorce and may play a role in savings behavior (Fisher & Montalto, 2011). Light & Ahn indicated those who get divorced are more likely to have higher risk tolerance, and the effect was greater in higher risk bands. This may indicate a willingness to allocate more resources to current income and less to savings for the future. There also may be a predilection towards not savings for emergencies because of this risky behavior (Light & Ahn, 2010). This is consistent with the previous research indicating less willingness to save (Fisher & Montalto, 2011).

In general, risky asset share tends to be a result of inertia (Brunnermeier & Nagel, 2008). Individuals often do not change the status quo unless there is some sort of catalyst (e.g., major capital market movement, changing financial advisors, etc.). Over time, risky assets increase in value at a higher rate than non-risky assets (Herring, 2005), thus if inertia is in effect individuals will have increased their risky assets share by doing nothing.

Divorce often acts as a catalyst for changes (Berkowicz, 2019) and many times, at least one divorced spouse changes advisors (Cummings & James, 2014). This catalyst may trigger a change in risky asset share that may or may not persist over time. Further, often the assets an individual receives as a result of a divorce may be imbalanced (Tessler & Thompson, 2007). For example, a household may possess a retirement portfolio and a marital home, and the distribution will be uneven because the marital home may be worth more than the retirement portfolio, or vice versa. Still another example is where much of the household wealth is tied to company stock for one spouse, causing the other spouse to take assets that are more diversified and maybe tax-sheltered in a reirement plan.

Evidence garnered from Denmark suggests men decrease their risky asset share when married, and increase it after divorce (Christiansen, Joensen, & Rangvid, 2015). Women on the other hand increase their share of risky assets when married and decrease it after divorce. The Danish researchers find the effects are muted with men, and do not examine if this effect persists, nor do they have information on how the asset distribution occurred post-marriage. It is possible, as noted above that men receive most of the risky assets post-divorce.

Bequest intention or asset distribution

Even within the professional wealth management world, work on estate planning is seen as the domain of attorneys, so little attention is paid to it by the financial professionals who often work directly with clients. However, this can be a mistake, given how many people die intestate (DiRusso, 2009). Examining the effects of divorce on estate planning are even less ubiquitous (Crozier, 2007).

There is some evidence wealthy households are less likely to distribute their assets to children or other relatives intentionally (Cox & Stark, 2008). In particular, it may depend upon how those individuals or couples came about their wealth, such as inheriting it themselves or having built the wealth from scratch. Even when they do distribute wealth to their heirs, it is often done unequally among them (Francesconi, Pollak, & Tabasso, 2015). Alternatives to leaving assets to heirs can include religious organizations or other charities (James, 2018).

A disconnect between intent and actual action taken exists (James, 2009). This phenomenon exists mainly for charitable intentions, since as noted many people die intestate. Thus, the blood relatives or other legal heirs may end up receiving the assets of the deceased individual. The percentage of people who actually follow through with charitable intentions is 37% (James, 2018; Cox & Stark, 2008), suggesting while people may have those intentions, they do not act on them in time. The same applies to bequests to individuals (Hurd & Smith, 2001).

Hypotheses

In order to form hypotheses, it is necessary to clearly define the possible outcomes. Due to the influence of the law on divorce outcomes, the expected directional effect of each aspect may be different. As an example, savings is not a requirement prior to divorce but may be required after divorce. Given these constraints, the following hypotheses are outlined:

H1: Individuals will have lower precautionary savings rates post-divorce.

H2: Single-income households prior to divorce will have lower precautionary savings rates post-divorce than double-income households.

H3: As wage income increases, post-divorce precautionary savings rates will increase.

H4: Individuals will have lower retirement savings rates post-divorce.

H5: As wage income increases, post-divorce retirement savings rates will increase.

H6: Individuals will have a higher proportion of their assets in risky assets post-divorce than prior to divorce.

H7: The proportion of risky assets will not change over time post-divorce.

H8: Single-income households will have a higher proportion of their assets in risky assets than double-income households.

H9: Divorced individuals will be less likely to leave money to children or other relatives.

H10: Divorced individuals will be less likely to leave money to religious organizations.

H11: Divorced individuals will be more likely to leave money to non-religious charities.

Summary and analysis of the literature as applied to the research problem

Given the legal-driven nature of divorce, and the historical view regarding sharing of resources post-divorce, the literature is ready for expansion into the realm of how to plan given a divorce event. The history of divorce has been driven more by religious context and historically most religions have looked at marriage as a state of being for life and planning for it should not happen. Studies into how dependent spouses are more likely to experience poverty as a result of divorce are important when discussing how to plan around the areas of savings, retirement, life insurance, bequests and investments.

The psychological effects are just as important as the legal framework, as the trauma caused by divorce may change behavior and cause specific financial behaviors. The research illustrating the strain of divorce, both in the moment and over time is compelling enough to examine how an individual financial plan may change.

Divorce stress adjustment is an appropriate lens with which to view wealth management behavior changes. The frequent diagnosis of adjustment disorder for individuals going through divorce illustrates that mental health intervention takes this adjustment into account. It is important to view aspects of wealth management through an adjustment to the “new normal” a divorced individual may be experiencing.

While there has been literature related to various aspects of financial planning and wealth management, little focus has been related to divorce, nor the long-term consequences of divorce. Financial plans are long-term living documents. Given the prevalence of wealth management and financial planning firms specializing in divorce and the need to assist in these changes and transitions, research in these areas may allow for evidenced-based practices as it relates to helping divorcing or divorced individuals in wealth management and financial planning. If changes to a plan negatively influence that plan, both the magnitude and duration are important in order for practitioners to help.

Chapter 3 - Methodology

This study examined primarily whether divorce leads to wealth management changes. Specifically, the study examines the effect of divorce on the following aspects of wealth management: precautionary savings, retirement savings, risky asset share and bequest intention. This study uses the Panel Study on Income Dynamics (PSID) to answer these questions.

Study design

Panel data were obtained from a large, nationally representative data set. In order to answer the research question and test the hypotheses, variables were created from questions within the survey. These variables were examined over time by using regression techniques suitable for longitudinal data. In addition, cross-sectional data were used to examine bequest intentions.

Data and sample

The Panel Study on Income Dynamics (PSID) collects data on U.S.-based respondents. The survey is housed at the University of Michigan Institute for Social Research and was originally sponsored by the Office of Economic Opportunity of the United States Department of Commerce. Currently the sponsors include the National Science Foundation, the National Institute on Aging, the Eunice Kennedy Shriver National Institute of Child Health and Human Development, the Indiana University Lilly Family School of Philanthropy and the Economic Research Service and U.S. Department of Agriculture. The purpose of the study is to gather data to examine trends in income and expenditures by individuals in the United States. These data include general wealth questions and detailed income questions. The survey comprises a RAND compiled survey dataset, Leave-Behind Psychosocial and Lifestyle surveys, and exit interviews after the death of a respondent. The dataset has over 37,000 individual participants and covers over 8,000 families. The PSID is the longest running longitudinal survey in the world and has been collecting data since 1968. Prior to 1997 data were collected every year but have since been collected every two years.

A useful characteristic of the PSID as compared to other large-scale surveys is that if a couple divorces, the survey follows both divorced individuals and not just the head of household. This allows for comparisons at different times where someone may not be divorced, then get divorced and answer questions differently. This is necessary in order to answer the research question.

The PSID has previously been used in research assessing marriage and divorce characteristics (Ciscato, 2018; McGonagle, Schoeni, Sastry, & Freedman, 2012). In addition, the data has been used on multiple occasions in assessing risky asset share (Christiansen et al., 2015). Studies have also examined savings data (Grossbard & Pereira, 2010) and bequest intentions (Hanke, Englebrecht, Di, & Bisping, 2012).

The PSID has been used in a number of ways and is found to be data of good quality (McGonagle, 2010). As with most surveys, there are a variety of challenges that can occur in self-reported data such as the PSID. In particular, national surveys have issues with representativeness, non-response bias, and self-reporting error. These can affect the validity and reliability of the instrument. Each of these potential concerns are addressed in the following discussion.

Representativeness

The PSID has been examined for representativeness as it relates to wealth data (Juster, Smith, & Stafford, 1999; Duncan & Hill, 1989) as well as data on marriage and divorce (Lillard

& Waite, 1995). Curtin and colleagues compared the PSID data against the Survey of Income and Program Participation (SIPP) and the Survey of Consumer Finances (SCF) and found the PSID data, while less suited to detailed wealth data, was more robust with respect to income data. The researchers concluded the measurement error in the PSID was better than either the SIPP or SCF. Lillard and Waite (1995) concluded the data of when and whether individuals were married and divorced lined up well and were internally consistent. Further, as with other national datasets, weights have been computed in complex sample design to compensate for other demographic non-response.

Non-response bias

One issue with longitudinal surveys is the problem with repeated responses. That is, people may not respond in follow-up years. The PSID estimates small amounts of attrition from cohorts beginning in 1968, that added up to a total response rate of 56.1 percent in 1988. However, the Unicon Study (Bound, Brown, Duncan, & Rodgers, 1989) found that this attrition had negligible effects on parameter estimates.

Self-reporting bias

To combat self-reporting bias, the PSID committee has over time attempted to collect as much physical evidence associated with reported values as possible. For example, respondents are directed to input information from bank statements, W-2s and other financial-related documents. This has been shown to reduce (but not eliminate) the measurement error. Lower income individuals over-reported income, and higher income individuals underreported income, and men tended to over-report, while women under-reported (Duncan & Hill, 1989). This is consistent with other literature in consumer sciences (Goldin, 2014; Tharp, Lurtz, Mielitz, & Kitces, in press).

Sample description

Data including divorced individuals was first reported in 1982 and observations from 1987 through 2007 were extracted from the PSID data repository. Both weighted and unweighted analyses were conducted on a reduced sample. The sample was reduced from 45,518 to 13,465 number of observations by only including divorced individuals. Total cross-sectional units examined ranged from 878 to 1,121. Since the goal is not to examine a between groups effect (i.e., divorced versus non-divorced), but within group and within person observations, all non-divorced individuals are excluded for purposes of precautionary savings, retirement savings and risky asset share analyses. Separated status is ignored. While it is estimated only 13% of all separated individuals eventually reconcile (Centers for Disease Control, 2017), this may bias estimates if included. Separated individuals divorcing will eventually be captured in the sample because of the longitudinal nature of the study. The sample was further reduced to only evaluate years 1997 through 2007, as those were the only years where savings rates and risky asset share could be measured. Individuals who remarried are included in order to examine the effect remarriage has on each variable. For bequest intention analyses, married individuals were appended to the dataset, resulting in 7,595 cross-sectional units to be examined.

Each individual questioned in the PSID survey is issued an identification number for tracking purposes. Identification numbers were checked against individuals identifying as divorced and subsequently identifying as single to be sure those individuals stayed in the sample. Care was taken to identify an individual who was not head of household previously and then subsequently as a single person as head of their individual household. Since the PSID follows both individuals, it is possible to do this, but care is taken to recognize each individual post-divorce.

Missing data

Missing data is assumed to be either missing completely at random (MCAR) or missing at random (MAR). Prior wave carryover is used for variables where prior wave data is likely to be similar to the current wave, such as wage income (Duffy, 2011). For continuous variables where prior wave information is not helpful, multiple imputation is used. Missing data for categorical variables is imputed using maximum likelihood estimation (Allison, 2011).

Operationalization of concepts

The study examines three separate but related concepts. The first concept of savings is operationalized by determining how much earnings an individual manages to exclude from income on an annual basis. This is described as the ratio of savings to income. The second concept deals with the investment of that savings and is described as the proportion of an individual's proportion of assets in risky investments. The third concept is the distribution of those assets saved and invested, specifically whether a bequest is being left.

Dependent variables: Savings, risky asset share and bequest intentions

Savings rate is a calculation of the individual's annual savings divided by their total annual income. Both the savings rate for precautionary savings and long-term savings (i.e., retirement savings) are analyzed. Evidence suggests individuals treat these savings differently in the best of circumstances (Shefrin & Thaler, 1988), when there are not emergencies, cash flow is positive or have a positive economic outlook.

Precautionary savings (1a)

Precautionary savings is defined as the dollar amount an individual places in checking accounts, money market accounts and savings accounts in a single year divided by that individual's gross income. Gross income is defined as income from all sources. Gittleman and

Wolff (2009) provide a method for calculating savings rates. The current period combination of all checking, money market and savings accounts are subtracted by the previous period combination of checking, money market and savings accounts as well as subtracting windfalls such as inheritances. Growth on these assets is accounted for by subtracting the interest increase calculated as a geometric return between periods, using bank rates during the specified time period. The net subtracted number is the amount saved in that time period. Extrapolating the savings rate is then the amount saved in that time period divided by wage income. This is the method that was applied.

Retirement savings (1b)

Retirement savings is defined as the dollar amount an individual places in retirement accounts such as IRAs, 401(k)s, and other defined contribution vehicles divided by their gross income. Defined benefit plans are not included in contributions. Gross income is defined as income from all sources. Growth on these assets is accounted for by subtracting the geometric return of a proportion of stock to total retirement assets, with the S&P 500 returns being used as the proxy for stock.

Dependent variable for analysis 2 - risky asset share

Risky asset share is defined as the dollar amount of stock assets owned, divided by the dollar amount of total liquid assets owned. Total assets include stocks, bonds, cash, checking accounts, savings accounts and money market accounts. These amounts are calculated in aggregate regardless of account type (e.g., taxable, tax-deferred). Home equity is excluded in part because it is not marked to market (i.e., it is not easily valued), in part because it is a use asset and in part because the value is dependent upon a proportion of leverage and property value. In order to account for stock market growth, the geometric mean return of the S&P 500 is calculated for each time period and subtracted from the the stock portion of the assets.

Dependent variable for analysis 3- Bequest intention

Unfortunately, after examining the data from the PSID in detail there is only one year where bequest intention data is gathered. In 2007, respondents were asked three separate bequest intention questions. One question asked if they intended to leave money to children or other relatives, another asked if they intended to leave money to a religious organization and the last asked if they intended to leave money to a charitable organization unrelated to religion. Each item had four possible responses. These were “not important”, “somewhat important”, “important” and “very important”. These responses were collapsed into a binary variable, where “important” includes “important” and “very important” and “not important” includes “not important” and “somewhat important”. If the outcome was “important” it was coded as a “1” and if it was “not important” it was coded as “0”.

Independent variables

Sex/Gender. Sex/gender is defined as “1” for female, “0” for male. No other identifiers are used for sex or gender. Observations including options other than male or female were excluded from the sample.

Race. Race included variables for Black, Hispanic, and Asian/other. White was used as the reference group.

Net worth. Net worth is the total of all assets, including real estate, minus all liabilities. Due to the possibility of negative values, an inverse hyperbolic sine transformation was used (Friedline, Masa, & Chowa, 2015) in order to account for negative values and zeroes in net worth.

Age. Age is treated as continuous and is represented by the numerical age of the individual respondent and only included individuals aged 25 to 55 in order to reduce the likelihood an individual was retired at some point during the period in question.

Wage/employment income. Income is a continuous variable totaling the wage, contract or self-employment income of an individual. Within this subsample, the number ranges between 0 and $428,000. This variable was log-transformed for ease of interpreting coefficients in regression models.

Alimony. Alimony is a cash payment from one spouse to another for the receiving spouse's benefit. For purposes of this study, this variable is categorical, and an individual is either "paying alimony", "receiving alimony" or "neither paying nor receiving alimony".

Child support. Child support are cash payments from one spouse to another for the benefit of mutually supported children. For purposes of this study, this variable is categorical and an individual is either "paying child support", "receiving child support" or "neither paying nor receiving child support".

Risk tolerance. Risk tolerance in the PSID is measured using income gamble questions. These questions are a way to approximate an individual tolerance for risk. While there are some problems with measurement of risk tolerance (Kimball, Sahm, & Shapiro, 2009; Lurtz, Archuleta, Kothakota, & Heckman, working paper), the income gamble questions have been used in many empirical studies.

Respondents are asked the income gamble questions in the following way:

"Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job, with a 50-50 chance it will double your (family) income and a 50-50 chance that it will cut your (family) income by X%. Would you take the new job?"

Depending upon the answer, the respondent is then given a similar question for a higher risk job or lower risk job. This continues until an individual is sorted into one of six types of risk preference. These categories are rank ordered from one (low risk) to six (high risk).

There are a few issues with using this measure in modeling. The first is that risk tolerance was only assessed in 1996. For purposes of this analysis, it is assumed that risk tolerance will not vary over time and was carried forward in the modeling process. The second issue involves how the question is asked in the PSID. Each member of the household is asked the income gamble questions (Kimble, Sahm & Shapiro, 2009). When dividing the household to examine divorced individuals, the risk tolerance question is not accurately assigned to the new ID for the non-head. In order to ameliorate this problem, 158 of the non-heads of the sample were chained to create a new sample by taking the average pre-divorce risk tolerance of the couple, then adding .07 if the non-head of household was male, and subtracting .13 if the non-head was female to account for gender variation contained within the sample (Kimble, Sahm & Shapiro, 2009). These values were rounded to the nearest whole number.

Education. Education is identified as a categorical variable and includes “did not complete high school”, “some college”, “bachelor’s degree”, “master’s degree”, “professional or doctorate degree”. “High school completion” was used as the reference group.

Employment. Employment is a categorical variable and includes “Employed”, “Unemployed” and “Other”. Employed includes self-employed, and multiple occupations. Unemployed includes temporarily looking for work, employed as a homemaker, or maternity leave. Other includes prison, disabled or other.

Sample descriptive statistics

The following tables illustrate sample descriptive statistics for the dependent and independent variables. Categorical variables are displayed by percentage and year. Continuous variables report mean and standard deviation by year. A check was made for same sex divorces and none occurred during the analysis time period. Dependent variables are shown first, beginning with precautionary savings, then retirement savings, then risky asset share.

Those calculated to have had mean precautionary savings rates that fell between 0.12% (SD: 4.30%) of savings and 3.85% (6.70%) of savings. These are mean numbers and represent the whole of each year cohort, including those just divorced in that given year. The retirement savings rates were reported as mean percentages between 1.12% (SD: 6.78%) and 8.66% (SD: 5.66%).

Table 1: Precautionary savings rate descriptive statistics

Year	*n*	Mean	Median	SD
1997	323	-3.85%	0.00%	6.70%
1999	445	0.12%	0.00%	4.30%
2001	918	-0.79%	0.00%	7.32%
2003	930	-1.28%	0.00%	16.83%
2005	890	-0.72%	0.00%	9.17%
2007	872	-1.00%	0.00%	22.81%

Table 2: Retirement savings rate descriptive statistics

Year	*n*	Mean	Median	SD
1997	323	-1.12%	0.00%	6.78%
1999	445	1.01%	0.00%	5.66%
2001	918	-5.06%	0.00%	18.61%
2003	930	-1.95%	0.00%	4.71%
2005	890	4.70%	0.00%	8.15%
2007	872	-2.40%	0.00%	6.45%

Table 3: Risky asset share descriptive statistics

Year	*n*	Mean	Median	SD
1997	289	17.00%	2.00%	31.00%
1999	371	11.00%	1.00%	26.00%
2001	456	10.00%	0.00%	24.00%
2003	810	8.00%	0.00%	22.00%
2005	793	8.00%	0.00%	22.00%
2007	814	7.00%	1.00%	20.00%

The sample skewed female with men representing as low as 39.30% and women as high as 60.70%. The majority of the sample were white (53.41% to 60.67%), while the next largest racial group were black (31.57% to 40.52%). Hispanics made up between 2.67% and 3.25% of the sample. Asian and other races ranged from 3.37% and 6.87% of the sample.

Table 4: Gender descriptive statistics

Year	*n*	Male	Female
1997	928	40.95%	59.05%
1999	1056	39.30%	39.30%
2001	1124	41.37%	58.63%
2003	1239	42.86%	57.14%
2005	1199	40.20%	59.80%
2007	1187	39.85%	60.15%

Table 5: Race descriptive statistics

Year	*n*	White	Black	Hispanic	Asian/other
1997	928	60.67%	31.57%	2.80%	4.96%
1999	1056	60.13%	32.67%	2.84%	4.36%
2001	1124	57.12%	33.99%	2.67%	6.22%
2003	1239	54.72%	35.59%	2.82%	6.87%
2005	1199	54.38%	38.37%	3.25%	4.00%
2007	1187	53.41%	40.52%	2.70%	3.37%

Most of the sample were working (68.64% and 82.92%), while between 1.12% and 8.26% were self-employed. Between 15.66% and 23.71% were unemployed or not looking for work. Between 29.98% and 33.53% were high school graduates, while 17.30% to 23.77% did not complete high school. Between 8.39% and 14.77% possessed bachelor's degrees with between 6.32% and 7.48% having some graduate schoolwork.

Table 6: Employment descriptive statistics

Year	*n*	Employed	Not working or retired	Self-employed	Self employed and working
1997	928	68.64%	23.71%	7.54%	0.11%
1999	1056	70.93%	21.88%	7.01%	0.18%
2001	1124	82.92%	15.66%	1.12%	0.30%
2003	1239	73.38%	15.74%	7.91%	2.97%
2005	1199	72.39%	18.85%	8.17%	0.59%
2007	1187	71.02%	20.05%	8.26%	0.67%

Table 7: Education descriptive statistics

Year	*n*	No high school	High school graduate	Some college	Bachelor's degree	Graduate work
1997	928	23.77%	32.00%	24.78%	12.01%	7.44%
1999	1056	22.23%	30.49%	26.04%	13.76%	7.48%
2001	1124	20.18%	29.98%	27.77%	14.77%	7.30%
2003	1239	17.36%	33.33%	34.30%	8.39%	6.62%
2005	1199	17.69%	32.94%	33.44%	9.09%	6.84%
2007	1187	17.03%	33.53%	34.11%	9.01%	6.32%

As expected, there were few individuals either saving or paying alimony. Those paying alimony ranged from 0.65% to 1.21%, while those receiving alimony ranged from 1.69% to 2.84%, with between 96.12% and 97.52% neither paying nor receiving alimony. Those paying child support ranged from between 8.76% and 12.11%. Those receiving child support ranged between 16.22% and 18.28% with between 71.67% and 75.48% neither paying nor receiving child support.

Table 8: Alimony descriptive statistics

Year	*n*	Paying alimony	Receiving alimony	Neither paying nor receiving alimony
1997	928	0.65%	1.83%	97.52%
1999	1056	0.85%	2.08%	97.06%
2001	1124	1.16%	1.69%	97.15%
2003	1239	1.21%	2.26%	96.53%
2005	1199	0.92%	2.84%	96.25%
2007	1187	1.10%	2.78%	96.12%

Table 9: Child support descriptive statistics

Year	*n*	Paying child support	Receiving child support	Neither paying nor receiving child support
1997	928	8.94%	17.67%	73.38%
1999	1056	9.09%	18.28%	72.35%
2001	1124	9.52%	17.17%	73.31%
2003	1239	12.11%	16.22%	71.67%
2005	1199	8.76%	16.26%	74.98%
2007	1187	8.76%	15.75%	75.48%

The risk tolerance measure was taken only in 1996, but the measure was appended to each cohort. Values ranged from 1 to 6, with a mean of 1.86 (SD: 1.76). The median was 2, suggesting this group of divorced individuals was on the lower risk side.

Table 10: Risk Tolerance descriptive statistics

Mean	Median	SD	*n*
1.86	2	1.76	1287

Rated on scale from 1 - 6, 1 being extremely low risk tolerance and 6 being extremely high

The mean income ranged between $20,865 and $27,822. The standard deviations were between $21,500 and $32,166 per year. The mean net worth was between $56,400 and $98,720 with standard deviations of $214,630 and $486,150.

Table 11: Income descriptive statistics

Year	*n*	Mean	Median	SD
1997	928	$ 20,865	$ 16,000	$ 21,817.00
1999	1056	$ 22,440	$ 21,000	$ 21,500.00
2001	1124	$ 26,265	$ 26,000	$ 24,602.00
2003	1239	$ 26,012	$ 24,000	$ 24,319.00
2005	1199	$ 27,473	$ 20,000	$ 32,166.00
2007	1187	$ 27,822	$ 23,000	$ 31,758.00

Table 12: Net worth descriptive statistics (in $1000s)

Year	n	Mean	Median	SD
1997	928	$ 58.21	$ 6.00	$ 287.64
1999	1056	$ 59.40	$ 12.10	$ 336.54
2001	1124	$ 56.44	$ 14.54	$ 214.63
2003	1239	$ 66.58	$ 17.15	$ 299.97
2005	1199	$ 98.72	$ 14.25	$ 486.15
2007	1187	$ 74.68	$ 16.00	$ 302.60

Ages of the sample had a mean between 41.95 and 48.75. The standard deviations were between 6.71 and 12.54. Ages ranged between 28 and 55 for the entire sample.

