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The social meaning of financial wealth: Relational accounting in the context of 401(k) retirement accounts

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Abstract

Behavioral economics has become a dominant set of theories in explaining economic behavior, yet such behavior remains under the limited purview of psychological, cognitive, or neural approaches. This article draws on and extends Viviana Zelizer's social meaning of money framework in conjunction with new work in 'relational accounting' to suggest a sociological counterpoint, focusing in particular on the social and symbolic meaning attached to individual 401(k) retirement accounts. Following a market downturn, neoclassical and behavioral economics predict various types of behavioral responses, in particular loss aversion – where investors seek to increase risk-taking rather than locking in a sure loss (a loss is more painful to bear than an equivalent gain). A sociological theory that understands the shared meaning of retirement saving would predict something different, a behavior I call *durable conservatism*. In this article, I show how this concept better explains observed risk behavior in Americans' 401(k) accounts following the 2002 and 2008 bear markets in stocks, and how that response differed from the behavior documented in non-retirement brokerage accounts.

Keywords

Economic sociology, relational accounting, retirement, financial risk, behavioral economics

Introduction

Behavioral economics is now a dominant academic discipline with a well-known set of theories that have been proposed to explain economic action. Despite its popularity and growing legitimacy alongside neoclassical economics, it remains under the limited purview of psycho-cognitive explanations, analyzing behavior at the level of individual minds in relative isolation. To be sure, Mullainathan and Thaler (2000) define behavioral economics as a "combination of psychology and economics that investigates what happens in markets in which some of the

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agents display human limitations and complications". Richard Thaler went on to win the Nobel Prize in 2017 for his work on "incorporating psychologically realistic assumptions into analyses of economic decision-making".[1] It is no surprise, then, that research associated with the field of behavioral economics has focused on predominantly cognitive factors as the likely source of 'irrational' decision making (see also DellaVigna, 2009; Camerer et al., 2005). This article seeks to confront such a taken-for-granted position by considering the social aspect of economic decisions that cannot be thoroughly explained by psychological factors alone.[2]

Recent work by sociologist Frederick Wherry (2016, 2017) marks out a distinction between the well-known behavioral economics concept of 'mental accounting' (Thaler, 1985) and what he refers to as 'relational accounting'. Mental accounting is the practice whereby people apportion certain pots of money to serve different practical purposes, rather than treating all money as fungible. "Money in one mental account is not a perfect substitute for money in another" (Thaler, 1999: 185). Following a social approach to money (Zelizer, 1989, 1997), relational accounting focuses on the cultural and symbolic value placed on certain transactions that imbue particular funds with special meaning. As Wherry (2017: 59) puts it,

> relational accounting represents the sociological counterpoint to mental accounting in that it uses cultural, moral, and relational processes to develop an interpretive science of choice and decision making … Unlike mental accounting, however, relational accounting locates individual decision making in the moments of the life cycle that are culturally meaningful and collectively enforced and in overarching moral structures.

Thus far, initial support for relational accounting has been found in the context of charitable donations (Bandelj et al., 2017) and with informal lending and borrowing (Wherry, 2017). This article extends the scope of relational accounting as justification for the fact that people are also apt to valorize different forms of household wealth (i.e., different types of financial accounts) based on distinguishable social and symbolic importance, especially if such accounts are earmarked for explicit ritual events or life stages.

In this study, I take as an illustrative case a particular pattern of risk behavior that presents itself in 401(k) accounts held by American retirement savers.[3] The distinction I will make is that the behavioral response to a market shock in a 401(k) retirement account differs in a novel way from that of a general investment account. Leading (behavioral) economic theories do a good enough job explaining the investor response in a general-purpose brokerage setting, but they cannot explain the case of the 401(k) since these theories overlook the specific social meaning attached to this form of financial wealth. Under normal conditions we observe retirement savers as either active investors who recalibrate their portfolio risk each year to some optimal level, or else passive investors who make fixed pension contributions that are invariant to the regular ups and downs of the market (Benartzi and Thaler, 2007; Chetty et al., 2014). An economic crisis, however, works as a convenient device to reveal a unique pattern of financial risk-taking. Due to the significance of retirement as a distinct life stage, it is reasonable to predict that 401(k) savers ought to feel compelled to shift funds out of risky stocks and into safer investments – such as bonds or cash instruments – and leave this new, more conservative strategy in place even as markets recover, lest they gamble away their future; what I call a pattern of *durable conservatism*. On the surface, this might be mistaken for the behavioral economics notion of loss aversion, which has in fact been identified in individual brokerage accounts. However, the correct way to interpret loss aversion is that in response to economic losses, people actually tend to *increase* their risk-taking in hopes of breaking even, since locking in a loss is psychologically uncomfortable – i.e., the pain of a realized loss exceeds the utility from an equivalent gain (Kahneman and

Tversky, 1979). Loss aversion thus tends to magnify losses that eventually can lead to financial ruin. What I am describing for retirement accounts is quite the opposite: when stocks fall, retirement savers have the propensity to lock in losses and protect what is left of their savings, reducing the perceived danger of financial ruin in the future. The primary goal is not to maximize expected return or shy away from losses but to protect and conserve what has been dutifully accumulated. In other words, the social and symbolic trappings that are tied to retirement savings supersede psychological tendencies observed elsewhere. So, while brokerage accounts that exhibit loss aversion can be explained by psychology, retirement accounts that show durable conservatism can best be explained by sociological theory.