Table 13: Age descriptive statistics

Year	*n*	Mean	SD
1997	928	41.95	6.71
1999	1056	45.19	12.39
2001	1124	46	12.02
2003	1239	46.49	11.86
2005	1199	47.47	12.25
2007	1187	48.75	12.54

Houses that were dual income prior to divorce ranged from 47.62% and 55.01%. This is compared to single income households where they ranged from 44.99% to 52.38%. As the years increased, the number of dual-income households increased, and the number of single income households decreased.

Table 14: Dual income and single income households

Year	*n*	Dual income households	Single income households
1997	928	47.62%	52.38%
1999	1056	50.19%	49.81%
2001	1124	51.61%	48.39%
2003	1239	50.67%	49.33%
2005	1199	53.48%	46.52%
2007	1187	55.01%	44.99%

Most households in the sample had less than one child at home. The mean number of children was between .67 (SD: 1.02) and .94 (SD: 1.18) and decreased over time. Respondents in the sample paying for college-related expenses were between 23.92% and 30.86% of the sample. Between 69.14% and 76.08% were not paying for college-related expenses.

Table 15: Minor children in household

Year	*n*	Mean	SD
1997	928	0.94	1.17
1999	1056	0.76	1.11
2001	1124	0.67	1.02
2003	1239	0.67	1.03
2005	1199	0.69	1.02
2007	1187	0.69	1.06

Table 16: Paying for college related expenses

Year	*n*	Yes	No
1997	928	23.92%	76.08%
1999	1056	25.66%	74.34%
2001	1124	30.34%	69.66%
2003	1239	28.89%	71.11%
2005	1199	30.86%	69.14%
2007	1187	27.21%	72.79%

A small number of the sample would indicate they were remarried. This number fell between 4.63% and 7.48%. This number included people previously divorced who indicated "married" as well as people who remarked they remarried between the last time and the current time.

Table 17: Remarried versus not remarried

Year	*n*	Remarried	Not remarried
1997	928	4.63%	95.37%

1999	1056	7.48%	92.52%
2001	1124	5.25%	94.75%
2003	1239	5.73%	94.27%
2005	1199	6.17%	93.83%
2007	1187	5.81%	94.19%

The analytic sample requires additional dimensionality, as there are new individuals divorced at any given time period. As an example, an individual may be divorced at *t*, and then be divorced for all five time periods. Or they may drop from the sample as they renewed their answer to the marital status question as "single". Or they may get remarried and eventually drop from the sample. In addition, someone may only get divorced at $t + 2$ or later and not be in the sample for all subsequent years.

Table 18: Sample size by time divorced

Time	*n* - Precautionary savings	*n* - Retirement savings	*n* - Risky asset share
$t + 2$	944	878	1121
$t + 4$	788	734	803
$t + 6$	656	602	647
$t + 8$	551	498	544
$t + 10$	389	321	408

Data analysis methodology

Exponential fractional response regression.

Analysis 1A

The savings rate is defined as a ratio of savings to income and ratio variables follow a sigmoidal distribution (Gallani, Krishnan, & Wooldridge, 2015). Ordinary least squares regression can be used to model ratio outcome variables provided all values fall along the linear portion of the distribution. However, the savings rate is often negative or zero in the US

(1)

(Desroches & Frances, 2010). For this study, the precautionary savings rate variables is constructed as follows:

$$S_p = \frac{(\sigma_s + \sigma_{mm} + \sigma_o)}{\theta}$$

where S_p is the precautionary savings rate, a ratio of sum of amounts of annual amount saved in a savings account, money market account and other short-term savings divided by annual wage income. Savings in a savings account, money market account and other short-term instruments are represented by σ_s, σ_{mm}, and σ_o, respectively. Wage income is defined as θ, which includes self-employment income, but excludes investment income and retirement income.

Given this equation, savings cannot fall below zero nor exceed one. There are many zeros associated with panel survey data for savings (Wooldridge, 2013). Many households will not have any savings and there are clusters of observations at zero. This would suggest an analysis method using a truncated model such as a Tobit regression (Ramalho, Ramalho, & Henriques, 2010). A tobit model is inappropriate because it is used with data that are censored and may have values above one and below zero.

Fractional response models are more appropriate for these data as a variable such as a savings variable is a percentage. In other words, an individual may save no less than 0% of their income (based on the definition of savings in this study) and no more than 100% of their income. Pooled fractional response probit models have been used for ratio variables in accounting and finance, such as in the case of business metrics (Papke & Wooldridge, 2008). However, fractional response probit models require unobserved data to be normally distributed. The fractional response model can be defined as a conditional expectation in the following form:

$$E(y_i|x_i) = N(x_i\partial) \tag{2.1}$$

where ∂ is a vector of variables describing the conditioned response and N is a nonlinear function bounded by 0 and 1. N is generally placed in a functional probit or logit model.

Fractional response models may be extended in order to account for time with fixed effects in panel data as outlined below:

$$E(y_{it}|\alpha_i x_{it}) = N(x_{it}\partial + \alpha_i) \tag{2.2}$$

where α_i is unobservable heterogeneity that does not vary by time. This method will not provide consistent estimators in panel data however due to the unobservable heterogeneity. While α_i could be estimated to account for this, normal data is required which is not present in a sigmoidal distribution (Loudermilk, 2007; Elsas & Florysiak, 2015). Including an unobserved heterogeneity term in the model is a catch-all for this type of model. The presence of an endogenous covariate would solve any simultaneity bias, for the one individual covariate. This model with and without fixed effects does require strict exogeneity for all other covariates however. This assumption is seldom met and there is ample evidence that many other variables are tied to savings.

The Exponential Fractional Response Model (EFRM) allows for analysis of ratio data bounded by 0 and 1, with clustering at one end of the distribution or both (Ramalho & Ramalho, 2018; Papke & Wooldridge, 1996). The model also allows for lagged dependent variables and does not require normal distribution of unobserved variables. A fully realized EFRM will produce consistent estimators and is therefore the model used in this study.

Econometric issues

Since the savings rate contains the income variable, there is a simultaneous bias problem (Firebaugh & Gibbs, 1985). This issue may be solved using an instrumental variable in a 2SLS model (Grossbard & Pereira, 2010). The instrument itself is a variable that is correlated with the outcome variable, but not the problem predictor variable. This model can reduce the endogeneity associated with the income and savings rate variables. However, finding an appropriate instrument for income can be challenging. Past research into proportions based on income suggest simultaneity is not that large of an issue. However, due to the two-stage nature of the EFRM, this problem of endogeneity is addressed. Multiple endogenous variables are allowed within the EFRM model because there are two sets of estimators. Three fixed effects estimators using mean differenced, quasi-differenced transformations make up the first set of estimators. The second set of estimators include correlated random effects, random effects and another fixed effects estimator. There is no need to specify a reduced model for endogenous explanatory variables as the quasi-differenced mean transformation uses the control function approach (Gallani, Krishnan & Wooldridge, 2015; Ramalho & Ramalho, 2015; Vinod & Rao, 2019).

There is a chance that a change in savings may be due to variables outside of the model. Other shocks or major expenses may cause an increase or decrease in savings. In order to address this, a mean-zero error term is added to the final model to account for any unobserved effects on the savings rate.

Life events. The outcome is conditioned upon several control variables noted in the variable section. Age and age-squared are designed to be indicators of life cycle changes. These along with dummy variables for gender, and employment variables are used to absorb any effects from any common life cycle events (e.g., children going to school, retiring, etc.).

Measurement error. Panel microdata from surveys bring to mind measurement error as a concern because the measurement error at a specific time period is compounded over time. That is, any deviation from the value a respondent gives and the true value can create bias in a model (Groves, Fowler, Couper, Lepkowski, Singer & Terangeou, 2009). An OLS equation will be less precise than a more robust model with an instrumental variable approach such as the Two-Stage Least Squares model (Brunnermeier & Nagel, 2008). However, a logit EFRM allowing for endogenous covariates should minimize this measurement error.

Estimating parameters in an EFRM can be described in the following way:

$$y_{it} = N[exp(x_{it}\partial + \alpha_i + v_{it})], \qquad (3.1)$$

where N is a logit, loglog or cloglog equation. The variable y_{it} is a fractional response variable, and x_{it} is a series of control and other explanatory variables , ∂ represents the parameters of interest, in this case the time from divorce variables and α_i is time-invariant heterogeneity. The v_{it} describes the time-varying unobserved heterogeneity. For the savings rate equation, th model can be re-written as follows:

$$S_{pt} = N[exp(e_{it}\partial + \alpha_i + v_{it})], \qquad (3.2)$$

where S_{pt} is the savings rate variable over time and e_{it} is the set of explanatory variables. These variables include sex, race, employment, education, age, income, net worth, number of children, remarriage, expenses for college, child support, alimony and risk tolerance.

An important aspect of the EFRM model is the ability to handle zero observations for the response variables. EFRM uses a logit-link function and is a major advantage since many fractional responses have data clustered at 1 or 0. This link function has the added benefit of producing interpretable coefficients directly in model output.

In summary, the EFRM model allows for analysis of fractional response dependent variables, where there are observations clustered at one end or both. Using time dummy variables and other econometric adjustments simultaneity bias can be accounted for. Using a fixed effects approach can allow for observation of any changes to the savings rate after divorce and allow for determination of whether or not that change persists over time.

Analysis 1B

Short-term and long-term savings can be assessed in similar ways. In order to examine longer term savings such as retirement savings, an EFRM model is used including the rate of long-term savings in vehicles normally reserved for retirement. The formula for the savings rate is identical to precautionary savings, with a substitution of S_{rt} to denote retirement savings rate over time.

Analysis 2

Risky asset share is described as the proportion of risky assets as defined by the proportion of stocks to risk-free assets plus the risky assets. As with the savings rate variable, there will be clusters of observations at zero. Risky asset share takes the following form:

$$R_p = \frac{\lambda}{(\mu + \lambda)} \tag{4.1}$$

where R_p is the risky asset share and λ is the amount invested in stock investments and μ is the amount invested in non-risky assets, exclusive of real estate. Risky asset share can be analyzed with a logit EFRM as well.

Inertia, sudden wealth change, life cycle events and market effects.

One issue with examining risky asset share has to do with the idea of inertia. Individuals may hold risky assets simply because they appreciate more (Campbell & Cochrane, 1999). Thus, it can be difficult to determine if someone is holding more risky assets due to gains in that asset class, or purposeful reallocation. Teasing this out of microdata and comparing individuals against themselves is problematic.

Evidence from the PSID suggests individuals are more likely to succumb to inertia in asset allocation (Brunnermeier & Nagel, 2008). Thus, any large shifts in allocation are likely to be because of some other cause or event omitted in the model. For purposes of this analysis, inertia is controlled for using time dummy variables.

An individual allocation may shift as a result of events other than divorce. As an example, an individual may inherit wealth in the form of either risky or non-risky assets. This could create a shift in balance of risky to non-risky assets or vice versa.

As with savings, there are events in the life cycle that can cause issues with risky asset share. For example, as individuals age conventional wisdom is to shift from risky assets to less risky assets. Time dummies should absorb any life cycle effects.

It is possible that systematic risk of global markets may cause an adjustment to risky asset share outside of the control of an individual household. That is, risky assets may lose or gain value as the result of a market event. It is estimated that the year variables should account for these effects and blunt any dramatic changes. In other studies (Brunnermeier & Nagel, 2008) local economic changes can affect a portfolio if locally sensitive assets are included in the ratio. Given housing and wealth is not included in the ratio, no estimation of geographic-specific parameters is necessary.

The logit EFRM for risky asset share can be described as follows:

$$R_{pt} = N[exp(e_{it}\partial + \alpha_i + v_{it})], \tag{5.1}$$

where R_{pt} is the savings rate variable over time and e_{it} is the set of explanatory variables.

While risky asset share has been examined using both OLS and 2SLS models (Brunnermeier & Nagel, 2008), in order to measure whether there is a reversion to previous allocation or the new adjustment appears to be permanent, using the EFRM model and examining those coefficients are more appropriate for this analysis.

Sub-analysis 1: Dual income versus single income

In order to examine differences in individuals who were part of either a dual income or single income households post-divorce, separate regressions were run to compare how individuals fare in these specific circumstances. Dual income households experience higher incomes and more financial resiliency than single income households (Thorne, 2010). A dual income household that divorces will conceivably end with both individuals having income post-divorce. While they will lose the economies of scale of one household such as sharing housing expenses, they will have employment income of their own allowing them to build Social Security credit for income in retirement as well as the human capital associated with work experience.

Single income households on the other hand will lose economies of scale in both directions. The party with income loses home and caregiving services, and the party with no income has no income of their own to use in the new household, unless transfers of child support and spousal support occur. Given the low propensity of alimony to be awarded (Ellman & Braver, 2012) and inadequacy of child support payments (Morgan, 2011) this will not likely be able to ameliorate the loss of the other spouse's income. Analysis was conducted on precautionary savings as well as retirement savings. Risky asset share on this sub-group was also assessed.

Sub-analysis 2: Male versus female

As outlined in the literature review, men and women have been shown to have differing behaviors when it comes to saving, investing and wealth distribution (Backcock, Recalde, Vesterlund & Weingart, 2017). Separate regressions allow for comparison among the sub-groups. Comparisons between groups are made.

Analysis 3

Bequest intention is only asked in 2007. This makes it difficult to draw longitudinal comparisons. Instead, differences are examined between divorced and non-divorced individuals and a number of dimensions. While this makes it difficult to examine any change over time, it will allow a confirmatory or contradictory analysis of previous research and can provide information to professionals on differences between married and divorced people.

Due to the imbalanced nature of the data a binary logistic regression is a preferable analysis technique compared to a multinomial model (Wooldridge, 2013). Therefore, "not important" and "somewhat important" are collapsed into a single category that is "not important" and "important" and "very important" are collapsed into a category of "important". For purposes of coding, "not important" is "0," while "important" is "1".

Binary logistic regression is used when the outcome variable takes one of two values. The model takes the following basic form:

$$Pr[y = 1|x, z] = p = \frac{exp(\partial + \beta\ *\ ln\,x\ + \gamma z)}{1\ +\ exp(\partial + \beta\ *\ ln\,x\ + \gamma z)} \tag{6}$$

Where $Pr[y = 1|x, z]$ is the probability of an outcome "1" given a set of linear predictors x and z. These predictor variables for this model include divorced or not, sex, race, age, education, employment, wages and net worth. Binary logit model uses maximum likelihood estimation to determine the log-odds of an outcome. In this case, the model is determining the direction and magnitude an independent variable will increase or decrease the log-odds of someone responding to the bequest intention question as "important."

Three separate regressions are completed for each question. Combining the questions makes little sense as it would be difficult to parse the influence of one on the other. In order to make the effect more interpretable, the “margins” package for R is used to estimate average marginal effects of each covariate, which makes the outcome more interpretable.

Chapter 4 - Results

Exponential fractional regression models were conducted for independent variables on precautionary savings, retirement savings and risky asset share. Employment was removed from all EFRM models due to convergence issues. In addition to the full sample analysis, a sub-analysis was conducted which separated respondents with dual income households prior to divorce from those with single income households prior to divorce. A sub-analysis was also completed comparing with separate regressions for males and females. These analyses were done for precautionary savings, retirement savings and risky asset share. Binary logit models were completed for bequest intention for children or other relatives, bequest intention for religious organizations and bequest intention for non-religious charities.

Due to self-reporting bias, estimates of precautionary and retirement savings rates changes for men and women should be interpreted with caution. Previous research indicates men indicate their income is higher than it actually is, and women indicate their income is lower than it actually is (Duncan & Hill, 1989; Goldin, 2014; Tharp, Lurtz, Mielitz, & Kitces, in press) . In the case of men, this will bias their savings estimates downward and for women it will bias the savings estimates upwards.

Precautionary savings – Overall

Exponential fractional regression results for precautionary savings are outlined in Table 18. Gender differences in precautionary savings were not significant in the full model (ß = 0.60; p = 0.62), nor was race. Age was not significant as a factor in precautionary savings (ß = 2.64; p = 0.86). Those paying alimony (ß = 1.28; p = 0.59) and those receiving alimony (ß = -0.35; p = 0.90) were not significantly different from those neither paying nor receiving. Those paying child support (ß = -0.44; p = 0.52) and those receiving child support (ß = -0.34; p = 0.89) were not significantly different from those neither paying nor receiving child support. Risk tolerance was not a significant factor in precautionary savings (ß = -0.30; p = 0.84). Education was not significant as a factor in change in precautionary savings. Income was not significant (ß = 0.78; p = 0.16) and neither was net worth. The number of children had a positive association with precautionary savings (ß = 0.97; p = .09). Paying for college was significant at the $p < .01$ level (ß =-2.52) suggesting a negative association with precautionary savings. Getting remarried was positively associated (ß =3.94; $p < .05$) with precautionary saving.

Table 19: Exponential fractional regression results – Precautionary savings

Variable		ß	S.E.	t value	*p*-value
Sex (Male)		-	-	-	-
	Female	0.60	1.21	0.49	0.62
Race (White)		-	-	-	-
	Black	-2.57	1.89	-1.36	0.17
	Hispanic	-1.07	0.96	-1.11	0.27
	Asian/other	0.06	0.64	0.09	0.93
Age		2.64	1.58	1.92	0.86
Alimony (Neither pays nor receives)		-	-	-	-
	Pay	1.28	2.42	0.53	0.59
	Receive	-0.35	2.67	-0.13	0.90
Child Support (Neither pays nor receives)					
	Pay	-0.44	0.68	-0.64	0.52
	Receive	-0.34	2.67	-0.12	0.89
Risk tolerance		-0.30	1.45	-0.20	0.84
Education (High school graduate)		-	-	-	-
	No high school	-0.45	1.57	-0.29	0.77
	Some college	0.78	0.56	1.39	0.16
	4-year degree	1.02	1.65	0.62	0.54
	Some graduate	0.68	1.20	0.71	0.61
Income		0.78	0.56	1.39	0.16

Net Worth		0.62	0.85	0.73	0.47
Number of children		0.97	0.57	1.71	*0.09
School expenses (No school expenses)		-2.52	0.95	-2.66	***<.01
Remarried (Not remarried)		3.94	2.04	1.78	**0.04
Time		-	-	-	
	$t + 2$	-2.21	1.03	-1.84	**0.03
	$t + 4$	1.02	1.78	0.71	0.48
	$t + 6$	-0.86	1.21	-0.71	0.47
	$t + 8$	-0.46	1.58	-0.29	0.77
	$t + 10$	1.93	1.06	-1.83	*0.07

n = 944; J-test for overidentification = 48.67 (p<.01); R-squared = .03;

Time results

Time results indicate a decrease in the period immediately following divorce. There is an initial drop in precautionary savings after the divorce (ß =-2.21; $p = .03$). There are no significant results at $t + 4$, $t + 6$, or $t + 8$. Results at $t + 10$ show an increase (ß =1.93; $p = 0.07$) in precautionary savings rate.

Precautionary savings results– Dual income versus single income

Results for the exponential fractional regression model are outlined for dual income versus single income households as it relates to precautionary savings. Dual income results are outlined in Table 19, and single income results are outlined in Table 20. Only significant non-time results are shown. There were only two significant results for effects on precautionary savings for divorced households that were dual income prior to divorce. Individuals paying child support had their savings rate lowered (ß = -5.17; p < .05). In addition, as the number of children increased, the precautionary savings was reduced (ß = -2.28; p < .05). Time was not a factor in whether an individual changed their savings behavior.

Table 20: Exponential fractional regression model results – Precuationary savings – Dual income

Variable		ß	S.E.	t value	*p*-value
Sex (Male)		-	-	-	-
	Female	1.01	1.39	0.58	0.55
Race (White)		-	-	-	-
	Black	-2.81	1.21	-1.12	0.26
	Hispanic	-1.05	0.91	-1.13	0.28
	Asian/other	-0.87	0.99	-0.11	0.87
Age		1.97	2.41	1.64	0.62
Alimony (Niether pays nor receives)		-	-	-	-
	Pay	1.86	2.61	0.53	0.47
	Receive	-1.77	2.81	-0.99	0.74
Child Support (Neither pays nor receives)					
	Pay	**-5.17**	**2.03**	**-2.55**	****0.01**
	Receive	1.99	3.31	-1.21	0.56
Risk tolerance		-0.31	1.43	-0.21	0.78
Education (High school graduate)		-	-	-	-
	No high school	-0.38	1.82	-0.35	0.71
	Some college	0.42	2.70	0.16	0.88
	4-year degree	-0.99	1.22	-0.82	0.41
	Some graduate	0.59	3.89	0.15	0.88
Income		0.57	2.47	0.24	0.81
Net Worth		0.72	3.87	0.03	0.94
Number of children		-2.96	2.11	-1.40	0.16
School expenses (No school expenses)		**-2.52**	**0.95**	**-2.66**	*****<.01**
Remarried (Not remarried)		2.36	1.28	0.87	0.31
Time		-	-	-	-
	$t + 2$	-0.25	1.46	-0.17	0.83
	$t + 4$	-0.32	1.46	-0.22	0.68
	$t + 6$	-0.61	1.47	-0.42	0.89
	$t + 8$	-0.33	2.30	-0.15	0.40
	$t + 10$	-1.43	1.69	-0.85	0.90

n = 727 ; J-test for overidentification = 56.54 (p<.01); R-squared = 0.06;

In situations where there was a single income household prior to divorce, the only finding having an effect on precautionary savings was whether the individual was employed or not. Since both individuals (employed and not employed) were included, this makes sense. Being employed was positively associated (ß = 1.28; p = < .01) with precautionary savings. At time t + 2 there is a drop in the savings rate (ß = -1.12; p < .05). No subsequent years were significant.

Table 21: Exponential fractional regression model results - Precautionary savings - Single income

Variable		ß	S.E.	t value	*p*-value
Sex (Male)		-	-	-	-
	Female	0.56	0.77	0.74	0.46
Race (White)		-	-	-	-
	Black	0.16	0.10	0.50	0.62
	Hispanic	0.11	0.14	0.77	0.44
	Asian/other	0.55	0.41	1.36	0.17
Age		0.10	0.18	0.53	0.60
Alimony (Neither pays nor recieves)		-	-	-	-
	Pay	1.02	1.78	0.72	0.46
	Receive	-0.86	1.23	-0.77	0.44
Child Support (Neither pays nor receives)					
	Pay	1.41	1.06	0.89	0.16
	Receive	-0.44	0.67	-0.66	0.51
Risk tolerance		-1.31	1.98	-1.01	0.64
Education (High school graduate)		-	-	-	-
	No high school	0.02	0.78	0.03	0.97
	Some college	0.78	0.56	1.39	0.16
	4-year degree	0.68	1.65	1.41	0.38
	Some graduate	1.11	1.20	1.21	0.41
Income		0.78	0.56	1.39	0.16
Net Worth		-0.07	0.24	-0.27	0.79
Number of children		0.24	0.34	0.70	0.49

School expenses (No school expenses)		0.91	0.71	1.26	0.18
Remarried (Not remarried)		1.53	0.57	1.04	0.14
Employed		**1.28**	**1.12**	**0.89**	*****p<.01**
Time		-	-	-	-
	***t* + 2**	**-1.12**	**1.04**	**-1.87**	****.04**
	t + 4	0.78	0.56	1.39	0.16
	t + 6	0.62	0.85	0.73	0.47
	t + 8	-0.42	0.81	-0.63	0.54
	t + 10	-0.88	2.42	-0.26	0.82

n = 217; J-test for overidentification = 71.16 (p < .01); R-squared = 0.11;

Precautionary savings results – Male versus female

Exponential fractional regression model results are outlined for males and females as it relates to precautionary savings. Male results are outlined in Table 21, and female results are outlined in Table 22. Remarriage for males has a positive association with precautionary savings (ß = 6.28; p < .01). Males with responsibility for school expenses experienced a negative a negative effect on their precautionary savings rate (ß = -2.27; p < .05). At t + 4, there is an increase in savings (ß = 1.17; p < .10 level).