My claim may at first seem straightforward: that when markets crash people recoil and decrease their risk exposure for long periods. Yet, this apparently prima facie case, as I will show, challenges several predominant theories of economic action. This article proceeds as follows. In the first section, I describe how expectations of retirement in contemporary society are bound up with individual retirement accounts. In the next section, I briefly sketch out current theories of financial risk-taking from the perspective of neoclassical and behavioral economics, highlighting in particular the findings related to loss aversion. Next, I show empirically that severe bear market years in 2002 and 2008 caused Americans to actively recalibrate their 401(k) investment portfolios, reducing risk exposure where it then remained moderated.[4] The study utilizes these bear market events as quasi-natural experiments using interrupted time series analysis (ITSA) to help make these claims. Finally, I present a theoretical discussion before concluding. The contributions of this article are relevant for social science research and moreover have practical implications for the financial industry, policymakers, and retirement savers themselves

The locus of individual retirement accounts

Saving for retirement is a financial priority for many Americans, a pursuit that ever more relies on ordinary individuals to make their own investment decisions and bear the brunt of market risk (Hacker, 2006; Ghilarducci, 2010).[5] As the practice of saving for retirement shifts from corporate pension guarantees to the sole responsibility of individual workers, the intense emotional and symbolic value placed on the institution of retirement – understood as an aspirational phase of life in which it is socially acceptable to be without work (Weiss, 2005) – is magnified. Robert Weiss' (2005) ethnography of retirees speaks to the romanticism that is associated with this 'Third Age' of the life cycle, as well as the anxiety surrounding the prospect of a disappointing retirement. Collective definitions of what retirement means and what financial security in retirement entails exert a powerful normative pressure not to 'gamble' with one's retirement savings.

As a social institution, retirement involves prevalent beliefs and ideologies that result from an interplay among various interest groups such as management, labor, and the government (Atchley, 1982). Until the American Civil War, retirement was infrequent and employer pensions did not exist. People worked until they could no longer, and the elderly tended to be valued for their wisdom, virtue, and experience (Fischer, 1978). The mid-1800s saw the rapid growth of industrialization, which changed the social logics of retirement. The rising need of employers to cut costs led to obligatory retirement of the oldest (and typically most expensive) workers. Private pensions sprung up as an immediate solution; but while an ideology of publicly-supported retirement arose in Europe (notably in Bismarck's Germany), the American government chose to leave retirement security to employers. Structural changes in

the early 1900s associated with Taylorism rationalized the industrial workforce, where attitudes toward retirement were shaped by the growing belief that older workers were useless (Atchley, 1982). The turn to 'scientific' management led corporations to rebuff their pension obligations, and the poverty rate among the older population in the US rose to over 40% in the 1920s (Fischer, 1978). Only the Great Depression encouraged the creation of social security, which arose out of political pressure to provide economic security to those rendered destitute by forced retirement, age discrimination, and pressure to reduce the size of the labor force (Graebner, 1980); it had little to do with the concept of retirement as a reward for a lifelong career (Atchley, 1982). During World War II, the image of retirement began to move in this direction. With much of the younger labor force enlisted in the Army, older workers were suddenly seen as useful. In 1940, Congress drafted tax advantages for employers who contributed to pension plans, and in 1947, the Taft-Hartley Act established retirement pensions as a legitimate issue for collective bargaining (Graebner, 1980). These policy measures greatly incentivized corporations to offer private pensions and encouraged unions to demand them as a standard benefit. Attitudes among workers were also advancing. In 1951, Ash (1966) surveyed steelworkers and found that most saw retirement only appropriate for the sick or disabled; a decade later the majority believed that it was justified if the worker wanted to retire and could afford it. By the 1970s Americans had learned to want retirement, and the clear majority of workers could rely on their employer to support their standard of living in old age. Retirement became a rite of passage, ritualized through workplace farewell parties and commemorated with gold watches.[6]

Changes in how Americans save for retirement since the 1980s – in particular, the shift from guaranteed pensions to individual retirement accounts – have fashioned a generation of self-responsible retirement savers. Under rules established by the Employee Retirement Income Security Act of 1974 (ERISA) and the Revenue Act of 1978, the 401(k) plan quickly evolved from its original purpose as a Supplemental Executive Retirement Plan – intended as an enhancement to traditional pensions for use by upper management – into the primary retirement savings vehicle utilized by all employees in an organization. The arrival of the 401(k) plan marked an institutional shift in the employer-employee relationship, where companies transferred the burden of investment management and market risk directly on to the individual worker, while at the same time reinforcing one's moral duty to achieve a comfortable retirement in spite of that. The 401(k) became a staple benefit advertised by employers, and by virtue of these accounts stock ownership in the US has grown from a contrivance of the affluent to a phenomenon that now involves the attention of more than half of all households who no longer find themselves mere bystanders to market jolts.[7] Those who would otherwise possess little material exposure to stocks find themselves de rigueur market participants, with their retirement security intrinsically linked to the successes and failures of the market – risk that had been shouldered by employers in the past. In 1979, nearly two-thirds of newly hired private-sector employees enjoyed a guaranteed defined-benefit pension plan for their retirement security; by 2013, that number had fallen to just 3%.[8] Over the same period the number of households with a 401(k) rose to nearly 70%.[9]

Today, retirement is an expected and salient life stage, yet without the assurance of a company pension to fall back on, individuals implicitly have nobody to blame but themselves for accumulating too small of a nest egg. A recent financial services industry survey finds that more than 2 out of 3 Americans in a representative sample said that they believed they had "a moral obligation to manage investments responsibly" (Brodeur, 2015: 8). At the same time, the report concludes that such a moral obligation tends to be focused on one undivided goal: "Americans showed considerable ambivalence about the importance of leaving a financial

legacy for family and dependents. They were more interested in a comfortable retirement". The retirement account itself comes to signify the aspirations for the future – a dénouement of leisure and freedom after work has ceased – and the 401(k) embodies the potential to validate that accomplishment. Saving for retirement thus turns out to be laden with personal as well as social meaning: a share of stock in your 401(k) plan is valorized with emotional and symbolic importance that differs qualitatively from the same share held in another type of account. Moral beliefs about being a responsible retirement saver are fundamentally external to the individual and so structure reactions to financial risk. Wherry (2017: 67) argues that moral considerations vis-à-vis relational accounts more generally "are not only privately and individually held but are also collective and intersubjectively shared".

It is useful here to contrast the retirement account with the designated brokerage account as a locus for stock ownership. While most Americans own stocks through any means, just 4% of households in 2013 owned a brokerage account (Panis and Brien, 2015). This location typically serves the aim of general wealth accumulation as opposed to the singular goal of retirement security, making these accounts far less likely to carry the same shared symbolic value, and accordingly brokerage accounts may be treated in a more instrumentally rational fashion, but nonetheless subject to cognitive errors or individual affective dispositions. It is true that owning either type of account is voluntary, yet there is a strong normative pressure in American society to be a diligent retirement saver; this norm does not carry over to investing in general (Thaler and Benartzi, 2004). Brokerage accounts are also most likely to be owned by financially sophisticated individuals or the wealthy. Indeed, Panis and Brien (2015) show that approximately half of those who do own brokerage accounts occupy the top decile of the income distribution and around three-quarters belong to the top quartile. As I will explain in greater detail in the following section, empirical work on brokerage accounts shows that investors typically fall victim to the biases of behavioral economics, and especially to loss aversion.

Theories of financial risk-taking in mainstream and behavioral economics

Much of the economics literature views risk-taking as a rational calculation, with informed agents weighing risk decisions against their utility function (Arrow, 1965). Consistent with a rational actor model, risk aversion is endowed as a constant for each individual, stable over time. In support of this claim, several survey studies have shown remarkable constancy of risk tolerance for individuals over time (Sahm, 2012; Roszkowski et al., 2005). This reasoning predicts that a downturn in stocks should induce *no* change in risk-taking, and that portfolio composition should be rebalanced regularly to the utility-maximizing level of risk. Allowing for some leniency, some economists have adopted the Arrow-Pratt model that treats risk aversion as a function of wealth (Pratt, 1964; Pratt and Zeckhauser, 1987). Under these assumptions, risk-taking would indeed decrease following a downturn, but would have an equal tendency to increase following market gains.

Observations suggest that far from maximizing rational expectations, individuals are influenced by emotions and cognitive errors, especially when it comes to financial decision making. Foundational work by Kahneman and Tversky (1979) has cataloged dozens of biases to which people are prone, collectively assembled under the umbrella of 'prospect theory'. Loss aversion reveals that people systematically prefer to avoid losses to a much greater extent than to receive an equivalent gain: losing twenty dollars is more agonizing than the delight of receiving the same amount. The so-called disposition effect predicts that because of

loss aversion, investors are hesitant to sell losing stocks and realize their losses (Shefrin and Statman, 1985). Rather than lock in a sure loss, investors choose not to sell during a downturn and will, in fact, be tempted to increase their exposure to risk in the hopes of breaking even. Doubling down at the casino after a run of bad luck is one example of loss aversion in practice. Odean (1998) studied trading records of 10,000 individual brokerage accounts and found evidence that people showed a strong preference for holding on to losers and selling winners. In experimental studies of simulated stock trading, Weber and Camerer (1998) as well as Chui (2001) find further evidence of the so-called disposition effect in the lab. This phenomenon has also been shown to occur in real estate markets (Genesove and Mayer, 2001) and in the context of corporate mergers and acquisitions (Baker et al., 2012), to name just a few. Loss aversion will be expanded upon in the following sub-section, but it is important to identify other potential outcomes grounded in prospect theory in order to rule them out as explaining investment behavior in retirement accounts.