Table 22: Exponential fractional regression model results - Precautionary savings - Male

Variable		ß	S.E.	t value	*p*-value
Race (White)		-	-	-	-
	Black	-2.12	2.14	-0.89	0.72
	Hispanic	-0.22	2.62	-0.11	0.92
	Asian/other	0.18	2.17	0.06	0.91
Age		1.98	1.27	1.21	0.22
Alimony (Neither pays nor recieves)		-	-	-	-
	Pay	3.87	4.12	1.21	0.31
	Receive	-2.11	2.12	-0.81	0.56

Child Support (Neither pays nor receives)					
	Pay	-0.43	0.59	-0.77	0.42
	Receive	-0.24	1.87	-0.35	0.68
Risk tolerance		-0.59	3.89	0.15	0.88
Education (High school graduate)		-	-	-	-
	No high school	-0.25	7.88	-0.18	0.98
	Some college	0.58	2.46	0.24	0.81
	4-year degree	0.72	3.82	0.44	0.91
	Some graduate	1.70	3.86	0.41	0.82
Income		-1.08	1.24	-0.83	0.38
Net Worth		-2.95	2.11	-1.40	0.15
Number of children		0.23	0.33	0.68	0.46
School expenses (No school expenses)		**-2.27**	**0.98**	**-2.15**	****0.02**
Remarried (Not remarried)		**6.28**	**2.18**	**2.64**	*****<.01**
Employed (Not employed)		1.04	2.02	1.01	0.32
Time		-	-	-	-
	t + 2	-0.32	1.70	-0.15	0.78
	***t* + 4**	**1.17**	**1.01**	**-0.67**	***0.08**
	t + 6	0.34	0.85	0.41	0.68
	t + 8	0.02	0.78	0.03	0.97
	t + 10	0.52	0.34	1.53	0.13

n = 434; J-test for overidentification = 38.21 (p<.01); R-squared = 0.14

Females who remarry also have a positive association with precautionary savings rates (ß = 3.18; $p < .01$). There is evidence of positive association of income with precautionary savings rates for females (ß = 1.02; $p < .10$). There were no significant time estimates for females and precautionary savings.

Table 23: Exponential fractional regression model results – Precautionary savings – Female

Variable	ß	S.E.	t value	*p*-value

Race (White)		-	-	-	-
	Black	0.34	0.53	0.61	0.52
	Hispanic	0.28	0.98	0.42	0.34
	Asian/other	0.04	0.61	0.31	0.74
Age		1.24	2.91	1.09	0.38
Alimony (Niether pay nor receive)		-	-	-	-
	Pay	0.03	0.58	0.06	0.95
	Receive	0.84	1.21	0.98	0.76
Child Support (Neither pay nor receive)					
	Pay	-0.61	1.24	-0.79	0.39
	Receive	0.44	1.01	1.01	0.31
Risk tolerance		-0.33	2.16	-0.15	0.88
Education (High school graduate)		-	-	-	-
	No high school	0.71	12.16	0.01	0.98
	Some college	2.35	8.44	0.02	0.97
	4-year degree	2.16	11.21	0.04	0.91
	Some graduate	1.69	10.88	0.08	0.93
Income		**1.02**	**1.04**	**1.07**	***.07**
Net Worth		0.87	1.87	0.73	0.63
Number of children		1.54	3.88	1.41	0.18
School expenses (No school expenses)		-1.88	3.12	-1.21	0.14
Remarried (Not remarried)		**3.18**	**1.87**	**2.34**	*****p<.01**
Employed (Not employed)		1.21	4.44	0.64	0.68
Time		-	-	-	-
	$t + 2$	-0.45	1.57	-0.29	0.77
	$t + 4$	-1.07	0.96	-1.11	0.27
	$t + 6$	0.06	0.64	0.09	0.93
	$t + 8$	-0.44	0.67	-0.66	0.51
	$t + 10$	-1.32	1.44	-0.93	0.89

n = 510; J-test for overidentification = 64.587 (p <. 01); R-squared = 0.09

Retirement savings – Overall

Results for exponential fractional regression model for retirement savings are outlined in Table 23. Gender differences were not significant (ß = 0.24; *p* = 0.82). With respect to white, black respondents did not have a significant difference in retirement savings rates (ß = -0.53; *p* = 0.36), nor were Hispanics who had an estimate of ß = -0.28 (*p* = 0.15) when compared to whites and Asian/other had an estimate of ß = -.03 (*p* = 0.95) when compared to whites. Neither those paying alimony nor those receiving alimony had a significant impact on retirement savings compared to those neither paying nor receiving alimony. Their estimates were ß = 0.02 (*p* = .95) and ß = 0.34 (p = 0.76) respectively. Child support was also not significant either for the individual paying, or the individual receiving the support when compared to those neither paying nor receiving child support. Their estimates were ß = -0.07 (p = 0.89) and ß = 0.14 (*p* = 0.64) respectively. Risk tolerance was also not significantly associated with retirement savings and reported an estimate of ß = -1.36 (*p* = 0.32). None of the education variables were significant. Income did not appear to be a factor as either, with an estimate of ß = 0.15 (*p* = 0.86), nor did net worth with an estimate of ß = 0.60 (*p* = 0.51). Number of children in the family was not significant with an estimate of ß = -0.88 (*p* = 0.49). School expenses were not significant with respect to retirement savings with an estimate of ß = -1.75 (*p* = 0.28). Individuals who remarried had a positive association with retirement savings (ß = 5.01; *p* < .10).

Table 24: Exponential fractional regression results – Retirement savings

Variable		ß	S.E.	t value	*p*-value
Sex (Male)					
	Female	0.24	1.06	0.23	0.82
Race (White)					
	Black	-0.53	0.58	-0.92	0.36
	Hispanic	-0.28	0.41	-0.69	0.15
	Asian/other	-0.03	0.39	-0.07	0.95
Age		0.16	1.02	0.16	0.87

Alimony (Neither pays nor receives)					
	Pay	0.02	0.37	0.07	0.95
	Receive	0.34	1.11	0.3	0.76
Child Support (Neither pays nor receives)					
	Pay	-0.07	0.51	-0.13	0.89
	Receive	0.14	0.36	0.24	0.64
Risk tolerance		-1.36	1.36	-1.00	0.32
Education (High school graduate)					
	No high school	-0.94	1.17	-0.81	0.42
	Some college	0.21	1.51	0.79	0.38
	4-year degree	-0.05	1.03	0.05	0.96
	Some graduate	0.19	1.15	0.167	0.87
Income		0.15	0.82	0.18	0.86
Net Worth		0.60	1.31	0.62	0.51
Children in family		-0.88	1.31	-0.68	0.49
School expenses (No school expenses)		-1.75	1.41	-1.12	0.28
Remarried (Not remarried)		5.01	2.87	1.67	*0.08
Time					
	t + 2	-0.89	0.76	-1.12	**.02
	t + 4	-1.96	1.39	-1.408	0.17
	t + 6	-2.32	1.18	-1.955	*.05
	t + 8	0.74	1.58	0.47	0.64
	t + 10	0.18	2.37	0.09	0.93

n = 878 ; J-test for overidentification = 48.70 (p<.01); R-squared =.09 ;

Time results

Time results indicate changes at $t + 2$ and $t + 6$. There is an initial decrease at $t + 2$ in retirement savings rate of (ß = -0.07; $p < .05$). At the next time stage ($t + 4$) the estimate is not significant with respect to changes in retirement savings (ß = -1.96; $p = 0.17$). However, at $t + 6$, there is an increase in retirement savings (ß = 2.32; $p = 0.02$). Both $t + 8$ (ß = 0.74; $p = 0.64$) and $t + 10$ (ß = 0.18; $p = 0.93$) show no significant changes in retirement savings.

Retirement savings – Dual income and single income

Results for exponential fractional regression model for retirement savings for dual income and single income households as it relates to retirement savings are outlined in tables 24 and 25. Dual income results are outlined in Table 24, and single income results are outlined in Table 25. For dual income households, income was significant and positively associated with retirement savings rates (ß = 4.17; $p < .01$), while being remarried was positively associated with retirement savings rates (ß = 3.43; $p < .10$). No other covariates significantly affected retirement savings rates for dual income households. The time estimates were all insignificant.

Table 25: Exponential fractional regression results – Retirement Savings – Dual income

Variable		ß	S.E.	t value	*p*-value
Sex (Male)					
	Female	0.28	2.12	0.06	0.87
Race (White)					
	Black	-0.52	0.68	-0.87	0.56
	Hispanic	-0.26	0.98	-0.06	0.87
	Asian/other	-0.06	0.44	-0.03	0.96
Age		0.28	1.04	0.21	0.86
Alimony (Neither pays nor receives)					
	Pay	0.03	0.41	0.06	0.94
	Receive	0.31	1.88	0.24	0.72
Child Support (Neither pays nor receives)					
	Pay	-0.48	1.21	-0.21	0.72
	Receive	0.66	2.14	0.19	0.33
Risk tolerance		-1.02	1.48	-0.58	0.31
Education (High school graduate)					
	No high school	-0.93	1.17	-0.62	0.39
	Some college	0.24	1.64	0.82	0.41
	4-year degree	-0.04	2.64	0.06	0.97
	Some graduate	0.64	1.88	0.22	0.81
Income		**4.17**	**0.87**	**1.44**	*****<.01**
Net Worth		0.68	2.66	0.42	0.43
Children in family		-1.21	3.45	-0.12	0.77

School expenses (No school expenses)		-2.88	4.66	-0.98	0.81
Remarried (Not remarried)		**3.43**	**1.21**	**1.71**	***.05**
Time		-	-	-	-
	$t + 2$	-0.12	1.57	-0.21	0.81
	$t + 4$	-0.42	1.43	-0.38	0.71
	$t + 6$	-0.58	1.43	-0.39	0.88
	$t + 8$	-0.32	1.87	-0.18	0.52
	$t + 10$	-0.77	2.11	-0.44	0.68

n = 673 ; J-test for overidentification = 64.61 (p < .01); R-squared = 0.05

For single income households being remarried had a positive effect on the retirement savings rate (ß = 2.86; $p < .05$). No other covariates had a significant effect on retirement savings for single income households prior to divorce. None of the time estimates were significant with respect to single incomes and retirement savings.

Table 26: Exponential fractional regression results – Retirement Savings – Single income

Variable		ß	S.E.	t value	*p*-value
Sex (Male)					
	Female	0.18	1.44	0.18	0.89
Race (White)					
	Black	-0.44	1.24	-0.67	0.41
	Hispanic	-0.31	1.22	-0.87	0.18
	Asian/other	-0.12	2.45	-0.03	0.98
Age		0.44	2.02	0.33	0.84
Alimony (Neither pays nor receives)					
	Pay	0.88	1.64	0.68	0.64
	Receive	1.21	2.44	0.59	0.68
Child Support (Neither pays nor receives)					
	Pay	-0.55	1.21	-0.28	0.88
	Receive	0.18	0.98	0.17	0.63
Risk tolerance		-1.58	2.28	-1.21	0.14
Education (High school graduate)					
	No high school	0.24	1.06	0.23	0.82
	Some college	-0.53	0.58	-0.92	0.36

	4-year degree	-0.03	0.41	-0.07	0.95
	Some graduate	0.16	1.02	0.16	0.87
Income		0.13	0.71	0.18	0.86
Net Worth		0.34	1.10	0.30	0.76
Children in family		-1.21	1.44	-0.89	0.30
School expenses (No school expenses)		-1.22	2.45	-0.45	0.54
Remarried (Not remarried)		**2.86**	**0.98**	**1.22**	****.02**
Time		-	-	-	-
	t + 2	-2.64	2.86	-1.68	0.21
	t + 4	-1.87	1.99	-1.32	0.24
	t + 6	0.08	0.68	0.03	0.94
	t + 8	-2.21	2.44	-1.33	0.17
	t + 10	0.98	1.56	-0.44	0.69

n = 205 ; J-test for overidentification = 48.67 (p<.01); R-squared = 0.12;

Retirement savings – Male and female

Results for exponential fractional regression model for male and female households as it relates to retirement savings are outlined in tables 26 and 27 respectively. Results are displayed regardless of significance. Results for sub-group male show there is a positive association of income with retirement savings (ß = 0.83; p<.10). There is a negative association (ß = -1.08; p<.05) of child support paid with retirement savings. There is a negative association of (ß = -2.44; p<.10) of school expenses with retirement savings. Time results at t + 2 show a decrease in retirement savings rate (ß = -1.68; p<.10) and an increase at t + 10 (ß = 2.14; p<.05).

Table 27: Exponential fractional regression results – Retirement savings – Male

Variable		ß	S.E.	t value	*p*-value
Race (White)					
	Black	-0.19	22.61	-0.01	0.95
	Hispanic	0.25	23.01	0.01	0.99
	Asian/other	0.08	24.99	0.02	0.97
Age		0.21	0.5	0.42	0.68
Alimony (Neither pays nor receives)					

	Pay	-2.91	2.22	-1.46	0.15
	Receive	0.14	1.89	0.44	0.54
Child Support (Neither pays nor receives)					
	Pay	**-1.08**	**0.79**	**-1.02**	****.01**
	Receive	0.29	1.05	0.78	0.31
Risk tolerance		0.58	2.47	0.24	0.80
Education (High school graduate)					
	No high school	0.42	2.70	0.18	0.82
	Some college	0.60	3.90	0.19	0.84
	4-year degree	0.58	2.47	0.28	0.79
	Some graduate	0.96	3.05	0.32	0.76
Income		**0.83**	**0.28**	**0.67**	***.05**
Net Worth		0.60	1.31	0.62	0.51
Children in family		-0.88	1.31	-0.68	0.49
School expenses (No school expenses)		**-2.44**	**1.11**	**-1.65**	***.06**
Remarried (Not remarried)		3.24	4.68	1.02	0.17
Time		-	-	-	-
	***t* + 2**	**-1.68**	**1.54**	**-1.20**	***.07**
	t + 4	1.02	2.18	0.77	0.29
	t + 6	0.37	0.98	0.55	0.48
	t + 8	-0.18	0.57	-0.17	0.86
	***t* + 10**	**2.14**	**1.33**	**1.12**	****.01**

n =404 ; J-test for overidentification = 62.22 (p < .01); R-squared = .13

Results for the female sub-group show a positive association of retirement savings with income (ß = 4.12; p<.01). No other covariates were significant with respect to females and retirement savings. No time results were significant with respect to females and retirement savings.

Table 28: Exponential fractional regression results – Retirement savings – Female

Variable		ß	S.E.	t value	*p*-value
Race (White)					
	Black	0.81	0.96	0.85	0.38
	Hispanic	0.35	2.21	0.16	0.87
	Asian/other	0.09	2.14	0.05	0.97
Age		0.47	0.41	1.135	0.26

Alimony (Neither pays nor receives)					
	Pay	-0.11	0.25	-0.44	0.66
	Receive	4.46	2.36	1.22	0.11
Child Support (Neither pays nor receives)					
	Pay	-0.73	1.07	-0.92	0.42
	Receive	0.84	1.33	0.72	0.48
Risk tolerance		0.62	2.17	0.29	0.78
Education (High school graduate)					
	No high school	-2.09	3.44	-0.61	0.54
	Some college	-1.67	3.29	-0.51	0.61
	4-year degree	-0.85	3.25	-0.26	0.73
	Some graduate	-0.61	3.29	-0.22	0.81
Income		**4.12**	**1.98**	**-2.87**	*****<.01**
Net Worth		1.04	1.88	0.44	0.52
Children in family		-1.21	2.45	-0.27	0.61
School expenses (No school expenses)		-1.88	3.01	-0.085	0.22
Remarried (Not remarried)		1.04	2.18	0.64	0.44
Time		-	-	-	-
	t + 2	-0.45	1.57	-0.29	0.77
	t + 4	-1.07	0.96	-1.11	0.27
	t + 6	0.72	0.54	1.28	0.16
	t + 8	1.08	1.45	0.44	0.66
	t + 10	-1.41	1.88	-0.86	0.72

Data source: Panel Study on Income Dynamics; n = 474 ; J-test for overidentification = 42.81 (p < .01); R-squared = .04;

Risky asset share – Overall

Exponential fractional regression model results for risky asset share are outlined in Table 28. Sex differences are insignificant with an estimate of (ß =-0.45; p = 0.56). Racial characteristics are also insignificant with respect to risky asset share with blacks having an estimate of 0.33 (p = 0.53) in comparison to whites, Hispanics an estimate of 0.35 (p = 0.68) when compared to whites and Asian/other with an estimate of 0.04 (p = 0.74) in comparison to whites. Age was not significant with an estimate of 0.28 (p = 0.34). Compared to individuals neither paying nor receiving alimongy paying alimony was not associated with risky asset share (ß = -0.45; *p* = 0.76) nor was receiving (ß = -0.37; *p* = 0.61) respectively. Compared to those neither paying nor receiving child support, paying child support was negatively associated with risky asset share (ß = -3.94; *p* < .10), while receiving child support was not significant with an estimate of (ß = 1.00; *p* = 0.36). Risk tolerance was not significant with an estimate of (ß =1.58; *p* = 0.34) with respect to risky asset share. Compared to high school graduates, none of the other education variables were significant with respect to risky asset share. Wage income was positively associated with risky asset share (ß = 1.24; *p* < .05), while net worth was not significant (ß = 0.23; *p* = 0.73). Number of children in the family were not significant with an estimate of (ß = 0.19; *p* = 0.79). Individuals paying college expenses showed a negative association with risky asset share (ß = -2.07; *p* < .10). Being remarried was negatively associated with risky asset share (ß = -4.38; *p* < .05).

Table 29: Exponential fractional regression results – Risky asset share

Variable		ß	S.E.	t value	*p*-value
Sex (Male)					
	Female	-0.45	0.77	-0.58	0.56
Race (White)					
	Black	0.33	0.54	0.62	0.53
	Hispanic	0.35	0.85	0.41	0.68
	Asian/other	0.04	0.61	0.31	0.74
Age		0.28	0.98	0.42	0.34
Alimony (Neither pays nor receives)					
	Pay	-0.45	1.49	-0.301	0.76
	Receive	-0.37	0.74	-0.51	0.61
Child Support (Neither pays nor receives)					
	Pay	-3.94	2.21	-1.78	*0.07
	Receive	-1.00	1.10	-0.91	0.36
Risk tolerance		1.58	2.16	1.98	0.41
Education (High school graduate)					
	No high school	-0.61	1.24	-0.79	0.39
	Some college	0.44	1.01	1.01	0.31
	4-year degree	-0.09	1.37	0.54	0.71

Some graduate	1.1	2.12	0.98	0.88
Income	1.24	0.58	2.13	**0.03
Net Worth	0.23	0.66	0.35	0.73
Children in family	0.19	0.73	0.26	0.79
School expenses (No school expenses)	-2.07	1.22	-1.69	*0.09
Remarried (Not remarried)	-4.38	1.71	-2.56	**0.01
Time				
t + 2	0.18	2.15	0.09	0.93
t + 4	-1.93	1.38	-1.43	0.16
t + 6	-2.26	0.96	-2.37	**0.01
t + 8	-0.75	1.59	-0.47	0.63
t + 10	-1.98	0.84	-2.35	*0.02

n = 1121 ; J-test for overidentification = 34.86 (p<.01); R-squared = 0.07;

Time results

Time results indicate changes at $t + 6$ and $t + 10$. Both t + 2 and t + 4 showed no significant changes in risky asset share. At t + 6 there is a decrease in risky asset share (ß = -2.26; $p < .05$). At $t + 8$ there is no significant reduction, but at $t + 10$ there is a reduction in risky asset share (ß = -1.98; $p < .05$).

Risky asset share – Dual income and single income

Results for exponential fractional regression model for retirement savings for dual income and single income households as it relates to retirement savings. Dual income results are outlined in Table 29, and single income results are outlined in Table 30. When looking at couples that were dual income prior to divorce, the only non-time covariate that is significant is net worth with a positive association with risky asset share (ß = 2.98; $p <. 01$). At $t + 8$ there is a decrease in risky asset share (ß = -0.88; $p < .05$). At $t + 10$ there was a continued negative association with risky share (ß = -2.68; $p < .01$).

Table 30: Exponential fractional regression results – Risky asset share – Dual income

Variable		ß	S.E.	t value	*p*-value
Sex (Male)					
	Female	-0.44	0.68	-0.66	0.51
Race (White)					
	Black	0.84	3.76	0.24	0.81
	Hispanic	1.6	3.67	0.44	0.66
	Asian/other	1.99	2.88	0.68	0.48
Age		0.03	0.37	0.08	0.94
Alimony (Neither pays nor receives)					
	Pay	1.58	0.99	1.59	0.11
	Receive	0.82	0.86	1.12	0.21
Child Support (Neither pays nor receives)					
	Pay	-3.24	1.97	-1.02	0.15
	Receive	1.94	1.31	1.49	0.14
Risk tolerance		1.57	1.25	1.26	0.21
Education (High school graduate)					
	No high school	1.04	4.00	0.262	0.79
	Some college	1.17	4.08	0.29	0.76
	4-year degree	0.91	3.94	0.29	0.74
	Some graduate	0.32	3.96	0.08	0.93
Income		0.4	0.61	0.66	0.51
Net Worth		**2.98**	**1.68**	**2.04**	*****<.01**
Children in family		-0.14	0.23	-0.78	0.51
School expenses (No school expenses)		-0.75	1.87	-0.98	0.31
Remarried (Not remarried)		-0.28	0.71	-0.41	0.58
Time		-	-	-	-
	t + 2	-0.41	1.01	-0.22	0.81
	t + 4	-1.68	2.77	-1.02	0.44
	t + 6	0.28	1.15	0.08	0.91
	***t* + 8**	**-0.88**	**0.78**	**-0.58**	****<.04**
	***t* + 10**	**-2.68**	**1.55**	**-1.01**	*****<.01**

Data source: Panel Study on Income Dynamics; n = 807 ; J-test for overidentification = 78.34 (p <. 01); R-squared = .05;

When looking at couples where there was a single income prior to divorce, school expenses were negatively associated with risky asset share (ß = -3.21; $p < .05$). Income was also positively associated with risky asset share at (ß = 2.48; $p < .05$). In the period immediately following divorce at $t + 2$ there is an increase in risky asset share of (ß = 1.14; $p < .05$). There is a decrease in risky asset share at $t + 10$ of (ß = -2.01; $p < .05$).

Table 31: Exponential fractional regression results – Risky asset share – Single income

Variable		ß	S.E.	t value	*p*-value
Sex (Male)					
	Female	-0.28	1.48	-0.71	0.48
Race (White)					
	Black	-0.45	0.77	-0.58	0.56
	Hispanic	0.62	0.85	0.73	0.47
	Asian/other	0.37	0.98	0.55	0.48
Age		0.18	2.14	0.21	0.87
Alimony (Neither pays nor receives)					
	Pay	-0.61	1.24	-0.79	0.39
	Receive	0.44	1.01	1.01	0.31
Child Support (Neither pays nor receives)					
	Pay	-2.91	2.22	-1.46	0.15
	Receive	0.14	1.89	0.44	0.54
Risk tolerance		0.27	1.19	0.23	0.82
Education (High school graduate)					
	No high school	0.14	0.71	0.17	0.85
	Some college	0.34	1.10	0.30	0.76
	4-year degree	0.72	3.82	0.44	0.91
	Some graduate	1.86	2.91	0.84	0.78
Income		**2.48**	**1.67**	**1.61**	****.02**
Net Worth		0.97	1.37	0.70	0.48
Children in family		0.21	0.98	0.44	0.71
School expenses (No school expenses)		**-3.21**	**1.31**	**-2.04**	****.01**
Remarried (Not remarried)		2.61	1.41	1.28	0.13
Time		-	-	-	-
	***t* + 2**	**1.14**	**1.02**	**1.71**	****.03**

	t + 4	0.44	0.78	0.98	0.54
	t + 6	0.61	0.78	0.44	0.68
	t + 8	-1.09	0.78	-1.04	0.21
	***t* + 10**	**-2.01**	**1.44**	**1.01**	****.03**

Data source: Panel Study on Income Dynamics; n = 314 ; J-test for overidentification = 26.21 (p = . 04); R-squared = .08

Risky asset share – Male versus female

Results for exponential fractional regression model for for male and female households as it relates to risky asset share are outlined in tables 31 and 32. Male results are outlined in Table 31, and female results are outlined in Table 32. For males, being remarried had a negative association with risky asset share of (ß = -1.58; p <.10). Net worth had a positive association with risky asset share (ß = 5.28; p <.01). At t + 2 there is an increase in risky asset share for males (ß = 2.18; p <.05) of risky asset share. There is an additional increase in risky asset share at t + 4 (ß = 1.28, p < .10).

Table 32: Exponential fractional regression results – Risky asset share – Male

Variable		ß	S.E.	t value	*p*-value
Race (White)					
	Black	-0.54	0.51	-0.87	0.38
	Hispanic	-0.28	0.41	-0.69	0.15
	Asian/other	-0.04	0.41	-0.06	0.98
Age		0.44	1.28	1.02	0.18
Alimony (Neither pays nor receives)					
	Pay	1.39	1.05	0.91	0.15
	Receive	-0.48	1.87	-0.61	0.48
Child Support (Neither pays nor receives)					
	Pay	0.88	1.64	0.68	0.64
	Receive	1.21	2.44	0.59	0.68
Risk tolerance		0.78	3.41	1.21	0.78
Education (High school graduate)					
	No high school	0.68	3.48	0.04	0.97

	Some college	2.31	4.21	0.03	0.96
	4-year degree	2.98	4.22	0.02	0.99
	Some graduate	1.48	3.87	0.12	0.91
Income		0.98	2.12	1.04	0.18
Net Worth		**5.28**	**2.38**	**2.44**	****.01**
Children in family		0.77	1.66	0.58	0.48
School expenses (No school expenses)		-1.22	2.24	-1.08	0.25
Remarried (Not remarried)		**-1.58**	**1.38**	**-1.28**	***.05**
Time		-	-	-	-
	***t* + 2**	**2.18**	**1.44**	**1.54**	****<.04**
	***t* + 4**	**1.28**	**1.18**	**1.21**	***0.08**
	t + 6	-0.16	0.84	-0.18	0.81
	t + 8	1.28	0.65	0.87	0.19
	t + 10	0.48	0.85	0.34	0.22

Data source: Panel Study on Income Dynamics; n = 527 ; J-test for overidentification = 49.67 (p < .01); R-squared = .14

For females, there is a positive association of remarriage with risky asset share (ß = 1.32; $p < .05$). Income had a positive association with risky asset share as well (ß = 1.02; $p<.10$). No time effects were significant.

Table 33: Exponential fractional regression results – Risky asset share – Female

Variable		ß	S.E.	t value	*p*-value
Race (White)					
	Black	0.33	0.58	0.72	0.49
	Hispanic	0.28	1.04	0.98	0.34
	Asian/other	0.22	0.92	0.48	0.61
Age		0.08	2.45	0.07	0.95
Alimony (Neither pays nor receives)					
	Pay	2.87	5.11	0.78	0.56
	Receive	-2.18	1.05	-1.02	0.16
Child Support (Neither pays nor receives)					
	Pay	-0.43	0.59	-0.77	0.42
	Receive	-0.24	1.87	-0.35	0.68
Risk tolerance		1.58	2.16	1.98	0.41

Education (High school graduate)					
	No high school	-0.27	3.87	-0.08	0.97
	Some college	0.42	2.64	0.25	0.82
	4-year degree	0.75	3.83	0.47	0.90
	Some graduate	1.24	2.68	0.70	0.84
Income		**1.02**	**1.04**	**1.07**	***.07**
Net Worth		0.29	1.27	0.38	0.67
Children in family		0.22	0.98	0.18	0.66
School expenses (No school expenses)		-1.08	2.87	-0.44	0.32
Remarried (Not remarried)		**1.32**	**1.01**	**1.12**	****.02**
Time		-	-	-	-
	$t + 2$	0.58	1.04	0.32	0.67
	$t + 4$	-0.45	0.77	-0.58	0.56
	$t + 6$	0.62	0.85	0.73	0.47
	$t + 8$	0.37	0.98	0.55	0.48
	$t + 10$	-1.21	1.89	-0.87	0.64

Data source: Panel Study on Income Dynamics; n = 594 ; J-test for overidentification = 44.51 (p < .01); R-squared = .04

Bequest intention analysis

Binary logit model results are reported for bequest intention. Table 33 shows results for bequest intention for children or other relatives, Table 34 shows results for bequest intention for religious organizations and Table 35 shows results for bequest intention for non-religious charities.

For the response of bequest intention to children and other relatives, being divorced was not significant (p = .48), suggesting there was no difference between married and divorced individuals when it comes to leaving money to children. When compared to whites, blacks had a 5% increase in the probability they intend to leave a bequest to children (p = .02), while Asian/other had a 7% increase in the probability they intend to leave a bequest to children. As an individual aged, they had a 5% decrease in the likelihood they would leave money to children (p

< .01). Those with a bachelor's degree or greater had a 4% decrease (*p* = .03) in the probability they would leave money to children or other relatives when compared to high school dropouts. Those with some college and those who were high school graduates only did not have significant differences from high school dropouts. Whether employed, unemployed by choice or unemployed not by choice there were no significant differences in employment levels. Income was not a significant factor in whether someone would leave a bequest. Net worth was significant at $p < .01$ level and as net worth increased there is a 3% increase in the probability an individual would leave a bequest to children or other relatives.

Table 34: Binary logit – Bequest intention for children and other relatives

Variable		ß	AME	OR	OR Lower	OR Upper	*p*-value
Intercept		1.73		5.62	4.03	7.93	***p<.01
Divorced (Married)		-0.06	-0.01	0.94	0.79	1.12	0.48
Sex (Female)							
	Male	-0.07	-0.01	0.93	0.81	1.07	0.33
Race (White)							
	Black	0.37	0.05	1.44	1.05	1.96	**0.02
	Hispanic	0.21	0.02	1.33	1.09	2.01	***p<.01
	Asian/Other	-0.43	-0.07	0.65	0.48	0.87	***p<.01
Age		-0.35	-0.05	0.71	0.66	0.76	***p<.01
Education (High School dropout)							
	High school graduate	0.03	0.01	1.03	0.86	1.25	0.73
	Some college	-0.15	-0.02	0.87	0.71	1.05	0.15
	Bachelors or greater	-0.23	-0.04	0.79	0.65	0.97	**0.03
Employment (Employed)							
	Unemployed by choice	0.17	0.02	1.18	0.97	1.44	0.11
	Not unemployed by choice	-0.16	-0.03	0.85	0.70	1.05	0.12

Wages	0.00	0.06	1.00	0.94	1.09	0.92
Net Worth	0.20	0.03	1.22	1.09	1.40	***p<.01

n = 7595 ; Degrees of freedom = 7601; c = 0.73; R-squared = 0.08; -2 log likelihood = 7218; AIC = 7360

For the response of bequest intention to religious organizations, being divorced was significant ($p < .01$), and divorced individuals, when compared to married individuals had a 5% lower probability they would leave a bequest to a religious organization. When compared to whites, blacks had a 7% greater probability they intend to leave a bequest to a religious organization ($p = .02$), while Asian/other had a 13% greater probability they would leave a bequest to a religious organization, when compared to whites ($p<.01$). As an individual aged, they had a 3% lower probability they would leave money to religious organizations ($p<.01$). Those with a bachelor's degree or greater had a 8% lower probability ($p = .03$) they would leave money to a religious organization when compared to high school dropouts. Those with some college and those who were high school graduates only had a 7% and 3% decrease respectively in the probability they would leave a bequest to a religious organization respectively, when compared to high school dropouts. Whether employed, unemployed by choice or unemployed not by choice, there was no significant differences by employment levels in bequest intention for religious organizations. Income was not a significant factor in whether someone would leave a bequest to religious organizations. Net worth was not significant in affecting the chances an individual would leave a bequest to a religious organization.

Table 35: Binary logit – Bequest intention for religious organizations

Variable	ß	AME	OR	OR Lower	OR Upper	*p*-value
Intercept	-0.23		0.79	0.60	1.04	0.09
Divorced (Married)	-0.27	-0.05	0.76	0.65	0.89	***p<.01
Sex (Female)						
Male	-0.11	-0.02	0.89	0.80	1.01	0.06

Race (White)							
	Black	0.28	0.07	1.32	1.04	1.69	**.02
	Hispanic	0.74	0.12	2.11	1.64	5.62	***p<.01
	Asian/Other	-0.62	-0.13	0.54	0.43	0.68	***p<.01
Age		-0.14	-0.03	0.87	0.82	0.92	***p<.01
Education (High School dropout)							
	High school graduate	-0.18	-0.03	0.83	0.72	0.97	**.02
	Some college	-0.34	-0.07	0.71	0.60	0.84	***p<.01
	Bachelors or greater	-0.40	-0.08	0.67	0.56	0.80	***p<.01
Employment (Employed)							
	Unemployed by choice	0.15	0.03	1.17	0.97	1.40	0.10
	Not unemployed by choice	0.03	0.01	1.03	0.88	1.22	0.70
Wages		-0.09	-0.02	0.92	0.83	0.99	0.06
Net Worth		0.05	0.01	1.05	1.00	1.11	0.06

n = 7595 ; Degrees of freedom = 7585; c = 0.76; R-squared = 0.17; -2 log likelihood =8855; AIC = 8947

For the response of bequest intention to non-religious charities, being divorced was significant ($p <. 01$), and divorced individuals had a 4% lower probability they would leave a bequest to a non-religious organization when compared to married individuals. When compared to whites, blacks did not have a significant difference when compared to whites, while Asian/other had a 16% ($p < .01$) higher probability they intend to leave a bequest to a non-religious charity. As an individual aged, they had a 7% lower probability they would leave a bequest to a non-religious charity ($p < .01$). Those with a bachelor's degree or greater had a 4% lower probability ($p = .05$) they would leave money to non-religious charity when compared to high school dropouts. Those with some college and those who were high school graduates only each had a 5% lower probability they would leave a bequest to a non-religious charity respectively, when compared to high school dropouts.When compared to employed individuals, those unemployed by choice and unemployed not by choice were significant and had a 4% lower probability they would leave money to a non-religious charity. Income was not a significant factor. As net worth increases there is a 2% increase in the probability an individual will leave a bequest to a non-religious charity.

Table 36: Binary logit – Bequest intention for non-religious charities

Variable		ß	AME	OR	OR Lower	OR Upper	*p*-value
Intercept		0.07		1.07	0.82	1.40	0.60
Divorced (Married)		-0.20	-0.04	0.82	0.71	0.95	***p<.01
Sex (Female)							
	Male	-0.20	-0.04	0.82	0.73	0.92	***p<.01
Race (White)							
	Black	-0.12	-0.03	0.89	0.70	1.13	0.34
	Hispanic	-0.14	-0.04	0.92	0.78	1.11	0.21
	Asian/Other	-0.69	-0.16	0.50	0.40	0.63	***p<.01
Age		-0.32	-0.07	0.73	0.69	0.77	***p<.01
Education (High School dropout)							
	High school graduate	-0.23	-0.05	0.80	0.69	0.93	***p<.01
	Some college	-0.25	-0.05	0.78	0.66	0.92	***p<.01
	Bachelors or greater	-0.17	-0.04	0.84	0.71	1.00	**.05
Employment (Employed)							
	Unemployed by choice	0.20	0.04	1.22	1.02	1.45	**.03
	Not unemployed by choice	0.20	0.04	1.22	1.04	1.43	**.02
Wages		0.02	0.01	1.02	0.96	1.08	0.56
Net Worth		0.08	0.02	1.08	1.02	1.15	**.02

n = 7595 ; Degrees of freedom = 7594; c = 0.81; R-squared = 0.19; -2 log likelihood =9098; AIC = 9384

Research questions and hypotheses

The research question is: What effect does divorce have on wealth management? In certain circumstances and sub-groups there does appear to be an effect of divorce on the aspects of accumulation and management of wealth. Analysis of overall groups of divorced people indicate certain consistent covariates associated with increases or decreases in the rates of precautionary savings, retirement savings and risky asset share. Bequest intentions confirmed some previous research and did not confirm others.

There is an overall decrease in precautionary savings for divorced individuals after divorce consistent with H1. This decrease appeared to persist until $t + 10$, where there was an increase in precautionary savings. This suggests reaching an equilibrium of some sort after the initial drop and then a reversal of that decrease. Comparing single-income households to dual income households, single-income households experience a drop in precautionary savings rates, while dual income households do not, consistent with H2. While wage income was not significant as it relates to precautionary savings and as a result does not uphold H3.

Table 37: Summary table of results

Hypothesis	Predicted direction	Result	Consistent
H1: Individuals will have lower precautionary savings rates post-divorce.	Negative	Negative	Yes
H2: Single-income households prior to divorce will have lower precautionary savings rates post-divorce than double-income households.	Negative	Negative	Yes
H3: As wage income increases post-divorce precautionary savings rates will increase.	Positive	Not significant	No
H4: Individuals will have lower retirement savings rates post-divorce.	Negative	Negative	Yes
H5: As wage income increases post-divorce retirement savings rates will increase.	Positive	Not significant	No

H6: Individuals will have a higher proportion of their assets in risky assets post-divorce than prior to divorce.	Positive	Negative	No
H7: The proportion of risky assets will not change over time post-divorce.	Neutral	Negative	No
H8: Single-income households will have a higher proportion of their assets in risky assets than double-income households.	Positive	Positive	Yes
H9: Divorced individuals will be less likely to leave money to children or other relatives.	Negative	Positive	No
H10: Divorced individuals will be less likely to leave money to religious organizations.	Negative	Negative	Yes
H11: Divorced individuals will be less likely to leave money to non-religious charities.	Positive	Negative	No

Overall results suggest after divorce, individuals decrease their retirement savings rates and continue to decrease retirement savings, consistent with H4. Wage income does not have a positive association with retirement savings and is not consistent with H5. There does not appear to be a difference when comparing dual income to single income households as far as the time from divorce changes. However, both single and dual income households show an increase in retirement savings rates if remarried. Dual income households have a positive association with income. For males, there is a decrease in retirement savings at divorce, that is recovered at $t + 10$. Females on the other hand show no significant changes with retirement savings post-divorce. However, females do experience increased retirement savings rates with an increase in income.

Overall results for risky asset share suggest there is a decrease in risky assets over time for individual post-divorce. This is not consistent with H6 and there appears to more of a decrease of risky assets later after divorce so does change over time which is not consistent with H7, nor previous research. Single income households do experience an increase in risky asset share post-divorce consistent with H8, but risky asset share does decrease in later years.

Results for the binary logistic regression comparing married and divorced individuals as it relates to leaving money to children and other organizations do not uphold H9. Results were not significant, suggesting there are no differences in the groups. However, when it comes to leaving money to religious organizations, being divorced is in line with H10 as they are less likely to leave money to religious organizations as a bequest. The opposite was found for H11 where divorced were less likely to leave a bequest to non-religious charities, while the hypothesis was they would be more likely to leave a bequest.

Summary of findings

There is an effect after divorce on precautionary savings, retirement savings and risky asset share. Some effects are only noticeable when examining sub-groups. Precautionary savings is affected just after divorce overall and does reverse later. Other than men increasing their precautionary savings, this is consistent with theory. Retirement savings has an overall negative effect as it relates to divorce and in particular men tend to reduce their retirement savings. There is no difference between dual and single income households as it relates to retirement savings for divorced individuals. Risky asset share showed an overall decrease, but certain differences in dual and single income households were surprising as single income households increased their risky asset share. Men increased their risky asset share and kept increasing it, while there did not appear to be a change for women. Bequest intention gave both confirmatory and contradictory results.

Some of the most surprising effects came from covariates. Being remarried appeared to have a positive effect in almost every situation. School expenses had a negative effect on situations where it was significant. By themselves, most demographic characteristics did not have any effect. Race, age and education had no significant impact on any of the outcome variables. Alimony as expected had no effect on any of the outcome variables. In some cases, paying child support had an effect on precautionary and retirement savings. Income and net worth had an occasional positive effect, while number of children in the family typically reduced the savings rates, both precautionary and retirement.

Chapter 5 - Discussion

Discussion of research findings

This study sought to discover the effect of divorce on wealth management and to determine the extent to which these effects continued over time. By examining precautionary savings and retirement savings from the point of divorce, in two-year intervals using exponentional fractional regression models there were situations where there were both short- and long-term effects. The same exponential fractional regression models were applied to the proportional of risky assets held by divorced individuals and results were mixed. Finally, cross-sectional analysis of bequest intentions confirmed some previous research and contradicted others.

Precautionary savings

The results from precautionary savings highlight how some of the idiosyncrasies of divorce can affect savings behavior. Divorced persons who pay for college expenses save less than those without college expenses. Remarriage has a positive effect on precautionary savings. This makes logical sense, as there are economies of scale being married (Cherchye, 2016). The divorce process removes economies of scale that are achieved while living together (e.g., shared housing payments or shared household production roles). Interestingly, the number of children an individual had overall indicated a positive effect on precautionary savings. It is expensive to raise children, thus on the surface these results seem counterintuitive. However, it may be that unexpected medical bills, or the need for purchasing vehicles or insurance for children may prompt savings. In divorce situations, there may be a court order or separation agreement mandating planned expenses for children get paid by a given spouse or shared in a non-equal proportion with their former spouse (Garrison, 2011). With college having a negative effect on the savings rate, perhaps those with children ameliorate this drop by saving for their children.

The time effects of divorce show that immediately after the divorce, there is a decrease in savings rate. This makes sense, as there may be fewer resources to pay for increased expenses (Kothakota & Heckman, 2018). However, there is a reversal of this rate change after 10 years. This may mean an equilibrium has been reached. There is also the possibility that there has been a decrease in expenses as children age out, or an increase in income as individuals spend more time in the workforce, as some of the sub-analyses seem to suggest increased income helps with savings rates.

It is also telling that many covariates such as race and education do not appear to have an effect on the precautionary savings rate. This may mean that divorce is an equalizer of sorts and has little to no effect on these financial behaviors in that people of all education and races behave similarly post-divorce. Risk tolerance also did not appear to have an effect on the savings rate. While Light and Ahn (2010) found a positive association with divorce and risky behavior, they were comparing between married and divorced, while this study compared within group. This could be because risk tolerance is not thought about as much under divorce constraints, or that the differences in risk tolerances within the divorce group is so small as to show no effect. Alimony may have an effect, but the sample is too small to tell, and child support while effective in sub-group analyses, was not significant in the overall analysis. This suggests transfer payments have little to no effect on savings.

Dual income and single income sub-analysis

In situations where the divorced individual came from a dual-income household and was paying child support, there was a negative effect on the savings rate. This suggests that in this case there is an effect of transfer payments: either the individual is paying more than they can afford and reducing their disposable income, or in situations where there are minor children there is not enough money to go around. Since the number of children also has a negative effect, the effect of paying child support and number of children may have a multiplicative effect on savings. While there are no significant time effects, this may simply mean that those with dual incomes have the ability to continue saving as before absent children and transfer payments.

Single income households, on the other hand, showed an increase in savings rates if they were employed. This makes sense whether they were employed previously or not. There is an initial time effect after the divorce that has a negative influence on savings rates. This could be the result of simply increased expenses. It also could be the result of taking time to find employment if they were one of the individuals not employed at the time of divorce.

Male and female sub-analysis

Examining precautionary savings results among males shows that they increase their precautionary savings after divorce. This could be the result of being remarried as they show a marked increase in precautionary saving if they have remarried. They do experience a negative influence on savings rates if they are responsible for expenses related to college. While most states do not require the payment of college by divorced parents (Turley & Desmond, 2011)), it is possible many males opt to cover college expenses and may agree to do so as part of marital dissolution in exchange for some other concession (Smyth, Vnuk, Rodgers & Son, 2014).

There were no time effects illustrating either crisis mode or chronic strain in the female regression as it relates to precautionary savings. Being remarried does have a positive effect on the precautionary savings rate, however. This is consistent with other results from remarriage and is likely a result of having more resources or economies of scale. In addition, having income is positively associated with increased precautionary savings.

Retirement savings

Overall retirement savings indicate a decrease in the retirement savings rate after divorce. There does not appear to be a reversal of this trend within the PSID data. This could be from required shifting of expenses prior to divorce. Previous retirement contributions may not be sustainable given the new divorced circumstances. These contribution reductions may be the result of orders from the court or necessary changes as a result of divorce negotiation (Fields, 2016). The only other significant factor was whether an individual was remarried, and this may include new spouse retirement savings. The time effects do not indicate that this change in retirement savings rate adjusts, even as distance with respect to the divorce increases.

It is surprising that most of the other covariates are not significant. Retirement savings is in the United States is a behavior that must be elected. And at least income and education would be thought to play a role in whether an individual is saving for retirement. It is also possible with so few saving for retirement, the group that does actually share a common omitted variable. Transfer payments would likely reduce the ability to save for retirement, but neither alimony nor child support are significant. Again, risk tolerance is not significant, suggesting that the risk tolerance questions may not be useful in identifying propensity to save with these data.

Dual income and single income sub-analysis

There were no time effects with individuals divorced from a previous two-income household. This suggests individuals maintained the status quo and did not make any changes post-divorce. This is logical, given that both individuals had income and may be able to adjust to their individual income and expense paradigms post-divorce.

Income had a positive association with dual income divorced individuals. This is consistent with expectations as income can be helpful in maintaining or increasing retirement savings. Again, being remarried has a positive influence on retirement savings. In the context of retirement savings, this likely means economies of scale as a married couple typically can share expenses and share non-income generating work (e.g., household chores).

Male and female sub-analysis

Retirement savings by males experience a negative association after divorce, and then does increase later. This suggests the initial reason for the decline is related to the divorce. Income was positively associated with retirement savings. Child support paid by males resulted in a negative association with retirement savings. As in other conditions, this makes sense. More paid out to an ex-spouse means less to put into retirement savings. School expenses have a negative influence on retirement saving – again, this is likely due to those expenses taking away income that could otherwise be deferred into retirement.

Retirement savings among females shows no time effects. This is consistent with the overall effects and suggest if someone was contributing before, they did not change their rate of contribution and if they were not contributing before they did not contribute after. Income did have a positive effect on retirement savings for females however. The income effect for females is consistent with males as well.

Risky asset share

Risky asset share overall analysis indicates that paying child support reduced the proportion of risky assets. This could be attributed to the need to meet expenses via liquidating investable assets. Income is positively associated with risky asset share, suggesting income may help someone take on more risk in investing as they have income as a buffer (Arianti, 2018). School expenses had a negative effect. Again, perhaps this had something to do with liquidating investable assets during college years. However, this could also be due to changing allocations so that investments designated for college are less subject to volatility (Woodside-Oriakhi, Lucas & Beasley, 2013). Unlike the savings variables, being remarried is negatively associated with risky asset share. This may be due to using a joint utility function of couples to invest the money, or what happens with the assets of each party combine, such as one person having nearly riskless assets or one of the excluded assets from the analysis (e.g., house).

The time effects show a risky asset share reduction well after the divorce event (at t + 6 and t + 10). This suggests the divorced individual is not beholden to inertia in their assets and does make changes as mentioned in other research (Brunnermeier & Nagel, 2008). However, there does not appear to be an effect initially after the divorce, suggesting these changes are due more to life cycle issues.

Dual income and single income sub-analysis

Divorced individuals who previously had dual incomes prior to marital dissolution showed a positive association with net worth and risky asset share. This may be due to being used to absorb market shocks (Seccombe, 2002) because of having two incomes in addition to a higher net worth. Time effects show a decrease in risky asset share in later years, but not immediately subsequent to divorce, suggesting those from a dual income previous marriage do not change their risky asset share because of the divorce event, but possibly due to life cycle changes (Games & Michaelides, 2005; Campbell, Cocco & Gomes, 2001).

Single income divorced individuals decrease their risky asset share when they have school expenses. As with the overall analysis, this may be due to the need to have fewer assets in volatile instruments. Income was positively associated with risky asset share. This may be because they are putting more money in 401(k)-type investments (Kwun, Mohebbi & Braunstein, 2010) or have confidence that their income will provide a buffer for volatile investment instruments (Seccombe, 2002). Time effects show an increase in risky asset share subsequent to divorce. This may be because of the divorce and a desire to make back what was lost due to the divorce (Charles & Stephens, 2004). Later, the time effect is reversed and there is a decrease in risky asset share, possibly meaning an adjustment to the new normal, or life cycle changes (Games & Michaelides, 2005; Campbell, Cocco & Gomes, 2001).