Behavioral economics also identifies the *status quo bias*, whereby investors are reluctant to make changes to portfolios due to the cognitive and emotional effort involved and so leave things as-is (Samuelson and Zeckhauser, 1988). In other words, the status quo bias produces passive investors. In a simulated investment setting, Brown and Kagel (2009) find that test subjects commonly ignore both favorable and unfavorable information and continue to hold on to a stock regardless of its performance. Closely related is *regret aversion*, where investors avoid taking decisive action because they fear that, in hindsight, whatever course they take will prove deficient (Loomes and Sugden, 1982). The fear of regret results in a passive investor paralyzed by imagined regrets, with a pattern of behavior that would mimic the status quo bias.

Finally, there exists a further bias that could produce yet a different result. The *availability heuristic* claims that people assign too much weight to recent events, causing them to overreact one way or the other (Tversky and Kahneman, 1973). For example, Frieder (2003) and Goetzmann et al. (2016) show that stock traders tend to overreact, both positively and negatively, to new information. Here, we would expect to see conservation strategies following shocks followed by aggressive strategies in the wake of bull markets. Behavioral economics thus predicts any of three outcomes: that a shock will tend to increase risk-taking due to loss aversion; induce a passive strategy due to regret aversion or the status quo bias; or fluctuate sharply with the ups and downs of the market due to availability. Table 1 summarizes how these theories predict the risk response to a market shock

Table 1. How exposure to severe losses in stocks ought to influence portfolio risk-taking.

Theory	Predicted ΔRisk-Taking
Rational Actor: Fixed & Stable	Increase, Re-adjust to baseline risk level
Rational Actor: Risk a Function of Wealth	Decrease, then increase with stock gains
Prospect Theory: Loss Aversion	Increase
Prospect Theory: Status Quo Bias	No change (passive)
Prospect Theory: Availability Bias	Decrease, then increase with stock gains
Relational Accounting	Decrease, then remain subdued despite stock gains

Loss aversion: How people behave in their brokerage accounts

Leading theories thus propose several potential outcomes that might describe investor behavior (although none would correspond with durable conservatism). Among these, patterns of loss aversion seem to be most commonplace in the scholarship looking at brokerage account data. As already mentioned, loss aversion manifests as a disposition effect among investors, "a reluctance to realize losses … even when the precepts of standard theory prescribe realization" (Shefrin and Statman, 1985: 777). With the availability of account-level transaction data, the disposition effect has become a widely documented empirical regularity (Frazzini, 2006). Notably, Odean (1998) found strong evidence of this behavior in the trading records of 10,000 individual brokerage accounts even after controlling for the effects of transaction costs, taxes, and portfolio rebalancing. Similar patterns of loss aversion were found to occur among Israeli investors (Shapira and Venezia, 2001), and in Finland drawing on a data set of the daily transactions and shareholdings of virtually all Finnish investors over a three-year period (Grinblat and Keloharju, 2001). Kaustia (2004) also shows that investors in initial public offerings are reluctant to sell their shares if there is an initial drop in price.

Closer analysis suggests that investor sophistication can result in somewhat less vulnerability (Dhar and Zhu, 2006), but professional traders are nevertheless quite susceptible to loss aversion in their own practice. Locke and Mann (2000) analyzed the trading behavior of professional futures traders and found that all members of their sample held on to losers longer than winners. Coval and Shumway (2000) reported similar evidence of loss aversion among professional market-makers at the Chicago Board of Trade, and with regard to mutual funds, Wermers (2003) showed that portfolio managers of underperforming funds, too, appeared reluctant to sell their losing stocks.

It is clear from these studies that investors are likely to exhibit loss aversion in their brokerage accounts as they experience market swings – they hold on to risky assets when they experience a price decline rather than locking in a sure loss. Yet, a systematic market failure like that which accompanied the 2008-09 financial crisis could plausibly produce different results. However, this does not seem to have been the case based on several studies looking specifically at that episode. Dorn and Weber (2013), for example, found that the overall allocation to stocks of individual investors in a representative sample of 40,000 self-directed clients at one of Germany's largest retail banks remained stable between 2007 and 2011, suggesting that people did not rotate out of stocks. Likewise, Hoffman et al. (2013) combined monthly survey data with matching trading records of more than 1,500 individual investors to examine what drove trading and risk-taking behavior during the 2008-09 crisis. They concluded that people did *not* de-risk their investment portfolios by shifting out of risky investments; instead, "individual investors use the depressed asset prices as a chance to enter the stock market" (Hoffman et al., 2013: 72). Furthermore, Liu and Wang's (2014) study of more than 15,000 individual investors in China during the same period showed that people did not withdraw their capital from the equity market during the crisis. Instead, "the net flow patterns were consistent with the disposition effect, *which was even stronger during the crisis* … that behavioral biases such as the disposition effect are *amplified* during a crisis" (Liu and Wang, 2014: 6-7, emphasis added). These studies indicate that loss aversion actually increased in brokerage accounts during the market crash as investors intensified exposure to risky assets.

If bear markets induce a different aggregate pattern of investor behavior in retirement accounts as opposed to the findings referenced above – indeed, if a crisis provokes exactly the opposite of the disposition effect, where people sell their losses and reorient toward more

conservative allocations – it would speak to a qualitatively unique outcome that affirms a symbolic meaning that can only be explained by social forces that permeate 401(k) money but not brokerage accounts.

Data and methods

401(k) accounts and individual investment selection

401(k) data are especially useful for several reasons. First, companies offer the same list of investment options for all their employees to choose between, from entry level to senior managers. This implies that all eligible employees in an organization, regardless of rank or income, are exposed to the same opportunity set of potential investment options in their retirement plans. Second, qualified retirement accounts are structurally illiquid, intended as deferred savings vehicles. Early withdrawals carry a deterrent financial penalty of 10% and are further subject to immediate payment of any deferred tax liability. All contributions made to a 401(k) plan are thus presumed to be long-term savings where consumption using those funds is postponed until retirement, making explicit this location is not only designated as a retirement savings vehicle, but also conforms to institutional restrictions that limit alternative uses.

A third feature is that 401(k) allocations are strictly self-selected by employees without any input or nudging from their employer; people choose their own portfolios. This is accomplished by choosing from among a menu of investment options, by choosing a target-date fund, or by filling out a risk profiling questionnaire administered by a financial advisor. Regardless of how the initial asset allocations are made, 401(k) plan participants are free to change their portfolio weights at any time, at little or no cost. It is important to realize that it is the individual saver that changes their asset allocations and not professional portfolio managers. Savers invest in mutual funds with a stated investment mandate that will not deviate from its strategy based on market conditions. For example, investing in a bond fund will yield a portfolio consisting always of 100% bonds, and although the exact composition of bonds may change, the overall asset class allocation does not. Any changes in asset class distribution are left up to the individual saver

Data and measurement of risk taking

A concern in the financial risk literature is that the bulk of empirical evidence so far comes from experimental or survey sources. It is not convincing that these instruments portray actual risk-taking behavior. Real financial risks are likely to be perceived quite differently from hypothetical ones, and in a much more complex way than in an experimental set-up (Slovic, 1969; Kuhberger et al., 2002). Moreover, many experiments rely on undergraduate volunteers who are unlikely to have practical experience with financial decision making. Lönnqvist et al. (2015: 263) crucially find that commonly used survey and laboratory measures of risk that ask respondents if they would opt for risky bets “show no construct validity, almost no predictive power, and most importantly no robust test-re-test stability”. In this study, I make use of data realistically free from these issues.

Specifically, I draw on aggregate end-of-year 401(k) asset allocations taken from repeated cross-sections published by the Employee Benefit Research Institute (EBRI) in collaboration with the Investment Company Institute (ICI), annually from 1997-2016 (see Holden and VanDerhei et al., 2000-2018).[10] These published results summarize data found in the EBRI/ICI

401(k) database, which consists of many millions of individual 401(k) retirement accounts across tens of thousands of participating employer plans in the United States.[11] Although I did not have direct access to the 401(k) database itself, the aggregated data are nevertheless conducive for my analysis. Market analyses are often undertaken at this level by economists (see e.g. Shleifer, 2000; Fehr and Tyran, 2005), who typically maintain that individual idiosyncrasies in market behavior are cancelled out by aggregation (cf. Yan, 2010).

The data presents 401(k) portfolio weights for each year broken down by asset class. To make the analysis more generalizable, I simplify these to three archetypal asset classes: stocks; bonds; and money market.[12] I make use of large, representative mutual funds as standard benchmarks for historical stock and bond asset class performance over the study period: The Vanguard Total Stock Market Index Fund (VTSMX) for stocks;[13] and the Vanguard Total Bond Index Fund (VBMFX) for bonds. I proxy 3-month US Treasury bills for money market funds.[14] The correlation matrix and annualized standard deviation of returns for these asset classes over the study period are summarized in Table 2.

Using these asset class weights, I construct a quantified measure of portfolio risk. To naïvely consider weights to stocks, bonds, and cash may be a useful heuristic for gauging portfolio riskiness, however, it is not very precise. Modern portfolio theory (MPT) points out that interaction effects between asset classes matter when evaluating the risk of a diversified portfolio (Markowitz, 1952), and combining risky assets does not necessarily dictate that the overall portfolio risk will increase. In other words, adding risky assets to a portfolio is a process of diversification and not summation. Fortunately, it is possible to use MPT to back out risk more correctly, using portfolio standard deviation (σ_p) as a valid proxy for total financial risk (Fama and MacBeth, 1973). The procedure for generating the portfolio standard deviation for a three-asset portfolio is defined by Equation 1:

$$\sigma(p_{a,b,c}) = (w^2{}_a\sigma^2{}_a + w^2{}_b\sigma^2{}_b + w^2{}_c\sigma^2{}_c + 2w_aw_b\sigma_a\sigma_b\rho_{a,b} + 2w_aw_c\sigma_a\sigma_c\rho_{a,c} + 2w_bw_c\sigma_b\sigma_c\rho_{b,c})^{1/2} \quad (1)$$

where σ_p is portfolio standard deviation, σ^2_i is the historical annualized variance of asset class *i* over the study period, w_i is the weight of asset class *i* in the portfolio in year *t*, and $\rho_{i,j}$ is the observed correlation of annualized returns for asset classes i and *j* over the study period. Table 2 indicates asset class performance during the study period in addition to the above calculations for overall 401(k) asset weights found in the data.