Male and female sub-analysis

Male divorced individuals decrease their risky asset share when remarried, consistent with previous literature (Grable, 2000). Having higher net worth is associated with higher risky asset shares. As in other situations, this may be entirely unrelated to being divorced and may actually involve reverse causality. That is, having a higher risky asset share may result in a higher net worth. Time effects for males show an increase in risky asset share after divorce. This may be because of purposeful rebalancing (Games & Michaelides, 2005; Campbell, Cocco & Gomes, 2001), the result of division of the marital estate (Garrison, 2008) or a desire to "get back what they lost" in the divorce. While excluding other assets such as a house and business from the calculation should help with reducing the effect of a an unbalanced division of the marital estate, it does not eliminate it entirely.

Female divorced individuals have a positive association with remarriage and risky asset share. This is also consistent with previous literature (Grable, 2000) that suggests women increase their risky asset share when getting married. In addition, income is positively associated with risky asset share for women. As with previous overall and sub-group analyses, this makes sense as the ability to earn income may help an individual feel more comfortable taking portfolio risk and think about the long-term. There were no time effects: this suggests female divorced individuals, absent intervention, are subject to inertia as it relates to portfolio allocation.

Bequest intention

This study found no differences between divorced and married individual's intent to leave a bequest to children or other relatives. In addition, there was a decrease in the likelihood they intended to leave a bequest to non-religious charities. These results are contradictory to previous research as it relates to children and non-religious charities (Kell, Jane & Rohrbacher, 2014). Bern and colleagues (2009) found divorced individuals were less likely to leave money to children than married individuals, while this study did not find a relationship. Further, this study also found being divorced decreased the probability they would leave a bequest to a non-religious charity, which is the opposite of Bern and colleagues' research. This could be that Bern and colleagues also included single individuals in their sample, while this study's sample compared only divorced and married individuals. There is also the possibility that remarriage in the current study created an issue.

The results from the current study did confirm the decrease in the likelihood that a divorced individual would leave money to a religious organization when compared to married individuals. Importantly, the ability to leave money to any group is impacted by actually having money to leave. Net worth is tied inextricably to this and as can be noted in both the leaving money to children and money to non-religious charity questions, net worth increases the probability of a bequest being made.

EFRM

Use of the Exponential Fractional Regerssion models provided an opportunity to both look at causality in the short-term and long-term, and provided nuance not examined before. Other models have difficulty incorporating endogenous variables, while EFRM allows full inclusion of both endogenous and exogenous variables. Importantly, EFRM extends the use of other fractional response models to longitudinal data, while traditional FRM can only be applied to cross-sectional models.

In terms of replication of previous research, the results are confirmatory of economic hardship associated with divorce. Specifically, there are decreases in precautionary savings rates. This decrease indicates a reduced financial ability to handle hardships that may come from emergencies. Thus, future financial shocks would be difficult to manage and may lead to debt or possibly bankruptcy. Past research has not examined the role of dual income households and single income households as being different with respect to absorbing the divorce shock. This particular study builds on previous research by expanding the detail in precautionary savings research with respect to divorce and buttresses research comparing single and dual income married households. In addition, the boost to savings from remarriage provides additional evidence for married couples that precautionary savings is increased when economies of scale are present. Use of the EFRM provided an opportunity to both look at causality in the short-term and long-term, and provided nuance not examined before.

The decreases in retirement savings also confirm previous research associated with retirement savings. Specifically, as current household expenses increase then retirement savings has been found to decrease. As with precautionary savings, examining the dual income and single income divorced households separately creates more nuance in the results. Dual income households appear to be more robust to negative changes in retirement savings behavior.

The contradictory nature of divorce and risky asset share compared to previous research suggests that the divorced sub-group acts differently. Surprisingly, these individuals act in accordance with best practices by reducing their risky asset share over time. This may be because protective factors such as divorce professionals provide perspective on how they should be allocating assets. Conversely, it may simply be that higher risk assets are being withdrawn to pay for current consumption, leaving non-risky assets as the only remaining amount. This makes if there are few cash assets to begin with. Withdrawing retirement assets to pay for current consumption, as an example will naturally result in a reduction in risky asset share.

Despite previous research suggesting divorced individuals are less likely to leave a bequest to children or other relatives, compared to married individuals there does not appear to be a difference. This contradiction points to divorced parents still feeling financially responsible for their children. Previous research did indicate less of a desire to leave money to religious organizations, although the results of this study with the reference group being white may simply point to white individuals leaving less. Black and Hispanic individuals are more likely than whites to leave more money to religious organizations. This is also consistent with previous research. There is a contradiction with individuals who divorce not having a bequest intention towards non-religious charities. This contradiction points to possible variation between data sources.

Divorce stress adjustment theory

In some ways, the results are generally in line with the divorce stress adjustment theory. Overall results with both precautionary and retirement savings provide some evidence that in certain circumstances, individuals who are divorced experience crisis mode and chronic stress. Sub-group analyses provide further insight into which groups' financial behaviors may be more subject to the stress of divorce than others.

Precautionary savings, crisis moments and chronic strain

The overall results of the precautionary savings analysis suggest there is a decrease in precautionary savings post-divorce and that this rate of savings does not change for some time. There is evidence that there is a reversal years later, suggesting this is a chronic strain stressor. At the same time, this could be seen as a temporary effect since it does eventually reverse. Adding school expenses into a divorce situation appears to have a negative effect on this by exacerbating the downward direction of the savings rate. Conversely, remarriage has a positive effect on precautionary savings.

Examining divorced individuals coming from dual income household is interesting because it suggests that dual income households are robust to the divorce event and do not have any changes simply because those households divorce. There does appear to be a negative effect when paying child support, as well as the number of children in the household, which would both be negative stressors.

However, coming from a situation where the household is dual income creates an effect prior to the divorce event as there is no noticeable effect at the time of divorce. This lack of a time effect may be simply because the couple was not saving prior to the divorce, and so there would be no change. Precautionary savings though is to provide a buffer in the case of an emergency or a long-term event such as a job loss. Since dual income households have lower proportional expenses, they should be able to save more prior to divorce. That there is no decrease in a savings rate post-divorce may mean structural financial issues within the household, such as not having an actual savings plan. This may create stress on a marriage and actually be a catalyst for the couple to divorce.

Single income divorced individuals however show signs of chronic strain as there is a negative effect subsequent to divorce that does not change. There is a positive effect of being employed. This makes sense as the employment can likely boost income, allowing the individual to save more for emergencies.

When looking at males, there is an increase in savings rates sometime after divorce. This suggests that there is neither a crisis moment nor chronic strain when males get divorced as it relates to precautionary savings. This may be because of remarriage working as a positive influence on savings and males getting married quickly after divorce (Spanier & Glick, 1980). School expenses do act as a negative stressor and can reduce precautionary savings.

In the case of females, there is also no crisis moment or chronic strain associated with the divorce. As with males, remarriage does appear to have a positive effect on precautionary savings. Income is also a positive for females and has a positive influence on whether they can save or not.

Retirement savings, crisis moments and chronic strain

Overall results for retirement savings suggest retirement savings rates are subject to chronic strain. Not only do they decrease after divorce, they decrease more sometime after divorce. The only effect in the case of retirement savings rates is whether the individual was remarried, which had a positive effect on retirement savings.

Dual income households had neither a crisis moment nor chronic strain. However, single income households likewise experienced neither a crisis moment nor chronic strain in retirement savings rates suggesting the income share prior to divorce has little to do with retirement savings. Income had a positive effect on those with higher incomes who had higher retirement savings rates. Remarriage also had a positive effect on retirement savings.

When looking only at males they experienced a crisis moment as they had a decrease in retirement savings rate initially after divorce, and later reversed this decrease. There was a positive effect on income. School expenses and child support paid, however, were stressors that can decrease retirement savings rates. Females had neither an increase nor a decrease in retirement savings rates. Income was a protective factor as it had a positive association with retirement savings rates.

Risky asset share, crisis moments and chronic strain

Risky asset share as it relates to divorce-stress adjustment theory is difficult to say whether a change is positive or negative, as increasing risky asset share can be good in many cases. It may depend on perspective, as one individual may feel that taking more risk is necessary to "get back what they lost from the divorce and may be more aggressive, while another individual may fear "losing" more by taking on more risk. Measurement of substantial changes is the key factor in this analysis.

Overall results indicate that contrary to previous research there is no evidence of inertia and there does not appear to be an effect of the divorce on risky asset share. However, when looking at the sub-group analysis for single income household divorced individuals there is an increase in risky asset share just after divorce followed by a decrease later, suggesting individuals coming from single income households increase their risky asset share as a result of divorce-stress. In the case of these individuals, income causes an increase in risky asset share, while school expenses also may have a positive or negative effect, depending upon whether the decrease in risky assets is considered a good thing for that specific situation.

Interestingly, dual income households appeared to follow a pattern of decreasing their risky asset share over time. This is often recommended by financial planners (Finke & Huston, 2003). There does not appear to be either a crisis moment or chronic strain associated with reallocating risky assets post-divorce, and net worth is the only variable with an effect for increased risky asset share. Single income households experience a crisis moment initially after divorce and increase their risky asset share, while following generally recommended advice and decreasing it in later years. In addition, single households with higher incomes have a higher proportion of risky assets, and a lower proportion of risky assets with school expenses, suggesting these are positive and negative effects respectively.

In the case of males, there does appear to be chronic strain of risky asset share immediately subsequent to divorce. However, this could be simply the nature of males as previous research indicates they tend to have a higher risky asset share (Grable, 2000). Remarriage tends to increase this effect, while net worth tends to increase the willingness to have a higher proportion of assets in risky investments. Females on the other hand do not experience either a crisis moment or chronic strain as it relates to risky asset share. For females, getting remarried increases their propensity to put more assets in risky investments. Since previous research indicates getting married increases risky asset share for females (Grable, 2000), this could simply an effect of marriage found previously on female risky asset share. Having more income also increases the amount females put in risky assets. This increased income may have a negative effect in the sense that income in general may make individuals feel as if they can take more risk, or a positive influence in the sense that having more income provides a feeling of safety and riskier may be taken with investments.

Bequest intention, crisis moments and chronic strain

Unfortunately, there is not enough information in the PSID to draw any conclusions about crisis moments and chronic strain. There are differences between divorced and married individuals when it comes to bequest intentions, but it is difficult to tell if these differences are the result of a divorce, an whether they would persist or not. It is important to take note of the differences however, and how they differ from previous research. Stronger research design is needed to determine the idiosyncrasies and subtle differences in bequest intention and the effect divorce and time has on it.

Implications

Given the lack of significance of many demographic variables, these results present an opportunity for financial planners and wealth managers to assist clients of varying demographics without treating them differently because of race or education when it comes to those divorced. While this study does discuss how divorce effects precautionary savings, retirement savings and risky asset share, caution should be used in applying the generalizations to specific situations. Several themes did emerge from the analysis however that should help guide how professionals interact with clients going through divorce.

Precautionary savings

Getting divorced does have an effect on the ability to save for emergencies. This should be considered when negotiating a divorce and or creating a financial affidavit for court proceedings. In particular, situations where there is one earner spouse prior to divorce should be considered. The focus should be on employment and empowering the individual not working.

This may reduce the financial strain associated with the divorce and allow both individuals to save. Another remedy may be to have established savings distributed differently to account for any differences. In the case of males, they do appear to be able to increase their savings sometime after divorce, perhaps suggesting a different asset division.

Retirement savings

In the case of retirement savings, the negative influence after the divorce and continually should have individuals and advisors to divorced individuals concerned. Articles on divorce and retirement security suggest getting divorced impacts the ability of a divorced individual to retire severely (Munnell, Hou & Sanzenbacher, 2018). Financial planners and wealth managers armed with this information should keep a careful eye on how these savings rates might change. More check-ins in the years after divorce may be necessary to keep them on the right track. The reduction in retirement savings is more obvious for males and thus for male clients the professional should be especially aware.

Risky asset share

The variation in risky asset share results may simply mean divorced individuals are more engaged in their financial future. While overall results point to a decrease in risky asset share, there is an increase among males. Professionals should check-in and make sure this is a choice that is being rationally considered in the context of the individuals total wealth plan.

Bequest intentions

While not specifically examined over time or in the immediate context of divorce, there is information in the study that can be useful to professionals. Knowing that there are differences can help starting a conversation around bequests. Often charitable trusts are suggested by financial planners (Brown, 2004), which may be a mistake given the likelihood that a divorced individual may not be charitably inclined, at least at some point.

School expenses

School expenses or paying for the post-secondary education of children has a negative effect on both savings rates and risky asset share. For precautionary savings, this may simply mean once the money is spent it no longer needs to be saved and so a reduced savings may make sense. However, for retirement savings planners need to be aware and perhaps counsel clients that reducing retirement savings to pay for college will reduce their ability to spend in retirement. The decrease in risky asset share may simply be a result of liquidating risky assets to pay for school, but it may also be the result of fear so that money used to pay those expenses is not volatile. Planners should take into account the time horizon and purpose of the money and caution that reducing risky asset share may have long-term negative consequences.

Income

It may seem obvious, but income needs to be considered part of a post-divorce wealth plan. Financial planners can assist in helping divorced individuals find new careers. Partnering with occupational specialists would be useful in identifying opportunities for divorced clients. A financial planner should have knowledge of the marketplace for careers and also be able to help the client move in the right direction. Keeping in mind those in the divorced situation may need more prompting than those not, given the traumatic nature of divorce. The positive influence of income on savings is non-trivial, as is the ability to feel as if one may invest in riskier assets. Income is often tied to employment, which is tied with self-efficacy and is considered a factor in the success of individuals post-divorce (Warrener, Koivunen & Anderson, 2014).

Remarriage

One of the most persistent themes in the analysis is that remarriage has a positive effect on both precautionary and retirement savings rates. This makes sense for a variety of reasons, as there may be economies of scales associated with a new marriage. This information is less helpful for financial planners as they may not necessarily work as a matchmaker. However, this may simply mean that the divorced individual needs more support and time with the planner. Perhaps getting the individual to focus on finances and being a partner in the decision-making process can assist clients in making choices that mirror the effects of getting remarried.

Remarriage has a mixed effect on risky asset share consistent with previous literature around males and females. Since males tend to be more risk tolerant prior to marriage and less risky during marriage and females are vice versa, this effect makes sense. However, just like with savings, understanding where the client is and providing more time and education to the client may help them make adjustments to fit their plan. The inertia issue with some sub-groups can be helped with check-ins and counseling on why adjustments may need to be made to risky assets.

Limitations

The results should be interpreted with caution in light of the limitations of the study. This study was conducted using a secondary dataset not designed for this analysis. The PSID does not ask every question in every year. Further, since the dataset is designed to mirror the population of the United States, and most households do not have any savings (Butrica & Smith, 2012), the savings estimates have less power, as does the risky asset share. If someone does not have any precautionary savings or in fact is going into debt to finance their lifestyle, then measurement of this variable is difficult. If someone does not have any retirement savings, there is no rate of savings and there is no variation being captured, and it is difficult to see if that individual changes their savings preferences over time. Risky asset share is also difficult to measure since an individual must have risky assets to have a proportion of assets in them. This is compounded by the issue of divorced individuals skewing lower income and not having assets and sometimes a negative net worth (Butrica & Smith, 2012).

The risk tolerance question is problematic for a number of reasons. First, it is only asked in 1996. If risk tolerance is assumed to be constant, this is less of a problem. However, risk tolerance may affect risky asset share and savings, and divorce may affect risky asset share mechanically on how assets are divided. It is difficult to tease out what is mechanical and what is an individual risk preference with one year of information. In addition, the risk tolerance questionnaire asks all family members this question. Unfortunately, not all family members complete the questionnaire, and when splitting the divorced couple, the questions are not assigned directly to the non-head divorced spouse. This required creative variable coding to account for the discrepancy.

Variable measurement for the key response variables of precautionary savings, retirement savings and risky asset share required specific handling as those measures could not be made in every year in the analysis. A dataset with those measures at every stage would be more helpful in identifying variation within group and within individual across years. On savings the calculations involve accounting for investment experience and assuming that there are no withdrawals. For retirement savings, this means not accounting for taxes in any withdrawals. Since tax return data is not included in the sample, it would be non-trivial to attempt to calculate an estimate of taxes on any retirement account withdrawal.

Calculating risky asset share is less precise than desired. Typically, retirement funds at employers are located within mutual funds or other multi-investment option accounts. These types of funds reduce idiosyncratic risk but are still affected by the volatility of capital markets (Spiegel & Zhang, 2013). Self-reported references to “stock” in an account is an issue since most individual Americans are not financially literate (Kothakota & Kiss, 2019) and have trouble differentiating between different types of investments (Grinblatt & Kelharju, 2000). Further, individuals may own a single stock or a series of individual stocks that are highly volatile. This increases the relative risk of their portfolio when compared to a portfolio with less idiosyncratic risk, such as mutual funds.

This study excluded businesses from assets. Individuals with businesses tend to invest more into their businesses (Lusardi & Mitchell, 2011) and depending upon the stage of business may carry debt as part of their capital structure (Ammerman, 2017). Divorce can harm a family business, but usually one person keeps operation of the business (Stafford, Duncan, Dane & Winter, 1999). This may cause that person to have no risky assets at all in this study, even though they carry the full idiosyncratic risk of their business. Business owners are also less likely to invest in retirement accounts in early business stages (Bowen & Charles, 2003). Increases in retirement contributions could coincide with more disposable income in later business stages and have less to do with stress adjustment. Not including business owners as a covariate and interacting with other variables does not allow examination of this effect.

While child support and alimony are included as explanatory variables, the number of individuals receiving child support and alimony is small. Lower income individuals are more likely to divorce, they are less likely to receive alimony and child support (Kothakota & Heckman, 2018). A sample including more wealthy households would help determine whether the short- and long-term effects on precautionary savings, retirement savings and risky asset share are affected by these types of transfer payments.

Disposition of marital estate

Since the analysis excludes assets such as vehicles and real estate, the effect of the disposition of the marital estate is not included in the analysis. As an example, a couple with a retirement account and house as their only assets might get divorced. One spouse receives all of the retirement funds and the other receives the house. In this situation, the spouse receiving the house has a zero risky asset share according to this analysis, while simultaneously carrying all of the risk associated with the real estate market. In addition, if there is an unequal distribution of assets the spouse receiving fewer assets may have a greater desire to save than the spouse receiving more assets.

Methodology

The Exponential Fractional Regression Model is helpful in identifying measuring significant changes to savings rates and risky asset share. It is less helpful in determining if equilibrium to previous behavior is achieved. A duration or survival analysis model may be helpful in identifying whether this occurs. Austin (2014) has suggested using a multivariable fractional polynomial model to assess survival curves, while Tang, Jeong & Song (2017) suggest the use of a fractional logistic regression model. While less equipped to handle zeroes and ratio variables in general, a more robust data set with fewer extreme values may allow for this type of analysis.

Future studies

Given the promising nature of these results, there is an opportunity to build on this research in the area of divorce and wealth management. Future studies can be conducted on other longitudinal datasets such as the Health and Retirement Savings Survey. Since each survey has varying degrees of detail within the financial questions that are asked, more detailed investment and savings data may be obtained. This may allow for more precise measurement of risky asset share as well as illustrate actual savings rates. A project of this scope further would provide validation or contradiction for the current study, advancing the scientific knowledge of this area of inquiry.

Given the dearth of surveys focused on divorcing, primary research by collecting data on divorcing couples and divorced individuals may help in obtaining more accurate information. Specifically, a study tailored to assess the varying financial, emotional and structural dimensions of divorce may provide better estimates on behavior of savings and investing. Primary research may also allow for collecting of very specific savings and investing information by designing questions to obtain that information.

This study only examined divorces from heterosexual couples. Future research should include results for same sex divorces. Same sex divorces may have different outcomes than heterosexual divorces. For example, it would be interesting to examine results from same sex dual income households and same sex single income households and compare them to heterosexual households. Examining male-male and female-female differences would also be interesting to see how the gender differences compare from heterosexual couples and same sex couples.

The definition of wealth management used in the introduction includes protection of assets. Protecting assets is usually done with various insurance and estate planning tools. This is an important part of the wealth management process that should be explored in the future. Analysis of how divorced individuals use or do not use insurance products can open conversations for wealth managers to provide adequate protection following a divorce. As an example, someone who is reliant on child support and alimony may be advantaged to purchase life insurance on their former spouse in case that spouse dies, and transfer payments stop.

Given the often negative savings rates of individuals and negative net worth associated with individuals in this sample, research on debt and how it changes over time and interventions to assist with that debt can be helpful in finding the causes of spiraling debt for divorced individuals. Examining the differentiating factors between divorced individuals in debt and those not in debt can be helpful in developing interventions to assist with debt management. Studies can use both cross-sectional and longitudinal data to examine the effects of such interventions.

Almost one-third of the sample were paying for educational expenses associated with children. College tuition can affect wealth and the ability to save (Souleles, 2000). Further research on the effect of divorce on college planning, the choice of college by a financial dependent and the debt loads of children of divorce can be helpful to professionals in advising clients before, during and after divorce.

Pieces of estate planning can also be researched. How individuals decide to distribute their wealth upon their death is an important part of the wealth management process. The bequest intention results of this study provide a start to estate planning research but must be further examined before more robust recommendations can be made surrounding the research. In addition, the techniques individuals, both divorced and not use and how they wish to distribute those assets can be helpful in understanding a divorced population. Looking to see how these events change pre- and post-divorce and over their lifetime can assist wealth managers in advising their clients.

Since this study explicitly excludes business owners, a study including business owners would be useful. A business may be sold, it may convey to one spouse or it may continue to be owned by both parties. If sold, this would result in a large cash infusion and would necessitate management of that cash for current and future consumption. Understanding how each spouse operates post-divorce would be helpful in assisting wealth managers and financial planners to steer their clients in the direction that works best for that individual. If one spouse continues to own the business, and the owner-spouse must take on debt to but their spouse out of their portion of the business, it would be helpful to understand these effects immediately and long-term. And understanding how divorced couples who continue to do business together can help their advisor team assist them in operating smoothly and efficiently.

Finally, does having a wealth manager or financial planner help reduce negative effects of divorce? By studying the involvement of wealth managers and financial planners pre- and post-divorce, researchers can determine how helpful it is to have professionals assisting individuals who are divorced. Research of the effect of having a specific type of advisor, such as the differences between financial planners, attorneys and accountants may also be helpful in understanding which type of advisor is best for those going through divorce. For example, someone trained in understanding the consequences of divorce may be more helpful during a divorce but may be less helpful in later years following the divorce.

Conclusion

This study provided insight into changes that may occur over time with respect to savings and risky asset share. It also provided additional research in the area of bequest intention that confirmed some previous results and contradicted others. This simply means that more research is needed to create a robust body of work that can be useful to professionals working in wealth management. The study further provided detail in certain sub-groups and found a robust result with respect to remarriage and how it affects financial behaviors.

Finally, the use of Exponential Fractional Regression Modeling has been useful in explaining short- and long-term financial behavior consequences of divorce. The use of such methods in accounting and corporate finance has been translated to personal finance. Future studies using fractional response variables may be used to draw more insight in the areas of consumer economics, household finance, financial planning and wealth management.

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Appendix

R Code

```
# install packages from cran
cran_pkgs = c("tidyverse", 'devtools', "convey", "srvyr", 'e1071', 'frmpd')
for (pkg in cran_pkgs) {
	cat("Install the most recent version of", pkg, "\n")
	install.packages(pkg, dependencies = T, repos = "http://cran.rstudio.com/")
}

# install packages from github
github_pkgs = c("gmlang/ezplot", 'ajdamico/lodown')
for (pkg in github_pkgs) {
	cat("Install the most recent version of", pkg, "\n")
	devtools::install_github(pkg, dependencies = T, upgrade = 'always')
}

cat("### All required packages installed ###")
# data: https://psidonline.isr.umich.edu
# look up variables: https://simba.isr.umich.edu/VS/s.aspx

rm(list = ls())

source("R/00-set-up.R")
#source("R/01-download-data.R") # comment out to run, and only need to run once

cohort_year = 1987 # 1987, 1994, 1999
source('R/02-read-crossyear-individual-file.R')
source('R/03-prep-data-fixed-vars.R')
source('R/03-prep-data-yearly-vars.R')
source('R/04-choose-cohort.R')
source('R/05-chain-yearly-data.R')
source('R/06-join-fixed-n-yearly-vars.R')
source('R/07-fill-NAs.R')
source('R/08-calc-savings-rates-n-save.R')

rmarkdown::render("R/09-summary-stats.R",
		output_file = paste0("summ-stats-", cohort_year,
				"-divorced.pdf"),
		output_dir = pdf_path)
# library(readxl)
library(readr)
library(dplyr)
library(tidyr)
library(lodown)
# library(ezplot)
```

```
# library(ggplot2)

# set options
options(scipen = 999)

# set paths
data_path = "data"
out_path = "output"
pdf_path  = file.path(out_path, "pdf")
png_path  = file.path(out_path, "png")
csv_path  = file.path(out_path, "csv")
rds_path  = file.path(out_path, "rds")
dir.create(data_path, showWarnings = F, recursive = T)
dir.create(pdf_path, showWarnings = F, recursive = T)
dir.create(rds_path, showWarnings = F, recursive = T)
# dir.create(png_path, showWarnings = F, recursive = T)
dir.create(csv_path, showWarnings = F, recursive = T)

# load helper functions
helper_path = "R/helper"
for (fname in list.files(helper_path)) source(file.path(helper_path, fname))
# ref: http://asdfree.com/panel-study-of-income-dynamics-psid.html

all_cat = get_catalog("psid",
                      # dir to save downloaded files in the next step
                      output_dir = data_path,
                      your_email = "mkothakota@ksu.edu",
                      your_password = "useyourownpassword")

# choose data files to download
catalog_for_download = rbind(
    all_cat %>% filter(type %in% c('Family Files', 'Wealth Files'),
                       year >= 1987),
    all_cat %>% filter(
        table_name %in% c('Cross-year Individual: 1968-2017',
                          'Active Savings: 1989, 1994',
                          'Marriage History: 1985-2017'))
    )


lodown("psid",
    catalog = catalog_for_download,
    your_email = "mkothakota@ksu.edu",
    your_password = " useyourownpassword ")
df_ind = read_rds(
    file.path(data_path,
```

```
        'consumption expenditure data 1999-2013/cross-year individual 1968-2017.rds')
    )
---
# This script extracts time-invariant vars from the individual and family
# files and put them in a data frame with keys (family_id, person_id).
# ---


# get fixed vars from the individual file
df_ind_fixed = df_ind %>% select(ind_vars_fixed)
stopifnot(
    # df_ind_fixed should contain unique individuals (family_id+person_id)
    df_ind_fixed %>% select(keys) %>% distinct_all() %>% nrow() ==
        nrow(df_ind_fixed)
    )


# --- get risk tolerance vars --- #

# select unique (family_id, person_id, interview_id) from 1996 individual file
ind_vars_1996 = ind_vars_year_specific %>% filter(year == 1996) %>%
    select(interview_id, sequence_number, relation_to_head) %>% unlist()
df_ind_1996 = df_ind %>% select(ind_vars_fixed[keys], ind_vars_1996) %>%
    filter_responding_heads()
stopifnot(
    # df_ind_1996 should contain unique interview_id's
    length(df_ind_1996$interview_id) ==
        length(df_ind_1996$interview_id %>% unique()),
    # df_ind_1996 should contain unique individuals
    df_ind_1996 %>% count(family_id, person_id) %>% filter(n > 1) %>%
        nrow() == 0
    )

# assume risk tolerance is time invariant, extract it from the 1996 family file
#     since it only exists there.
source(paste0('R/get-risk-tolerance-1996.R'))

# df_ind_1996 has unique identifier (family_id + person_id) of the individual
#     and his or her 1996 interview id.
# df_risk_tolerance has unique 1996 interview ids and the corresponding
#     responses to the gambling questions.
# we want to associate those responses to the unique individual identifiers
tmp = left_join(df_ind_1996, df_risk_tolerance, by = 'interview_id')
stopifnot(nrow(tmp) == nrow(df_ind_1996),
     tmp %>% select(family_id, person_id) %>%
        distinct_all() %>% nrow() == nrow(tmp))
```

```
# move risk tolerance to df_ind_fixed
df_ind_fixed = left_join(df_ind_fixed, tmp %>% select(-interview_id), by = keys)
# nrow(df_ind_fixed)


# --- get bequest importance vars --- #

# select unique (family_id, person_id, interview_id) from 2007 individual file
ind_vars_2007 = ind_vars_year_specific %>% filter(year == 2007) %>%
	select(interview_id, sequence_number, relation_to_head) %>% unlist()
df_ind_2007 = df_ind %>% select(ind_vars_fixed[keys], ind_vars_2007) %>%
	filter_responding_heads
stopifnot(
	# df_ind_2007 should contain unique interview_id's
	length(df_ind_2007$interview_id) ==
		length(df_ind_2007$interview_id %>% unique()),
	# df_ind_2007 should contain unique individuals
	df_ind_2007 %>% count(family_id, person_id) %>% filter(n > 1) %>%
		nrow() == 0)

# assume bequest importance is time invariant, extract it from 2007 family file
#	since it only exists there.
source(paste0('R/get-bequest-importance-2007.R'))


# df_ind_2007 has unique identifier (family_id + person_id) of the individual
#	and his or her 2007 interview id.
# df_bequest has unique 2007 interview ids and the corresponding
#	responses to the bequest importance questions.
# we want to associate those responses to the unique individual identifiers
tmp = left_join(df_ind_2007, df_bequest, by = 'interview_id')
stopifnot(nrow(tmp) == nrow(df_ind_2007),
	 tmp %>% select(family_id, person_id) %>%
		distinct_all() %>% nrow() == nrow(tmp))

# move bequest importance to df_ind_fixed
df_ind_fixed = left_join(df_ind_fixed, tmp %>% select(-interview_id), by = keys)

nrow(df_ind_fixed)
head(df_ind_fixed)
# ---
# This script extracts time-varying (yearly) vars from the individual and family
# files and put them in a data frame with keys (family_id, person_id, year).
# ---
```

```
lst_of_yearly_dfs = vector('list', length(years_wea))
names(lst_of_yearly_dfs) = years_wea
for (yr in years_wea) {
	# yr = 1989
	cat(yr, "..\n")

	# get year-specific vars from individual file
	ind_vars_yr = ind_vars_year_specific %>%
		filter(year == yr) %>% select(-year) %>% unlist()
	df_ind_year = df_ind %>%
		select(ind_vars_fixed[keys], ind_vars_yr) %>%
		filter_responding_heads()

	# get vars from family file
	df_fam = read_rds(file.path(data_path, 'family files',
				paste0(yr, '.rds')))
	source('R/prep-family-files.R') # changes df_fam

	# get vars from wealth file
	df_wea = read_rds(file.path(data_path, 'wealth files',
				paste(yr, 'wealth.rds')))
	source('R/prep-wealth-files.R') # changes df_wea

	# join family and wealth sets by interview_id,
	#	both should have unique interview_id, but may not have
	#	the same number of records (some people might've only answered
	#	questions on family file, but weren't intereviewed or didn't
	#	respond to wealth related questions).
	df_fam_wea = left_join(df_fam, df_wea, by = 'interview_id')

	# join df_fam_wea and df_ind_year, where the former has unique interview_id
	stopifnot(length(df_fam_wea %>% pull(interview_id) %>% unique()) ==
			length(df_fam_wea %>% pull(interview_id)))

	dat = left_join(df_fam_wea, df_ind_year, by = 'interview_id')

	stopifnot(nrow(dat) == nrow(df_fam_wea),
		 dat %>% select(family_id, person_id) %>%
			distinct_all() %>% nrow() == nrow(dat))

	# add year to dat and rearrange columns
	dat = dat %>% mutate(year = yr) %>%
		# rearrange columns
		select(family_id, person_id, race, year, interview_id, age,
		     highest_education, employment, everything())
```

```
        # head(dat)

        lst_of_yearly_dfs[[as.character(yr)]] = dat
}

# cat('Number of families with more than 1 head:\n')
# lst_of_yearly_dfs[['1989']] %>% count(family_id) %>% filter(n > 1) %>% nrow()
# lst_of_yearly_dfs[['1994']] %>% count(family_id) %>% filter(n > 1) %>% nrow()
# lst_of_yearly_dfs[['1999']] %>% count(family_id) %>% filter(n > 1) %>% nrow()
# lst_of_yearly_dfs[['2001']] %>% count(family_id) %>% filter(n > 1) %>% nrow()
# lst_of_yearly_dfs[['2003']] %>% count(family_id) %>% filter(n > 1) %>% nrow()
# lst_of_yearly_dfs[['2005']] %>% count(family_id) %>% filter(n > 1) %>% nrow()
# lst_of_yearly_dfs[['2007']] %>% count(family_id) %>% filter(n > 1) %>% nrow()

        filter(year == cohort_year) %>%
        select(interview_id, sequence_number, relation_to_head) %>%
        unlist()

df_cohort_ids = df_ind %>%
        select(ind_vars_fixed[keys], ind_vars_cohort_year) %>%
        filter_responding_heads()


# --- only keep those divorced in the cohort year --- #

# marital status exists in the family file
df_fam = read_rds(file.path(data_path, 'family files',
                        paste0(cohort_year, '.rds')))

# look up the varname for marital status and interview id on family file
lookup_fam = fam_vars_year_specific %>% filter(year == cohort_year)
marital_status_varname = lookup_fam %>% pull(marital_status_var)
interview_id_varname = lookup_fam %>% pull(interview_id_var)

# marital status levels:
#       1 Married
#       2 Never married
#       3 Widowed
#       4 Divorced, annulled
#       5 Separated
is_divorced = df_fam[[marital_status_varname]] == 4
interview_ids_divorced = df_fam[is_divorced,][[interview_id_varname]]

df_cohort_ids = df_cohort_ids %>%
        filter(interview_id %in% interview_ids_divorced)
```

```
# nrow(df_cohort_ids)
# head(df_cohort_ids)

# --- find those (family_id, person_id) that appear in all wealth years,
#     stack them into one data frame
# ---

# print(keys)
df_common_keyvals = df_cohort_ids[keys]
for (yr in years_wea)
        df_common_keyvals = df_common_keyvals %>%
                inner_join(lst_of_yearly_dfs[[as.character(yr)]][keys],
                           by = keys)
nrow(df_common_keyvals)


df_chained = bind_rows(
        lapply(lst_of_yearly_dfs, function(year_data)
                inner_join(year_data, df_common_keyvals, by = keys))
        )

df_chained %>% count(year) %>% print()

df_chained = df_chained %>%
        # join the fixed (time-invariant) vars
        left_join(df_ind_fixed, by = keys) %>%
        recode_ind_vars() %>% # defined in R/helper
        # join sp500 returns
        left_join(lookup_sp500_rets %>% select(end_year, CAGR_sp500),
                  by = c('year' = 'end_year'))


# --- rearrange the columns --- #

df_chained = df_chained %>%
        select(family_id, person_id,
               # fixed vars:
               num_of_live_births, gender, race,
               risk_tolerance, importance_bequest_to_rels,
               importance_bequest_to_relorg, importance_bequest_to_charity,
               # yearly vars:
               year, interview_id, is_remarried, age,
               education_status, education_status_agg,
               employment_status, employment_status_agg,
               everything())
df_chained = df_chained %>% group_by(family_id, person_id) %>%
```

```
    fill(race, had_school_expenses,
        chld_supprt_paid, chld_supprt_net,
        alimony_paid, alimony_net,
        chld_supprt_alimony_tot_net,
        chld_supprt_status, alimony_status,
        .direction = 'up') %>%
    fill(education_status, education_status_agg,
        chld_supprt_paid, chld_supprt_net,
        alimony_paid, alimony_net,
        chld_supprt_alimony_tot_net,
        chld_supprt_status, alimony_status,
        had_school_expenses)

# --- missing filling strategies --- #
#
# race: fill by next non-NA val
# risk_tolerance: NA for all years, cannot fix
# importance_bequest_to_rels: NA for all years, cannot fix
# importance_bequest_to_relorg: NA for all years, cannot fix
# importance_bequest_to_charity: NA for all years, cannot fix
# education_status, education_status_agg, chld_supprt_paid, chld_supprt_net,
# chld_supprt_status:
#     Some have non-NA for early years and NA for later years,
#     fill those NA by previous non-NA val.
#     Others have NA for all years, cannot fix.
# had_school_expenses: fill by next non-NA val, then by previous non-NA val.
# num_of_live_births: NA for all years, cannot fix

# # --- manually check each var's missingness --- #
#
# # calc percent of NAs in each var
# na_pct = sapply(df_chained, function(col) sum(is.na(col))) / nrow(df_chained)
# na_pct[na_pct > 0]
#
#
# varname = 'num_of_live_births'
# varquo = as.name(varname)
#
# df_chained %>% filter(is.na(!!varquo)) %>%
#     count(family_id, person_id) %>% filter(n < length(years_wea))
#
# df_chained %>% filter(family_id == 414, person_id == 3) %>%
#     select(family_id, person_id, year, !!varquo) %>%
#     View()
#
# df_chained %>% filter(is.na(!!varquo)) %>%
```

```
#       select(family_id, person_id, year, !!varquo) %>%
#       View()
df_chained = df_chained %>%
    group_by(family_id, person_id) %>%
    mutate(savings_cash = pmax(cash - lag(cash), 0),
        savings_retirement = pmax(
            retirement_accts_value - lag(retirement_accts_value), 0),
        savings_rate_cash = case_when(
            is.na(savings_cash) ~ NA_real_,
            tot_labor_income_lastyr == 0 & savings_cash > 0 ~ 0.999,
            tot_labor_income_lastyr == 0 & savings_cash == 0 ~ 0,
            TRUE ~ savings_cash / tot_labor_income_lastyr),
        savings_rate_retirement = case_when(
            is.na(savings_retirement) ~ NA_real_,
            tot_labor_income_lastyr == 0 & savings_retirement > 0 ~ 0.999,
            tot_labor_income_lastyr == 0 & savings_retirement == 0 ~ 0,
            TRUE ~ savings_retirement / tot_labor_income_lastyr)
        ) %>% ungroup() %>%
    arrange(family_id, person_id, year)


# save
write_rds(df_chained,
     file.path(rds_path, paste0('divorced-', cohort_year, '.rds')))
write_csv(df_chained,
     file.path(csv_path, paste0('divorced-', cohort_year, '.csv')))

#' ---
#' title: Summary Stats
#' author: ""
#' date: "`r Sys.Date()`"
#' output: pdf_document
#' ---

#+ include = FALSE
knitr::opts_chunk$set(comment = "", tidy = F, echo = F, warning = F,
           message = F, fig.width = 8, fig.height = 6)
options(scipen = 999)

#' # `r cohort_year` Divorced
#'
#' This dataset contains info of the heads of families who were divorced in
#' `r cohort_year` over the years 1989, 94, 99, 2001, 03, 05 and 07.
#'

knitr::kable(freqtab(df_chained)('year') %>% arrange(year) %>% select(-pct),
```

```
        caption = 'Number of heads by year')

df_chained %>% group_by(year) %>%
    summarise(family_cnt = length(unique(family_id))) %>%
    knitr::kable(caption = 'Number of unique families by year')

#' ## Fixed (time-invariant) Variables

df_fixed = df_chained %>% filter(year == 1989) %>% # 1st year of data
    select(gender, num_of_live_births,
        risk_tolerance, importance_bequest_to_rels,
        importance_bequest_to_relorg, importance_bequest_to_charity)
f = freqtab(df_fixed)

#+ results = 'asis'

f("gender") %>% knitr::kable(caption = 'Gender') %>% print()
f("num_of_live_births") %>% knitr::kable(caption = 'Number of live births') %>%
    print()

cap = 'Risk tolerance (1 - lowest, 6 - highest)'
f("risk_tolerance") %>% knitr::kable(caption = cap) %>% print()

cap = 'Importance of leaving estate/inheritance to children/relatives'
f("importance_bequest_to_rels") %>% knitr::kable(caption = cap) %>% print()

cap = 'Importance of leaving estate/inheritance to religious organizations'
f("importance_bequest_to_relorg") %>% knitr::kable(caption = cap) %>% print()

cap = 'Importance of leaving estate/inheritance to charity'
f("importance_bequest_to_charity") %>% knitr::kable(caption = cap) %>% print()


#' ## Yearly (time-varying) Variables

#+ results = 'asis'

for (yr in years_wea) {
    # yr = years_wea[1]
    dat = df_chained %>% filter(year == yr)
    # glimpse(dat)
    get_freq_tbl = freqtab(dat)

    get_freq_tbl("race") %>% knitr::kable(caption = 'Race') %>% print()

    cap = paste(yr, 'Is remarried?', sep = ' - ')
```

```
get_freq_tbl("is_remarried") %>% knitr::kable(caption = cap) %>%
    print()

cap = paste(yr, 'Education Status', sep = ' - ')
get_freq_tbl("education_status") %>% knitr::kable(caption = cap) %>%
    print()

cap = paste(yr, 'Education Status Aggregated', sep = ' - ')
get_freq_tbl("education_status_agg") %>% knitr::kable(caption = cap) %>%
    print()

cap = paste(yr, 'Employment Status', sep = ' - ')
get_freq_tbl("employment_status") %>% knitr::kable(caption = cap) %>%
    print()

cap = paste(yr, 'Employment Status Aggregated', sep = ' - ')
get_freq_tbl("employment_status_agg") %>% knitr::kable(caption = cap) %>%
    print()

cap = paste(yr, 'Child Support Status', sep = ' - ')
get_freq_tbl("chld_supprt_status") %>% knitr::kable(caption = cap) %>%
    print()

cap = paste(yr, 'Alimony Status', sep = ' - ')
get_freq_tbl("alimony_status") %>% knitr::kable(caption = cap) %>%
    print()

cap = paste(yr, 'Had school related expenses?', sep = ' - ')
get_freq_tbl("had_school_expenses") %>% knitr::kable(caption = cap) %>%
    print()

cap = paste(yr, 'Age', sep = ' - ')
summary_stats(dat$age) %>% data.frame() %>%
    setNames(nm = 'age') %>%
    knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Number of children in family', sep = ' - ')
summary_stats(dat$num_of_chld_in_family) %>% data.frame() %>%
    setNames(nm = 'num_of_chld_in_family') %>%
    knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Wage Income Last Year', sep = ' - ')
summary_stats(dat$tot_wages_lastyr) %>% data.frame() %>%
    setNames(nm = 'tot_wages_lastyr') %>%
    knitr::kable(digits=2, caption = cap) %>% print()
```

```
cap = paste(yr, 'Total Labor Income Last Year', sep = ' - ')
summary_stats(dat$tot_labor_income_lastyr) %>% data.frame() %>%
	setNames(nm = 'tot_labor_income_lastyr') %>%
	knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Child Support Paid', sep = ' - ')
summary_stats(dat$chld_supprt_paid) %>% data.frame() %>%
	setNames(nm = 'chld_supprt_paid') %>%
	knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Child Support Received', sep = ' - ')
summary_stats(dat$chld_supprt_recd) %>% data.frame() %>%
	setNames(nm = 'chld_supprt_recd') %>%
	knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Child Support Net (Received - Paid)', sep = ' - ')
summary_stats(dat$chld_supprt_net) %>% data.frame() %>%
	setNames(nm = 'chld_supprt_net') %>%
	knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Alimony Paid', sep = ' - ')
summary_stats(dat$alimony_paid) %>% data.frame() %>%
	setNames(nm = 'alimony_paid') %>%
	knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Alimony Received', sep = ' - ')
summary_stats(dat$alimony_recd) %>% data.frame() %>%
	setNames(nm = 'alimony_recd') %>%
	knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Alimony Net (Received - Paid)', sep = ' - ')
summary_stats(dat$alimony_net) %>% data.frame() %>%
	setNames(nm = 'alimony_net') %>%
	knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Child Support + Alimony Total Net', sep = ' - ')
summary_stats(dat$chld_supprt_alimony_tot_net) %>% data.frame() %>%
	setNames(nm = 'chld_supprt_alimony_tot_net') %>%
	knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Total Cash', sep = ' - ')
summary_stats(dat$cash) %>% data.frame() %>%
	setNames(nm = 'cash') %>%
	knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Total Stocks Not in Retirement Accounts', sep = ' - ')
```

```
summary_stats(dat$stocks) %>% data.frame() %>%
    setNames(nm = 'stocks') %>%
    knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Total Retirement Accounts Value', sep = ' - ')
summary_stats(dat$retirement_accts_value) %>% data.frame() %>%
    setNames(nm = 'retirement_accts_value') %>%
    knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Networth', sep = ' - ')
summary_stats(dat$net_worth) %>% data.frame() %>%
    setNames(nm = 'net_worth') %>%
    knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Risky Share', sep = ' - ')
summary_stats(dat$risky_share) %>% data.frame() %>%
    setNames(nm = 'risky_share') %>%
    knitr::kable(digits=2, caption = cap) %>% print()

cap = paste(yr, 'Active Savings - Cash', sep = ' - ')
if (all(is.na(dat$savings_cash))) {
    data.frame(savings_cash = 'All NA') %>%
        knitr::kable(caption = cap) %>% print()
} else {
    summary_stats(dat$savings_cash) %>% data.frame() %>%
        setNames(nm = 'savings_cash') %>%
        knitr::kable(digits=2, caption = cap) %>% print()
}

cap = paste(yr, 'Active Savings - Retirement Account', sep = ' - ')
if (all(is.na(dat$savings_retirement))) {
    data.frame(savings_retirement = 'All NA') %>%
        knitr::kable(caption = cap) %>% print()
} else {
    summary_stats(dat$savings_retirement) %>% data.frame() %>%
        setNames(nm = 'savings_retirement') %>%
        knitr::kable(digits=2, caption = cap) %>% print()
}

cap = paste(yr, 'Active Savings Rate - Cash', sep = ' - ')
if (all(is.na(dat$savings_rate_cash))) {
    data.frame(savings_rate_cash = 'All NA') %>%
        knitr::kable(caption = cap) %>% print()
} else {
    summary_stats(dat$savings_rate_cash) %>% data.frame() %>%
        setNames(nm = 'savings_rate_cash') %>%
```

```
            knitr::kable(digits=2, caption = cap) %>% print()
    }

    cap = paste(yr, 'Active Savings Rate - Retirement Account', sep = ' - ')
    if (all(is.na(dat$savings_rate_retirement))) {
        data.frame(savings_rate_retirement = 'All NA') %>%
            knitr::kable(caption = cap) %>% print()
    } else {
        summary_stats(dat$savings_rate_retirement) %>% data.frame() %>%
            setNames(nm = 'savings_rate_retirement') %>%
            knitr::kable(digits=2, caption = cap) %>% print()
    }
}

# --- bequest importance vars only exist in 2007 family file, extract them --- #

df_bequest = read_rds(file.path(data_path, 'family files', '2007.rds')) %>%
    select(er36002, er37720, er37721, er37722) %>%
    transmute(interview_id = er36002,
         # how important of leaving estate/inheritance to children/relatives?
         importance_bequest_to_rels =
             case_when(er37720 == 1 ~ 'Very important',
                  er37720 == 2 ~ 'Quite important',
                  er37720 == 3 ~ 'Not important',