Interrupted time series analysis

Interrupted time series analysis (ITSA) is based on a multiple linear regression model where trends in the dependent outcome variable are observed over time. The objective of ITSA is to introduce one or more break points as explanatory variables, allowing the trend to break and change both in intercept and slope in a manner that cannot be explained by random variation. In this study, break points occur at the end of years 2002 and 2008.

Following the dotcom bubble of 2000-2001 and a brief slide post-9/11, the stock market experienced modest down years, but began a steep and steady decline beginning in March 2002, reaching lows not seen since 1997. 2002 ended up being the worst year for the stock market in three decades, with the S&P 500 index recording a 22% annual loss and the Nasdaq composite index down 31.5%. From their March 2000 highs to their October 2002 lows, the Nasdaq declined by nearly 80%, and the S&P 500 by 50%, causing investors to lose more than $9 trillion of market value. In 2008 the market again crashed, with the S&P 500 losing nearly 37% and the Nasdaq 41%, erasing $11 trillion of investor wealth and ushering in

the Great Recession, according to the Financial Crisis Inquiry Commission's 2011 report. Thus 2002 and 2008 represent the two bear market (treatment) years that went into the interrupted time series analysis.

Table 2. Historical annual asset class returns (%), Average 401(k) asset weights (%) and Portfolio risk, 1997-2016.

	Annual Returns			Avg 401(k) Asset Weights			Risk	
Year	Stocks	Bonds	T-Bills	Stocks	Bonds	MoneyMkt	σ_p	$\ln(\sigma_p)$
1997	30.99	9.44	5.05	74.10	15.60	9.40	13.58	2.6086
1998	23.26	8.58	4.73	74.20	15.00	8.40	13.60	2.6101
1999	23.81	-0.76	4.51	76.92	12.88	7.70	14.12	2.6476
2000	-10.57	11.39	5.76	76.46	12.84	7.50	14.04	2.6419
2001	-10.97	8.43	3.67	70.50	18.10	9.70	12.88	2.5557
2002	**-20.96**	8.26	1.66	62.18	24.02	11.10	11.28	2.4230
2003	31.35	3.97	1.03	66.14	22.66	8.30	12.03	2.4874
2004	12.52	4.24	1.23	66.24	22.66	6.60	12.05	2.4891
2005	5.98	2.40	3.01	67.96	23.64	6.00	12.36	2.5145
2006	15.51	4.27	4.68	68.48	21.32	7.40	12.48	2.5241
2007	5.49	6.92	4.64	68.74	21.56	6.90	12.52	2.5273
2008	**-37.04**	5.05	1.59	56.70	27.80	12.10	10.24	2.3263
2009	28.70	5.93	0.14	60.52	26.68	8.50	10.96	2.3943
2010	15.09	6.42	0.13	60.90	26.00	6.50	11.03	2.4001
2011	0.96	7.56	0.03	60.30	27.60	6.70	10.91	2.3900
2012	16.25	4.05	0.05	59.74	27.16	6.60	10.81	2.3805
2013	33.35	-2.26	0.07	63.84	22.96	6.30	11.60	2.4510
2014	12.43	5.76	0.05	65.16	23.24	5.30	11.85	2.4723
2015	0.29	0.30	0.21	65.68	22.22	5.20	11.96	2.4807
2016	12.53	2.50	0.51	66.22	23.38	4.60	12.04	2.4882

When judging the impact of market shocks on American retirement savers, the treated group is measured at the national level. In such situations, it is common that the only data available are reported as aggregates – such is the case with the EBRI/ICI data. With reference to using aggregate-level data with ITSA, Linden (2015: 389) advises, "if multiple observations on an outcome variable of interest in the pre-intervention and post-intervention periods can be obtained, an interrupted time-series analysis offers a quasi-experimental research design with a potentially high degree of internal validity" (see also Shadish, Cook, and Campbell, 2002). This analysis follows Linden to detect and measure the causal effect of bear market years on 401(k) portfolio risk, where the dependent variable in this study is the log-transformation of $\sigma(p_{a,b,c})$. The natural logarithm is used to stabilize regression variances and due to the nature of the data being naturally right-skewed – asset prices are bounded by zero to the downside but have unlimited upside potential, and so follow a log-normal distribution.

ITSA produces least-squares estimates along with Newey-West standard errors according to the generalized form in Equation 2, when the error terms follow a first-order autoregressive (AR[1]) process (Equation 3):

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \varepsilon_t \qquad (2)$$

$$\varepsilon_t = \rho \varepsilon_{t-1} + u_t \qquad (3)$$

where Y_t is the aggregated outcome variable measured at each equally spaced time point t, T_t is the time since the start of the study, X_t is a dummy variable representing pre- or post-intervention, and $X_t T_t$ is an interaction term (Linden and Adams, 2011; Linden, 2015). β_0 is the intercept at time 0 and β_1 represents the baseline linear trend prior to the treatment. β_2 is the

level shift immediately following the treatment event and is compared against the counterfactual: had the prior trend $\beta_0 + \beta_1 T_t$ continued uninterrupted. β_3 represents the change in trend slopes before and after treatment. A statistically significant coefficient in β_2 suggests a causal effect in the pre- and post-intervention level.

On top of this single-group analysis, I introduce simulations as controls to determine if a significant change in β_2 is the result of human agency or due to mechanical processes (see the following sub-section). Equation (2) is thus expanded to allow for a multi-group analysis that includes four additional terms (Linden and Adams, 2011; Linden, 2015):

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t T_t + \beta_4 Z + \beta_5 Z T_t + \beta_6 Z X_t + \beta_7 Z X_t T_t + \varepsilon_t \quad (4)$$

where Z is a dummy variable that labels placement in the treatment group or control (simulation) group. Here, β_4 represents the *difference* in initial level from the control to the treatment group, and β_5 the difference in initial trend. β_6 is the main coefficient of interest, representing the difference in level shift pre- and post-treatment between the simulation and observed groups. A statistically significant β_6 would indicate that the event causes an effect on the observed group that cannot be explained by the counterfactual represented by the simulation. I consider two treatment events over the study period: in 2002 and in 2008, reproducing equations (2) and (4) back-to-back as it were, where the post-treatment trend effectively becomes the succeeding pre-treatment trend line (Linden, 2015).

Simulations to control for mechanical effects

From the initial ITSA results, it is clear that there exist sharp drops in 401(k) portfolio risk at each treatment year. However, it is at this point unclear to what extent human agency is responsible. It is conceivable that these observations are due entirely to a mechanical mechanism, i.e. so-called portfolio effects. A portfolio of stocks and bonds becomes objectively less risky if the value – and corresponding portfolio weight – of stocks declines sharply. If this process alone can explain these results, then the hypothesis that market downturns cause retirement savers to re-orient their risk behavior is far less convincing.

To extricate human agency, I construct two alternative simulations that represent counterfactuals for what we would expect to see if portfolio effects explained everything. The first simulation makes the strong assumption that *all* retirement savers are 100% passive. A passive investor makes no active changes to their portfolio composition at any point in time; they 'set it and forget it'. To construct this, I model a hypothetical portfolio composed of 74.5% stocks, 16% bonds, and 9.5% money market as initial allocations, which corresponds approximately to the initial observed portfolio allocations at the beginning of the study period.[15] The relative weights of each asset class are then left to vary annually in-line with actual historical price returns (see the left-hand column of Table 2). I refer to this as the passive simulation.

The passive simulation is a conservative comparison as it makes the improbable assumption that everybody is completely passive. In fact, we know this is not the case. Some retirement savers are so-called active investors who systematically rebalance their portfolio weights on a regular basis to the initial levels, and industry estimates tell us that typically 20-30% of 401(k) savers do actively rebalance at least once a year.[16] There is also a growing normative message to encourage active rebalancing among retirement savers from investment professionals and academics alike (e.g. Benartzi and Thaler, 2007; Calvet et al., 2009). Moreover, 401(k) assets assigned to balanced funds and to target-date funds will

automatically rebalance to their intended strategic allocations even if a saver is otherwise passive. The EBRI/ICI data show that such allocations account for some 20-30% of total 401(k) assets. It is more realistic, then, that around half of retirement savers are active while the other half remains passive. I therefore create a second counterfactual that averages the passive simulation with a 100% active simulation (where each year portfolios are re-balanced to the initial baseline allocation weights).[17]

Control variables

Control variables are introduced to account for macroeconomic events or phenomena that might reasonably confound the analysis. The control variables include annual changes in: (1) civilian unemployment to account for job losses during economic downturns; (2) nominal GDP to control for economic growth and periods of recession; (3) 10-year treasury yields as a proxy for long-term credit risk, where higher yields signal greater risk; (4) Fed funds target rate which the central bank uses as a tool to spur or reign in economic activity, where lower rates signal greater risk; (5) Case-Shiller National Home Price Index to control for changes in housing wealth; (6) CBOE Volatility Index (VIX) as a measure of broad financial risk; and (7) the personal savings rate to control for non-retirement savings. All data for control variables were obtained from the St. Louis Federal Reserve's FRED tool.

Results

These are enumerated in Table 3 below and presented visually in Figure 1.

Table 3. ITSA estimates of the effect of severe bear stock markets on aggregate 401 (k) (log) portfolio as a proxy for risk aversion, 1997-2016.