                  er37720 == 4 ~ 'Not at all important',
                  TRUE ~ NA_character_),

         # how important of leaving estate/inheritance to religious organizations?
         importance_bequest_to_relorg =
             case_when(er37721 == 1 ~ 'Very important',
                  er37721 == 2 ~ 'Quite important',
                  er37721 == 3 ~ 'Not important',
                  er37721 == 4 ~ 'Not at all important',
                  TRUE ~ NA_character_),

         # how important of leaving estate/inheritance to charity?
         importance_bequest_to_charity =
             case_when(er37722 == 1 ~ 'Very important',
                  er37722 == 2 ~ 'Quite important',
                  er37722 == 3 ~ 'Not important',
                  er37722 == 4 ~ 'Not at all important',
                  TRUE ~ NA_character_)
         )
# --- gambling questions only exist in 1996 family file, extract them  --- #

df_risk_tolerance =
```

```r
        read_rds(file.path(data_path, 'family files', '1996.rds')) %>%
        select(er7002, er9103, er9104, er9105, er9106, er9107) %>%
        transmute(interview_id = er7002,
                risk_tolerance = case_when( # 1 - lowest risk; 6 - highest risk
                    er9107 == 1 ~ 6,  # 'Yes' on 75% INCOME CUT
                    er9107 == 5 & er9104 == 1 ~ 5,  # 'No' on 75% cut but 'Yes' on 50% cut
                    er9104 == 5 & er9103 == 1 ~ 4,  # 'No' on 50% cut but 'Yes' on 1/3 cut
                    er9103 == 5 & er9105 == 1 ~ 3,  # 'No' on 1/3 cut but 'Yes' on 20% cut
                    er9105 == 5 & er9106 == 1 ~ 2,  # 'No' on 20% cut but 'Yes' on 10% cut
                    er9106 == 5 ~ 1,  # 'No' on 10% cut
                    TRUE ~ NA_real_)
                )
# yr = 1989

lookup_fam = fam_vars_year_specific %>% filter(year == yr)

# --- some vars don't exist for all years, deal with them here --- #

if (is.na(lookup_fam$wages_xtra_job_lastyr_var)) {
        wages_xtra = rep(0, nrow(df_fam))
} else {
        wages_xtra = df_fam[[lookup_fam$wages_xtra_job_lastyr_var]]
}

if (is.na(lookup_fam$had_school_expenses_var)) {
        flag_school_expense = rep(NA_integer_, nrow(df_fam))
} else {
        flag_school_expense = df_fam[[lookup_fam$had_school_expenses_var]]
}

if (is.na(lookup_fam$tot_labor_income_lastyr_var)) {
        subtot_labor_income = df_fam[[lookup_fam$subtot_labor_income_lastyr_var]]
        subtot_labor_income = ifelse(subtot_labor_income == 9999999,
                                NA_real_, subtot_labor_income)
        biz_labor_income = df_fam[[lookup_fam$biz_labor_income_lastyr_var]]
        biz_labor_income = ifelse(biz_labor_income == 999999,
                                NA_real_, biz_labor_income)
        tot_labor_income = subtot_labor_income + biz_labor_income

} else {
        tot_labor_income = df_fam[[lookup_fam$tot_labor_income_lastyr_var]]
        tot_labor_income = ifelse(tot_labor_income == 999999, NA_real_,
                                tot_labor_income)
}

# --- some ad hoc codes look up --- #
```

```
na_codes_csal_paid = case_when(yr < 1993 ~ c(99998, 99999),
                         TRUE ~ c(9999998, 9999999))
na_codes_csal_recd = case_when(yr < 2003 ~ c(99998, 99999),
                         TRUE ~ c(999998, 999999))

race_code_white = 1
race_code_black = 2
race_code_aindian = 3
race_code_asian_pislander = ifelse(yr < 2005, 4, c(4, 5))
race_code_latino = ifelse(yr < 2005, 5, 9999) # 9999 means doesn't exist
race_code_more_colors = ifelse(yr < 2005, 6, 9998) # 9998 means doesn't exist
race_code_other = 7

# get the vars and prep

df_fam = df_fam %>%
    transmute(interview_id = !!as.name(lookup_fam$interview_id_var),
        race = !!as.name(lookup_fam$race1_var),
        marital_status_cng =
            !!as.name(lookup_fam$marital_status_cng_var),
        num_of_chld_in_family =
            !!as.name(lookup_fam$num_of_chld_in_family_var),
        flag_school_expenses = flag_school_expense,

        wages_lastyr = !!as.name(lookup_fam$wages_lastyr_var),
        wages_xtra_lastyr = wages_xtra,
        tot_labor_income_lastyr = tot_labor_income,

        chld_supprt_paid = !!as.name(lookup_fam$chld_supprt_paid_var),
        alimony_paid = !!as.name(lookup_fam$alimony_paid_var),
        chld_supprt_recd = !!as.name(lookup_fam$chld_supprt_recd_var),
        alimony_recd = !!as.name(lookup_fam$alimony_recd_var)
        ) %>%
    mutate(is_remarried = ifelse(marital_status_cng == 5, 'Yes', 'No'),

      race = case_when(race == race_code_white ~ 'White',
                race == race_code_black ~ 'Black',
                race == race_code_aindian ~ 'American Indian or Alaska Native',
                race == race_code_asian_pislander ~ 'Asian, Pacific Islander',
                race == race_code_latino ~ 'Latino origin or descent',
                race == race_code_more_colors ~ 'Color besides black or white',
                race == race_code_other ~ 'Other',
                TRUE ~ NA_character_),

      had_school_expenses = case_when(
```

```
			flag_school_expenses == 1 ~ 'Yes',
			flag_school_expenses == 5 ~ 'No',
			TRUE ~ NA_character_),

		tot_wages_lastyr = wages_lastyr + wages_xtra_lastyr,

		chld_supprt_paid = ifelse(
			chld_supprt_paid %in% na_codes_csal_paid,
			NA_real_, chld_supprt_paid),
		alimony_paid = ifelse(
			alimony_paid %in% na_codes_csal_paid,
			NA_real_, alimony_paid),

		chld_supprt_recd = ifelse(
			chld_supprt_recd %in% na_codes_csal_recd,
			NA_real_, chld_supprt_recd),
		alimony_recd = ifelse(
			alimony_recd %in% na_codes_csal_recd,
			NA_real_, alimony_recd),

		chld_supprt_net = chld_supprt_recd - chld_supprt_paid,
		alimony_net = alimony_recd - alimony_paid,
		chld_supprt_alimony_tot_net = chld_supprt_net + alimony_net,

		chld_supprt_status = case_when(
			chld_supprt_paid > 0 & chld_supprt_recd > 0 ~ 'both',
			chld_supprt_paid > 0 & chld_supprt_recd == 0 ~ 'paid',
			chld_supprt_paid == 0 & chld_supprt_recd > 0 ~ 'received',
			chld_supprt_paid == 0 & chld_supprt_recd == 0 ~ 'neither',
			TRUE ~ NA_character_),

		alimony_status = case_when(
			alimony_paid > 0 & alimony_recd > 0 ~ 'both',
			alimony_paid > 0 & alimony_recd == 0 ~ 'paid',
			alimony_paid == 0 & alimony_recd > 0 ~ 'received',
			alimony_paid == 0 & alimony_recd == 0 ~ 'neither',
			TRUE ~ NA_character_),

		marital_status_cng = NULL,
		wages_lastyr = NULL,
		wages_xtra_lastyr = NULL,
		flag_school_expenses = NULL

		)
# yr = 1989
lookup_wea = wea_vars_year_specific %>% filter(year == yr)
```

```
if (is.na(lookup_wea$ira_asset_var)) {
	ira_vec = rep(0, nrow(df_wea))
} else {
	ira_vec = df_wea[[lookup_wea$ira_asset_var]]
}
df_wea = df_wea %>%
	transmute(interview_id = !!as.name(lookup_wea$interview_id_var),
		cash = !!as.name(lookup_wea$cash_asset_var),
		stocks = !!as.name(lookup_wea$stocks_asset_var),
		other_paper_asset = !!as.name(lookup_wea$other_paper_asset_var),
		ira = ira_vec,
		net_worth = !!as.name(lookup_wea$net_worth_var)) %>%
	mutate(stocks = pmax(stocks, 0), # negative values are caused by market decline, not
	   indicative of sold stocks
	     retirement_accts_value = other_paper_asset + ira,
	     other_paper_asset = NULL,
	     ira = NULL,
	     risky_share = ifelse(stocks == 0, 0,
	                   stocks / (cash + stocks + retirement_accts_value))
	     )

# --- year-specific vars to be selected from family files --- #

years_fam = setdiff(c(1987:2017), seq(1998, 2016, 2))

fam_vars_year_specific = data.frame(
	year = years_fam,
	race1_var = c('v14612', 'v16086', 'v17483', 'v18814', 'v20114', 'v21420',
		'v23276', 'er3944', 'er6814', 'er9060', 'er11848',
		'er15928', 'er19989', 'er23426', 'er27393', 'er40565',
		'er46543', 'er51904', 'er57659', 'er64810', 'er70882'),
	interview_id_var = c('v13702', 'v14802', 'v16302', 'v17702', 'v19002',
		'v20302', 'v21602', 'er2002', 'er5002', 'er7002',
		'er10002', 'er13002', 'er17002', 'er21002',
		'er25002', 'er36002', 'er42002', 'er47302',
		'er53002', 'er60002', 'er66002'),
	marital_status_var = c('v14120', 'v15136', 'v16637', 'v18055', 'v19355',
		'v20657', 'v22412', 'er2014', 'er5013', 'er7013',
		'er10016', 'er13021', 'er17024', 'er21023',
		'er25023', 'er36023', 'er42023', 'er47323',
		'er53023', 'er60024', 'er66024'),
	marital_status_cng_var = c('v14713', 'v16188', 'v17566', 'v18917',
		'v20217', 'v21523', 'v23337', 'er4159b',
		'er6999b', 'er9250b', 'er12223b', 'er16424',
```

```
                    'er20370', 'er24151', 'er28050', 'er41040',
                    'er46984', 'er52408', 'er58226', 'er65462',
                    'er71541'),

wages_lastyr_var = c('v13898', 'v14913', 'v16413', 'v17829', 'v19129',
                'v20429', 'v21739', 'er4122', 'er6962', 'er9213',
                'er12196', 'er16493', 'er20425', 'er24117',
                'er27913', 'er40903', 'er46811', 'er52219',
                'er58020', 'er65200', 'er71277'),
wages_xtra_job_lastyr_var = c(rep(NA_character_, 1993-1987), 'v21801',
                    'er4138', 'er6978', 'er9229', 'er12212',
                    'er16509', 'er20441',
                    rep(NA_character_, length(seq(2003, 2017, 2)))
                    ),

tot_labor_income_lastyr_var = c('v14671', 'v16145', 'v17534', 'v18878',
                     'v20178', 'v21484', 'v23323',
                     rep(NA_character_, 14) # don't exist for years 1994 and beyond
                     ),
subtot_labor_income_lastyr_var =
      c(rep(NA_character_, 1994 - 1987), # don't exist for years before 1994
        'er4140', 'er6980', 'er9231', 'er12080', 'er16463', 'er20422',
        'er24116', 'er27931', 'er40921', 'er46829', 'er52237',
        'er58038', 'er65216', 'er71293'),
biz_labor_income_lastyr_var =
      c(rep(NA_character_, 1994 - 1987), # available but we're not getting them since we
   already got the total above
        'er4119', 'er6959', 'er9210', 'er12193', 'er16490', 'er20422',
        'er24109', 'er27910', 'er40900', 'er46808', 'er52216',
        'er58017', 'er65197', 'er71274'),


num_of_chld_in_family_var = c('v14117', 'v15133', 'v16634', 'v18052',
                    'v19352', 'v20654', 'v22409', 'er2010',
                    'er5009', 'er7009', 'er10012', 'er13013',
                    'er17016', 'er21020', 'er25020', 'er36020',
                    'er42020', 'er47320', 'er53020', 'er60021',
                    'er66021'),
had_school_expenses_var = c(rep(NA_character_, 1998-1987), 'er13201',
                   'er17212', 'er21848', 'er25804', 'er36822',
                   'er42813', 'er48135', 'er53829', 'er60888',
                   'er66936'),

chld_supprt_paid_var = c('v13922', 'v14937', 'v16437', 'v17853', 'v19153',
                  'v20453', 'v21961', 'er3715', 'er6717', 'er8835',
                  'er11717', 'er14985', 'er19181', 'er22546',
```

```
                         'er26527', 'er37545', 'er43536', 'er48861',
                         'er54604', 'er61715', 'er67768'),
        alimony_paid_var = c('v13923', 'v14938', 'v16438', 'v17854', 'v19154',
                         'v20454', 'v21962', 'er3717', 'er6719', 'er8837',
                         'er11719', 'er14987', 'er19183', 'er22548',
                         'er26529', 'er37547', 'er43538', 'er48863',
                         'er54606', 'er61717', 'er67770'),
        chld_supprt_recd_var = c('v13944', 'v14959', 'v16459', 'v17875',
                         'v19175', 'v20475', 'v22126', 'er3401',
                         'er6402', 'er8519', 'er11413', 'er14679',
                         'er18847', 'er22217', 'er26198', 'er37216',
                         'er43207', 'er48532', 'er54226', 'er61268',
                         'er67320'),
        alimony_recd_var = c('v13917', 'v14932', 'v16432', 'v17848', 'v19148',
                         'v20448', 'v21879', 'er3416', 'er6417', 'er8534',
                         'er11428', 'er14694', 'er18863', 'er22233',
                         'er26214', 'er37232', 'er43223', 'er48548',
                         'er54242', 'er61284', 'er67336'),
        stringsAsFactors = F
)
# names of the variables that serve as keys for merging different sets
keys = c('family_id', 'person_id')



# --- Compound Annual Growth Rates (CAGRs) of SP500 --- #
#
# obtained from this calculator: http://moneychimp.com/features/market_cagr.htm
# including dividends, not adjust for inflation

lookup_sp500_rets = data.frame(
        start_year = c(1987, 1989, 1994, 1999, 2001, 2003, 2005), # assume start at the last day of
           start_year (i.e., first day of year+1)
        end_year = c(1989, 1994, 1999, 2001, 2003, 2005, 2007),   # assume end at the last day of
           end_year
        CAGR_sp500 = c(24.08, 8.69, 28.76, -10.56, 0.03, 7.76, 10.48) / 100) %>%
        mutate(num_of_years = end_year - start_year,
             tot_ret_sp500 = (1+CAGR_sp500) ^ (num_of_years) - 1)

# --- time invariant vars to be selected from individual files --- #

ind_vars_fixed = c(
        # family_id + person_id is unique
        # they are extracted from 1968 individual file and serve as common keys
        #       for all following years
        family_id = 'er30001', person_id = 'er30002',
```

```
    # sampling_unit = 'er31997' ,     # primary sampling unit variable
    # strata = 'er31996' ,            # stratification variable
    gender = 'er32000',
    num_of_live_births = 'er32022')


# --- year-specific vars to be selected from individual files --- #

ind_vars_year_specific = data.frame(
    year = years_fam,
    interview_id = c('er30535', 'er30570', 'er30606', 'er30642', 'er30689',
                     'er30733', 'er30806', 'er33101', 'er33201', 'er33301',
                     'er33401', 'er33501', 'er33601', 'er33701', 'er33801',
                     'er33901', 'er34001', 'er34101', 'er34201', 'er34301',
                     'er34501'),

    # to select current heads, filter
    #     sequence_number == 1 & relation_to_head == 10
    sequence_number = c('er30536', 'er30571', 'er30607', 'er30643', 'er30690',
                        'er30734', 'er30807', 'er33102', 'er33202', 'er33302',
                        'er33402', 'er33502', 'er33602', 'er33702', 'er33802',
                        'er33902', 'er34002', 'er34102', 'er34202', 'er34302',
                        'er34502'),
    relation_to_head = c('er30537', 'er30572', 'er30608', 'er30644', 'er30691',
                         'er30735', 'er30808', 'er33103', 'er33203', 'er33303',
                         'er33403', 'er33503', 'er33603', 'er33703', 'er33803',
                         'er33903', 'er34003', 'er34103', 'er34203', 'er34303',
                         'er34503'),

    # AGE OF INDIVIDUAL
    age = c('er30538', 'er30573', 'er30609', 'er30645', 'er30692', 'er30736',
            'er30809', 'er33104', 'er33204', 'er33304', 'er33404', 'er33504',
            'er33604', 'er33704', 'er33804', 'er33904', 'er34004', 'er34104',
            'er34204', 'er34305', 'er34504'),

    employment = c('er30545', 'er30580', 'er30616', 'er30653', 'er30699',
                   'er30744', 'er30816', 'er33111', 'er33211', 'er33311',
                   'er33411', 'er33512', 'er33612', 'er33712', 'er33813',
                   'er33913', 'er34016', 'er34116', 'er34216', 'er34317',
                   'er34516'),

    highest_education = c('er30549', 'er30584', 'er30620', 'er30657',
                          'er30703', 'er30748', 'er30820', 'er33115',
                          'er33215', 'er33315', 'er33415', 'er33516',
                          'er33616', 'er33716', 'er33817', 'er33917',
```

```
                            'er34020', 'er34119', 'er34230', 'er34318',
                            'er34517'),

        stringsAsFactors = F)

# --- year-specific vars to be selected from wealth files --- #

years_wea = c(1989, 1994, 1999, 2001, 2003, 2005, 2007)

wea_vars_year_specific = data.frame(
        year = years_wea,
        interview_id_var =
                c('s201', 's301', 's401', 's501', 's601', 's701', 's801'),
        cash_asset_var = # assets at checking and savings accts
                c('s205', 's305', 's405', 's505', 's605', 's705', 's805'),
        stocks_asset_var = # assets at non-retirement accts
                c('s211', 's311', 's411', 's511', 's611', 's711', 's811'),
        other_paper_asset_var = # bond funds, life insurance, valuable collections, rights in a trust
            and etc
                c('s215', 's315', 's415', 's515', 's615', 's715', 's815'),
        ira_asset_var = # private annuities or Individual Retirement Accounts (IRAs)
                c(NA, NA, 's419', 's519', 's619', 's719', 's819'),
        net_worth_var = # total asset - total debt - home equity
                c('s216', 's316', 's416', 's516', 's616', 's716', 's816'),
        stringsAsFactors = F
)
crosstab = function(df) {
        function(xvar, yvar, type = "grand_pcts", show_total = TRUE,
                 decimals = 2) {

                # calc cross table
                if (type == "raw_cnts") {
                        tbl = table(df[[xvar]], df[[yvar]])
                } else if (type == "grand_pcts") {
                        tbl = prop.table(table(df[[xvar]], df[[yvar]]))
                } else if (type == "row_pcts") {
                        tbl = prop.table(table(df[[xvar]], df[[yvar]]), 1)
                } else {
                        tbl = prop.table(table(df[[xvar]], df[[yvar]]), 2)
                }

                # change tbl to a data frame
                vec_rowname = row.names(tbl)
                vec_colname = colnames(tbl)
                m = dim(tbl)[1]; n = dim(tbl)[2]
                tbl = data.frame(matrix(tbl, nrow = m, ncol = n))
```

```r
			# show row or column sums
			if (show_total) {
				tbl$Sum = rowSums(tbl)
				tbl = rbind(tbl, colSums(tbl))
				vec_colname = c(vec_colname, "Total")
				vec_rowname = c(vec_rowname, "Total")
			}

			# give row and column names and return
			names(tbl) = vec_colname
			row.names(tbl) = vec_rowname

			# format cell values as % if type is any kind of "pcts"
			if (grepl("pcts", type)) {
				tbl[] = lapply(tbl, function(x)
					formattable::percent(x, decimals))
				if (type == "row_pcts") tbl = tbl[-nrow(tbl),]
				if (type == "col_pcts") tbl = tbl[, -ncol(tbl)]
			}

			tbl
		}
}
filter_responding_heads = function(df) {
		# df: data frame with vars: interview_id, relation_to_head, sequence_number


		df %>% # discard people who didn't respond to interviews
			filter(interview_id != 0) %>%
			# only keep heads of the family
			filter(relation_to_head == 10 & sequence_number == 1) %>%
			select(-relation_to_head, -sequence_number)
}
freqtab = function(df) {
		function(catvar, order = "descend", as_pct = T, decimals = 2) {
			if (!order %in% c("descend", "ascend"))
				stop("Order must be either 'ascend' or 'descend'")

			tbl = dplyr::mutate(dplyr::count(df, !!as.name(catvar)),
						cnt = n, pct = cnt/sum(cnt), n = NULL)

			if (order == "descend")
				tbl = dplyr::arrange(tbl, dplyr::desc(cnt))
			else tbl = dplyr::arrange(tbl, cnt)
```

```
        if (as_pct)
            tbl = dplyr::mutate(
                tbl, pct = formattable::percent(pct, decimals))

        tbl
    }
}

recode_ind_vars = function(dat) {
    # dat: data frame of vars from the individual file
    dat %>% mutate(
        age = ifelse(age %in% c(0, 98, 99, 999), NA_real_, age),
        gender = case_when(gender == 1 ~ 'Male',
                           gender == 2 ~ 'Female',
                           TRUE ~ NA_character_),

        employment_status = case_when(
            employment == 1 ~ "Working now",
            employment == 2 ~ 'Only temporarily laid off, sick leave or maternity leave',
            employment == 3 ~ 'Looking for work, unemployed',
            employment == 4 ~ 'Retired',
            employment == 5 ~ 'Permanently disabled; temporarily disabled',
            employment == 6 ~ 'Keeping house',
            employment == 7 ~ 'Student',
            employment == 8 ~ 'Other; "workfare"; in prison or jail',
            TRUE ~ NA_character_),
        employment_status_agg = case_when(
            employment == 1 ~ "Working",
            employment %in% c(3, 2, 5, 8) ~ 'Not working (not by choice)',
            employment %in% c(4, 6, 7) ~ 'Not working (by choice)',
            TRUE ~ NA_character_),
        employment = NULL,

        education_status = case_when(
            highest_education == 0 ~ 'Completed no grades of school',
            highest_education == 1 ~ 'Completed grade 1',
            highest_education == 2 ~ 'Completed grade 2',
            highest_education == 3 ~ 'Completed grade 3',
            highest_education == 4 ~ 'Completed grade 4',
            highest_education == 5 ~ 'Completed grade 5',
            highest_education == 6 ~ 'Completed grade 6',
            highest_education == 7 ~ 'Completed grade 7',
            highest_education == 8 ~ 'Completed grade 8',
            highest_education == 9 ~ 'Completed grade 9',
            highest_education == 10 ~ 'Completed grade 10',
            highest_education == 11 ~ 'Completed grade 11',
```

```
          highest_education == 12 ~ 'Completed grade 12',
          highest_education == 13 ~ 'Completed 1st year college',
          highest_education == 14 ~ 'Completed 2nd year college',
          highest_education == 15 ~ 'Completed 3rd year college',
          highest_education == 16 ~ 'Completed 4th year college',
          highest_education == 17 ~ 'At least some post-graduate work',
          TRUE ~ NA_character_),
      education_status_agg = case_when(
          highest_education < 12 ~ 'Did not complete high school',
          highest_education == 12 ~ 'High school graduate',
          highest_education > 12 & highest_education < 16 ~ 'Some college',
          highest_education == 16 ~ "Bachelor's degree",
          highest_education == 17 ~ 'Graduate work',
          TRUE ~ NA_character_),
      highest_education = NULL,


      # race = case_when(race == 1 ~ 'White',
      #              race == 2 ~ 'Black',
      #              race == 3 ~ 'American Indian, Aleut, Eskimo',
      #              race == 4 ~ 'Asian, Pacific Islander',
      #              race == 5 ~ 'Mentions Latino origin or descent',
      #              race == 6 ~ 'Mentions color other than black or white',
      #              race == 7 ~ 'Other',
      #              TRUE ~ NA_character_),


      num_of_live_births = ifelse(num_of_live_births %in% 98:99,
                          NA_real_, num_of_live_births)

    )
}
summary_stats = function(x) {
    is_valid = is.finite(x)
    if (sum(is_valid) == 0)
        stop("The input vector contains only NA, NAN, Inf or -Inf.
           Please check.")

    x = x[is_valid]
    funs = c(length, summary, sd, e1071::skewness, e1071::kurtosis)
    setNames(unlist(lapply(funs, function(f) f(x))),
             c("n", "min", "q1", "median", "mean", "q3", "max",
               "sd", "skewness", "kurtosis"))
}
scale_this = function(x) (x - mean(x, na.rm=TRUE)) / sd(x, na.rm=TRUE)
```

```
modes = function(xs, na.rm = T) {
	if (na.rm) xs = xs[!is.na(xs)]
	ux = unique(xs)
	tab = tabulate(match(xs, ux))
	# note: instead of using which.max(), we are using == max()
	#	because it returns all the modes if multiple ones exist
	ux[tab == max(tab)]
}

sigmoid = function(x) {
	x[x > 10] = 10
	exp(x) / (exp(x) + 1)
}
# yr = 1989

lookup_fam = fam_vars_year_specific %>% filter(year == yr)

# --- some vars don't exist for all years, deal with them here --- #

if (is.na(lookup_fam$wages_xtra_job_lastyr_var)) {
	wages_xtra = rep(0, nrow(df_fam))
} else {
	wages_xtra = df_fam[[lookup_fam$wages_xtra_job_lastyr_var]]
}

if (is.na(lookup_fam$had_school_expenses_var)) {
	flag_school_expense = rep(NA_integer_, nrow(df_fam))
} else {
	flag_school_expense = df_fam[[lookup_fam$had_school_expenses_var]]
}

if (is.na(lookup_fam$tot_labor_income_lastyr_var)) {
	subtot_labor_income = df_fam[[lookup_fam$subtot_labor_income_lastyr_var]]
	subtot_labor_income = ifelse(subtot_labor_income == 9999999,
	                     NA_real_, subtot_labor_income)
	biz_labor_income = df_fam[[lookup_fam$biz_labor_income_lastyr_var]]
	biz_labor_income = ifelse(biz_labor_income == 999999,
	                    NA_real_, biz_labor_income)
	tot_labor_income = subtot_labor_income + biz_labor_income

} else {
	tot_labor_income = df_fam[[lookup_fam$tot_labor_income_lastyr_var]]
	tot_labor_income = ifelse(tot_labor_income == 999999, NA_real_,
	                    tot_labor_income)
}
```

```
# --- some ad hoc codes look up --- #

na_codes_csal_paid = case_when(yr < 1993 ~ c(99998, 99999),
                               TRUE ~ c(9999998, 9999999))
na_codes_csal_recd = case_when(yr < 2003 ~ c(99998, 99999),
                               TRUE ~ c(999998, 999999))

race_code_white = 1
race_code_black = 2
race_code_aindian = 3
race_code_asian_pislander = ifelse(yr < 2005, 4, c(4, 5))
race_code_latino = ifelse(yr < 2005, 5, 9999) # 9999 means doesn't exist
race_code_more_colors = ifelse(yr < 2005, 6, 9998) # 9998 means doesn't exist
race_code_other = 7

# get the vars and prep

df_fam = df_fam %>%
    transmute(interview_id = !!as.name(lookup_fam$interview_id_var),
          race = !!as.name(lookup_fam$race1_var),
          marital_status_cng =
              !!as.name(lookup_fam$marital_status_cng_var),
          num_of_chld_in_family =
              !!as.name(lookup_fam$num_of_chld_in_family_var),
          flag_school_expenses = flag_school_expense,

          wages_lastyr = !!as.name(lookup_fam$wages_lastyr_var),
          wages_xtra_lastyr = wages_xtra,
          tot_labor_income_lastyr = tot_labor_income,

          chld_supprt_paid = !!as.name(lookup_fam$chld_supprt_paid_var),
          alimony_paid = !!as.name(lookup_fam$alimony_paid_var),
          chld_supprt_recd = !!as.name(lookup_fam$chld_supprt_recd_var),
          alimony_recd = !!as.name(lookup_fam$alimony_recd_var)
          ) %>%
    mutate(is_remarried = ifelse(marital_status_cng == 5, 'Yes', 'No'),

        race = case_when(race == race_code_white ~ 'White',
                    race == race_code_black ~ 'Black',
                    race == race_code_aindian ~ 'American Indian or Alaska Native',
                    race == race_code_asian_pislander ~ 'Asian, Pacific Islander',
                    race == race_code_latino ~ 'Latino origin or descent',
                    race == race_code_more_colors ~ 'Color besides black or white',
                    race == race_code_other ~ 'Other',
                    TRUE ~ NA_character_),
```

```
        had_school_expenses = case_when(
            flag_school_expenses == 1 ~ 'Yes',
            flag_school_expenses == 5 ~ 'No',
            TRUE ~ NA_character_),

        tot_wages_lastyr = wages_lastyr + wages_xtra_lastyr,

        chld_supprt_paid = ifelse(
            chld_supprt_paid %in% na_codes_csal_paid,
            NA_real_, chld_supprt_paid),
        alimony_paid = ifelse(
            alimony_paid %in% na_codes_csal_paid,
            NA_real_, alimony_paid),

        chld_supprt_recd = ifelse(
            chld_supprt_recd %in% na_codes_csal_recd,
            NA_real_, chld_supprt_recd),
        alimony_recd = ifelse(
            alimony_recd %in% na_codes_csal_recd,
            NA_real_, alimony_recd),

        chld_supprt_net = chld_supprt_recd - chld_supprt_paid,
        alimony_net = alimony_recd - alimony_paid,
        chld_supprt_alimony_tot_net = chld_supprt_net + alimony_net,

        chld_supprt_status = case_when(
            chld_supprt_paid > 0 & chld_supprt_recd > 0 ~ 'both',
            chld_supprt_paid > 0 & chld_supprt_recd == 0 ~ 'paid',
            chld_supprt_paid == 0 & chld_supprt_recd > 0 ~ 'received',
            chld_supprt_paid == 0 & chld_supprt_recd == 0 ~ 'neither',
            TRUE ~ NA_character_),

        alimony_status = case_when(
            alimony_paid > 0 & alimony_recd > 0 ~ 'both',
            alimony_paid > 0 & alimony_recd == 0 ~ 'paid',
            alimony_paid == 0 & alimony_recd > 0 ~ 'received',
            alimony_paid == 0 & alimony_recd == 0 ~ 'neither',
            TRUE ~ NA_character_),

        marital_status_cng = NULL,
        wages_lastyr = NULL,
        wages_xtra_lastyr = NULL,
        flag_school_expenses = NULL

        )
# yr = 1989
```

```
lookup_wea = wea_vars_year_specific %>% filter(year == yr)


if (is.na(lookup_wea$ira_asset_var)) {
	ira_vec = rep(0, nrow(df_wea))
} else {
	ira_vec = df_wea[[lookup_wea$ira_asset_var]]
}
df_wea = df_wea %>%
	transmute(interview_id = !!as.name(lookup_wea$interview_id_var),
		cash = !!as.name(lookup_wea$cash_asset_var),
		stocks = !!as.name(lookup_wea$stocks_asset_var),
		other_paper_asset = !!as.name(lookup_wea$other_paper_asset_var),
		ira = ira_vec,
		net_worth = !!as.name(lookup_wea$net_worth_var)) %>%
	mutate(stocks = pmax(stocks, 0), # negative values are caused by market decline, not
	   indicative of sold stocks
	     retirement_accts_value = other_paper_asset + ira,
	     other_paper_asset = NULL,
	     ira = NULL,
	     risky_share = ifelse(stocks == 0, 0,
	                    stocks / (cash + stocks + retirement_accts_value))
	     )
	df = read_rds(file.path(rds_path, paste0('divorced-', cohort_year, '.rds')))


# --- one-hot encoding since frmpd::frmpd cannot work with char or factor vars --- #

df = df %>% mutate(
	male = case_when(gender == 'Male' ~ 1, TRUE ~ 0), # do NOT use ifelse() since it'll leave
	   NA as NA instead of 0

	gave_0live_birth = case_when(num_of_live_births == 0 ~ 1, TRUE ~ 0),
	gave_1live_birth = case_when(num_of_live_births == 1 ~ 1, TRUE ~ 0),
	gave_2live_births = case_when(num_of_live_births == 2 ~ 1, TRUE ~ 0),
	gave_3live_births = case_when(num_of_live_births == 3 ~ 1, TRUE ~ 0),
	gave_4live_births = case_when(num_of_live_births == 4 ~ 1, TRUE ~ 0),
	gave_5plus_live_births = case_when(num_of_live_births >= 5 ~ 1, TRUE ~ 0),

	risk_tolerance_lvl1 = case_when(risk_tolerance == 1 ~ 1, TRUE ~ 0),
	risk_tolerance_lvl2 = case_when(risk_tolerance == 2 ~ 1, TRUE ~ 0),
	risk_tolerance_lvl3 = case_when(risk_tolerance == 3 ~ 1, TRUE ~ 0),
	risk_tolerance_lvl4 = case_when(risk_tolerance == 4 ~ 1, TRUE ~ 0),
	risk_tolerance_lvl5 = case_when(risk_tolerance == 5 ~ 1, TRUE ~ 0),
	risk_tolerance_lvl6 = case_when(risk_tolerance == 6 ~ 1, TRUE ~ 0),
```

```
    bequest_to_rels_important = case_when(
        importance_bequest_to_rels %in%
            c("Quite important", "Very important") ~ 1,
        TRUE ~ 0),
    bequest_to_relorg_unimportant = case_when(
        importance_bequest_to_relorg %in%
            c("Not at all important", "Not important") ~ 1,
        TRUE ~ 0),
    bequest_to_charity_unimportant = case_when(
        importance_bequest_to_charity %in%
            c("Not at all important", "Not important") ~ 1,
        TRUE ~ 0),

    white = case_when(race == 'White' ~ 1, TRUE ~ 0),
    black = case_when(race == 'Black' ~ 1, TRUE ~ 0),
    remarried = case_when(is_remarried == 'Yes' ~ 1, TRUE ~ 0),

    hs_dropout = case_when(
        education_status_agg == 'Did not complete high school' ~ 1,
        TRUE ~ 0),
    hs_graduate = case_when(
        education_status_agg == 'High school graduate' ~ 1, TRUE ~ 0),
    co_dropout = case_when(
        education_status_agg == 'Some college' ~ 1, TRUE ~ 0),
    co_graduate_or_beyond = case_when(
        education_status_agg %in% c("Bachelor's degree", 'Graduate work') ~ 1,
        TRUE ~ 0),

    working = case_when(employment_status_agg == 'Working' ~ 1, TRUE ~ 0),

    paid_chl_supprt = case_when(chld_supprt_status == 'paid' ~ 1, TRUE ~ 0),
    recd_chl_supprt = case_when(chld_supprt_status == 'received' ~ 1, TRUE ~ 0),
    paid_alimony = case_when(alimony_status == 'paid' ~ 1, TRUE ~ 0),
    recd_alimony = case_when(alimony_status == 'received' ~ 1, TRUE ~ 0),

    had_school_expenses = case_when(had_school_expenses == 'Yes' ~ 1,
                        TRUE ~ 0)
)

# group vars
index_vars = c(keys, 'year')
yvars = c('risky_share', 'savings_rate_cash', 'savings_rate_retirement')
xvars_onehot = c('male', 'white', 'black', 'remarried',
          'working', 'had_school_expenses',

          'gave_0live_birth', 'gave_1live_birth',
```

```
            'gave_2live_births', 'gave_3live_births',
            'gave_4live_births', 'gave_5plus_live_births',

            'risk_tolerance_lvl1', 'risk_tolerance_lvl2',
            'risk_tolerance_lvl3', 'risk_tolerance_lvl4',
            'risk_tolerance_lvl5', 'risk_tolerance_lvl6',

            'bequest_to_rels_important', 'bequest_to_relorg_unimportant',
            'bequest_to_charity_unimportant',

            'hs_dropout', 'hs_graduate',
            'co_dropout', 'co_graduate_or_beyond',

            'paid_chl_supprt', 'recd_chl_supprt'
            # 'paid_alimony', 'recd_alimony' # ignore because nearly all have value 0
            )

xvars_num = c('age', 'num_of_chld_in_family',
          'tot_wages_lastyr', 'tot_labor_income_lastyr',

          'chld_supprt_net', # alternatively, we can use chld_supprt_alimony_tot_net
          # 'chld_supprt_alimony_tot_net'

          # 'chld_supprt_paid', 'chld_supprt_recd', # ignore because we use their sum, the net
        value
          # 'alimony_paid', 'alimony_recd' # ignore because nearly all have value 0

          'net_worth', 'CAGR_sp500')



cat('\nYears when risky share is available:\n')
df %>% filter(!is.na(risky_share)) %>% pull(year) %>% table() %>% print()

cat('\nYears when cash savings rate is available:\n')
df %>% filter(!is.na(savings_rate_cash)) %>% pull(year) %>% table() %>% print()

cat('\nYears when retirement savings rate is available:\n')
df %>% filter(!is.na(savings_rate_retirement)) %>% pull(year) %>% table() %>%
      print()
yvar = 'savings_rate_cash'
yvar_quo = as.name(yvar)

dat = df %>% filter(!is.na(!!yvar_quo)) %>%
      select(yvar, index_vars, xvars_num, xvars_onehot) %>%
      mutate(# some people have cash savings rate as big as 230, meaning
```

```
            # cash saved > total labor income. This can happen because
            # 1. they sold stocks and increased their cash position
            # 2. they funded their cash position using non-labor income such
            #    as inheritance or non-reported income
             #
             # frmpd does not allow yvar value to be 1
             savings_rate_cash = ifelse(savings_rate_cash >= 1, 0.999,
                                        savings_rate_cash)
             )
# hist(dat[[yvar]])
# glimpse(dat)

# check missings: should have no missings
na_pct = sapply(dat, function(col) sum(is.na(col))) / nrow(dat)
stopifnot(length(na_pct[na_pct > 0]) == 0)

# scale numeric data
xvars_scaled = setdiff(xvars_num, "CAGR_sp500") # CAGR_sp500 doesn't vary within the
        same year, so cannot scale. Plus, it's already between 0 and 1.
dat_norm = dat %>% group_by(year) %>%
      mutate_at(xvars_scaled, scale_this) %>%
      ungroup()

# exclude vars from entering the model due to high correlations
drop_xvars = c("tot_labor_income_lastyr", # used to define y
            "tot_wages_lastyr", # part of tot labor income, and hence indirectly defines y
            "chld_supprt_net", # correlated with chld_supprt_net
            "gave_0live_birth", "gave_1live_birth",
            "gave_2live_births", "gave_3live_births",
            "gave_4live_births", "gave_5plus_live_births"
            )

# specify endo- and exdo-genous vars
xvars_endo = c("remarried", "working", "num_of_chld_in_family",
            "had_school_expenses",  "net_worth",
            "risk_tolerance_lvl1", "risk_tolerance_lvl2",
            "risk_tolerance_lvl3", "risk_tolerance_lvl4",
            "risk_tolerance_lvl5", "risk_tolerance_lvl6"
            )
xvars_exdo = setdiff(c(xvars_num, xvars_onehot), c(xvars_endo, drop_xvars))

# make unique individual id
id = as.integer(paste0(dat$family_id, dat$person_id))


# recommended approach: using both endo- and exdo-genous vars
```

```
set.seed(42)
frmpd::frmpd(id, dat$year, y = dat[[yvar]], x = dat_norm[xvars_endo],
            z = dat_norm[xvars_exdo], x.exogenous=FALSE,
            type="GMMww", bootstrap = TRUE, B=100, tdummies= F)


# # --- experiment --- #
#
# # what if we ignore the endogenous vars?
# frmpd::frmpd(id, dat$year, y = dat[[yvar]],
#             x = dat_norm[xvars_exdo], x.exogenous=T,
#             type="GMMww", bootstrap = TRUE, B=100, tdummies= F)
#
# # what if we treat both endo- and exdo-genous vars as exdogenous?
# frmpd::frmpd(id, dat$year, y = dat[[yvar]],
#             x = dat_norm[c(xvars_exdo, xvars_endo)], x.exogenous=T,
#             type="GMMww", bootstrap = TRUE, B=100, tdummies= F)
yvar = 'savings_rate_retirement'
yvar_quo = as.name(yvar)

dat = df %>% filter(!is.na(!!yvar_quo)) %>%
      select(yvar, index_vars, xvars_num, xvars_onehot) %>%
      mutate(# some people have cash savings rate as big as 230, meaning
            # cash saved > total labor income. This can happen because
            # 1. they sold stocks and increased their cash position
            # 2. they funded their cash position using non-labor income such
            #    as inheritance or non-reported income
            #
            # frmpd does not allow yvar value to be 1
            savings_rate_retirement = ifelse(savings_rate_retirement >= 1,
                                  0.999, savings_rate_retirement)
      )
# hist(dat[[yvar]])
# glimpse(dat)

# check missings: should have no missings
na_pct = sapply(dat, function(col) sum(is.na(col))) / nrow(dat)
stopifnot(length(na_pct[na_pct > 0]) == 0)

# scale numeric data
xvars_scaled = setdiff(xvars_num, "CAGR_sp500") # CAGR_sp500 doesn't vary within the
            same year, so cannot scale. Plus, it's already between 0 and 1.
dat_norm = dat %>% group_by(year) %>%
      mutate_at(xvars_scaled, scale_this) %>%
      ungroup()
```

```
# exclude vars from entering the model due to high correlations
drop_xvars = c("tot_labor_income_lastyr", # used to define y
            "tot_wages_lastyr", # part of tot labor income, and hence indirectly defines y
              "chld_supprt_net",# correlated with chld_supprt_net
            "gave_0live_birth", "gave_1live_birth",
            "gave_2live_births", "gave_3live_births",
            "gave_4live_births", "gave_5plus_live_births", "bequest_to_rels_important",
          "bequest_to_relorg_unimportant",
            "bequest_to_charity_unimportant"
            )

# specify endo- and exdo-genous vars
xvars_endo = c("remarried", "working", "num_of_chld_in_family",
            "had_school_expenses","paid_chl_supprt","recd_chl_supprt", "net_worth"

            )
xvars_exdo = setdiff(c(xvars_num, xvars_onehot), c(xvars_endo, drop_xvars))

# make unique individual id
id = as.integer(paste0(dat$family_id, dat$person_id))


# recommended approach: using both endo- and exdo-genous vars
set.seed(42)
frmpd::frmpd(id, dat$year, y = dat[[yvar]], x = dat_norm[xvars_endo],
           z = dat_norm[xvars_exdo], x.exogenous=FALSE,
           type="GMMww", bootstrap = TRUE, B=100, tdummies= T)


# # --- experiment --- #
#
#
# frmpd::frmpd(id, dat$year, y = dat[[yvar]],
#         x = dat_norm[xvars_exdo], x.exogenous=T,
#            type="GMMww", bootstrap = TRUE, B=100, tdummies= F)
#
# # interaction effects?
#frmpd::frmpd(id, dat$year, y = dat[[yvar]],
 #           x = dat_norm[c(xvars_exdo, xvars_endo)], x.exogenous=T,
 #           type="GMMww", bootstrap = TRUE, B=100, tdummies= T)
yvar = 'risky_share'
yvar_quo = as.name(yvar)

dat = df %>% filter(!is.na(!!yvar_quo)) %>%
       select(yvar, index_vars, xvars_num, xvars_onehot) %>%
       mutate(# frmpd does not allow yvar value to be 1
```

```
            risky_share = ifelse(risky_share == 1, 0.999, risky_share))
# hist(dat[[yvar]])
# glimpse(dat)

# check missings: should have no missings
na_pct = sapply(dat, function(col) sum(is.na(col))) / nrow(dat)
stopifnot(length(na_pct[na_pct > 0]) == 0)

# scale numeric data
xvars_scaled = setdiff(xvars_num, "CAGR_sp500") # CAGR_sp500 doesn't vary within the
        same year, so cannot scale. Plus, it's already between 0 and 1.
dat_norm = dat %>% group_by(year) %>%
     mutate_at(xvars_scaled, scale_this) %>%
     ungroup()

# exclude vars from entering the model due to high correlations
drop_xvars = c("tot_labor_income_lastyr", # correlated with tot_wages_lastyr
          # correlated with chld_supprt_net
          "chld_supprt_net","gave_0live_birth", "gave_1live_birth",
          "gave_2live_births", "gave_3live_births",
          "gave_4live_births", "gave_5plus_live_births"
          )

# specify endo- and exdo-genous vars
xvars_endo = c( "paid_chl_supprt", "recd_chl_supprt","remarried", "working",
        "had_school_expenses",
          "num_of_chld_in_family",
          "tot_wages_lastyr",   "net_worth")
xvars_exdo = setdiff(c(xvars_num, xvars_onehot), c(xvars_endo, drop_xvars))


# make unique individual id
id = as.integer(paste0(dat$family_id, dat$person_id))


# recommended approach: using both endo- and exdo-genous vars
set.seed(42)
frmpd::frmpd(id, dat$year, y = dat[[yvar]], x = dat_norm[xvars_endo],
         z = dat_norm[xvars_exdo], x.exogenous=FALSE,
         type="GMMww", bootstrap = TRUE, B=100, tdummies= T)


# # --- experiment --- #
#
# # what if we ignore the endogenous vars?
# frmpd::frmpd(id, dat$year, y = dat[[yvar]],
```

```
#            x = dat_norm[xvars_exdo], x.exogenous=T,
#            type="GMMww", bootstrap = TRUE, B=100, tdummies= T)
#
# # what if we treat both endo- and exdo-genous vars as exdogenous?
# frmpd::frmpd(id, dat$year, y = dat[[yvar]],
#            x = dat_norm[c(xvars_exdo, xvars_endo)], x.exogenous=T,
#            type="GMMww", bootstrap = TRUE, B=100, tdummies= T)


#*********BEGIN DATA ANALYSIS FOR BEQUEST OUTCOME LOGIT
        #MODEL************************


rm(list = ls())

source("R/00-set-up.R")
#source("R/01-download-data.R") # comment out to run, and only need to run once

cohort_year = 2007
source('R/02-read-crossyear-individual-file.R')
source('R/03-prep-data-fixed-vars.R')
source('R/03-prep-data-yearly-vars.R')
source('R/11-bequest-diff-divorced-vs-nondivorced/01-choose-cohort.R')
source('R/11-bequest-diff-divorced-vs-nondivorced/02-derive-grouping-var-from-marital-
        status.R')
source('R/11-bequest-diff-divorced-vs-nondivorced/03-bin-xvars-n-deal-with-ord-xvars.R')
source('R/11-bequest-diff-divorced-vs-nondivorced/03-bin-yvars.R')

source('R/11-bequest-diff-divorced-vs-nondivorced/04-explain-bequest-rels.R')
source('R/11-bequest-diff-divorced-vs-nondivorced/05-explain-bequest-relorg.R')
source('R/11-bequest-diff-divorced-vs-nondivorced/06-explain-bequest-charity.R')

# glimpse(dat)

# check missings in xvars
na_pct = sapply(dat, function(col) sum(is.na(col))) / nrow(dat)
na_pct[na_pct > 0]
# stopifnot(length(na_pct[na_pct > 0]) == 0)

# drop records with NA in race, age,education_status_agg and employment_status_agg
#      since there's tiny amount of them
dat = dat %>% filter(!is.na(race), !is.na(age), !is.na(employment_status_agg),
               !is.na(education_status_agg))

# scale numeric data
xvars_scaled = c('age', "tot_wages_lastyr", "net_worth")
```

```
dat_norm = dat %>% mutate_at(xvars_scaled, scale_this)
# glimpse(dat_norm)

# fit logit model
f = formula(paste(yvar, paste(c(xvar_main, xvars_other), collapse = "+"), sep = '~'))
fit_bequest_rels = glm(f, data = dat_norm, family=binomial)

#+ include = FALSE
knitr::opts_chunk$set(comment = "", tidy = F, echo = F, warning = F,
                      message = F, fig.width = 8, fig.height = 6)
options(scipen = 999)

#' # `r cohort_year`
#'
#' This dataset contains info of the heads of families in `r cohort_year`.
#'

#+ results = 'asis'

cap = 'Importance of leaving estate/inheritance to children/relatives'
broom::tidy(fit_bequest_rels) %>%
      mutate(signif = case_when(`p.value` < 0.01 ~ '***',
                                `p.value` < 0.05 ~ '**',
                                `p.value` < 0.06 ~ '.',
                                TRUE ~ '')) %>%
      knitr::kable(caption = cap, digits = 3) %>%
      print()

cap = 'Importance of leaving estate/inheritance to religious organizations'
broom::tidy(fit_bequest_relorg) %>%
      mutate(signif = case_when(`p.value` < 0.01 ~ '***',
                                `p.value` < 0.05 ~ '**',
                                `p.value` < 0.06 ~ '.',
                                TRUE ~ '')) %>%
      knitr::kable(caption = cap, digits = 3) %>%
      print()

cap = 'Importance of leaving estate/inheritance to charity'
broom::tidy(fit_bequest_charity) %>%
      mutate(signif = case_when(`p.value` < 0.01 ~ '***',
                                `p.value` < 0.05 ~ '**',
                                `p.value` < 0.06 ~ '.',
                                TRUE ~ '')) %>%
      knitr::kable(caption = cap, digits = 3) %>%
      print()
```

```
#average marginal effects
#get from github

if (!require("remotes")) {
	install.packages("remotes")
	library("remotes")
}
install_github("leeper/prediction")
install_github("leeper/margins")

# building vignettes takes a moment, so for a quicker install set:
install_github("leeper/margins", build_vignettes = FALSE)

library("margins")

#fitted model for bequests to relatives
#fit_bequest_rels

marg_relatives <- margins(fit_bequest_rels)

#call marginal effects
summary(marg_relatives)

#fitted model fro bequests for religious organizations
#fit_bequest_relorg

marg_relorg <- margins(fit_bequest_relorg)

#call marginal effeicts

summary(marg_relorg)

#fitted model for bequests for non-religious charities
#fit_bequest_charity

marg_charity <- margins(fit_bequest_charity)

#call marginal effects

summary(marg_charity)
```