	(1) All 401(k) Assets	(2) Passive Simulation	(3) Differences (1-2)	(4) Active & Passive Simulation	(5) Differences (1-4)
Constant	2.539***	2.556***	-0.017	2.576***	-0.037
	(0.042)	(0.060)	(0.007)	(0.029)	(0.032)
Baseline trend	-0.003	-0.002	-0.001	-0.005	-0.002
	(0.009)	(0.011)	(0.010)	(0.015)	(0.007)
Level shift after 2002 bear mkt	-0.161***	-0.111***	-0.050*	-0.062*	-0.099***
	(0.032)	(0.034)	(0.028)	(0.029)	(0.053)
Trend shift after 2002 bear mkt	0.032*	0.042*	-0.010	0.021	0.011
	(0.015)	(0.018)	(0.007)	(0.008)	(0.013)
Trend 2002-08	0.0317**	0.0374***	-0.006	0.021	0.007
	(0.009)	(0.013)	(0.004)	(0.007)	(0.009)
Level shift after 2008 bear mkt	-0.226***	-0.181***	-0.045***	-0.097*	-0.129***
	(0.050)	(0.031)	(0.016)	(0.053)	(0.042)
Trend shift after 2008 bear mkt	-0.008	-0.004	-0.004	-0.007	-0.001
	(0.063)	(0.007)	(0.005)	(0.016)	(0.011)
Trend 2008-16	0.018***	0.028***	-0.010***	0.014*	0.004
	(0.005)	(0.003)	(0.002)	(0.009)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes
F	99.75	30.51	179.93	40.22	160.62

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

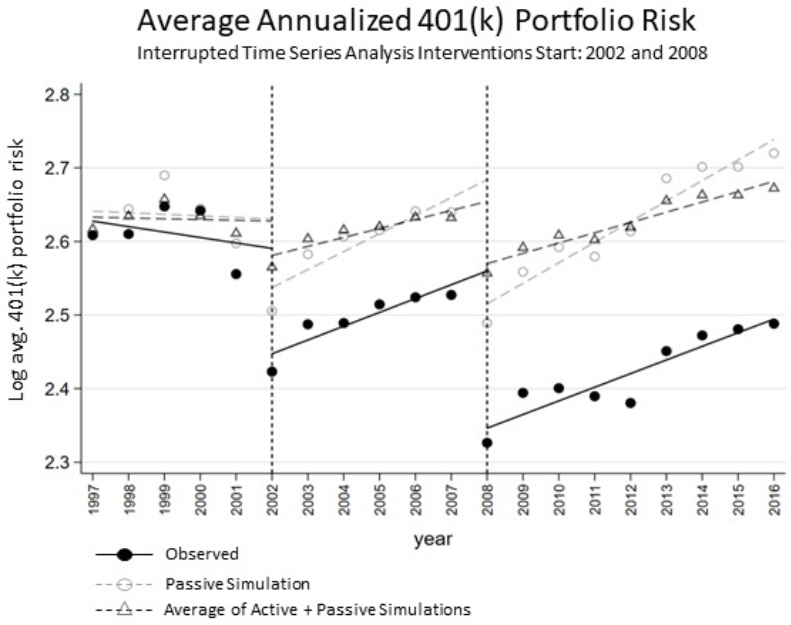


Figure 1. Graphical output from interrupted time series analysis of 401(k) portfolio risk.

Graphical output from the multi-group ITSA of average annualized 401(k) retirement portfolio risk over time compared to the passive simulation (open circles) and the average of the passive and active simulations (open triangles), with treatment events occurring at years 2002 and 2008. Observed data are plotted in black.

Column (1) in the regression table shows that the 2002 bear market caused a 16.1% decrease in the average level of 401(k) portfolio risk, and that 2008 caused a further 22.6% reduction (relative to the reference trend from 2002-08), both highly statistically significant drops. The slopes of the new trends after 2002 and 2008 are also statistically significant, implying that linear interpolation seems an appropriate fit.

Despite statistical significance in coefficients of interest, we are yet to rule out mechanical changes to portfolio composition. I compare these initial results first with the passive simulation: Column (2) shows that starting from effectively the same baseline level and trend, a fully passive investor would have seen her portfolio risk drop by 11.1% and 18.1% in 2002 and 2008, respectively. Column (3) estimates the differences-in-differences between the observed and passive simulation results with corresponding standard errors. The net effect from the 2002 bear market is large (5.0 percentage points), and significant at better than the 10% level. The difference attributed to the 2008 drop is statistically significant at the 1% level: 4.5 percentage points of the 22.6% change – or one-fifth of the total effect – cannot be attributed to passive investing and is therefore the result of investor behavior to create less risky allocations. The gradual rise in risk-taking post-2002 is parallel to that of the passive simulation, indicating that these non-crisis years are more or less described by passive investing, without any marked increases in risk behavior. However, the post-2008 trend does mark an increasingly risk-averse trajectory, with each year growing 1% more conservative relative to the passive simulation.

Columns (4) and (5) repeat the same exercise but use what I argue is the more realistic counterfactual, the average of the passive and active simulations. In this case, the changes in portfolio risk produced by both the 2002 and 2008 market events are highly statistically significant, with human agency explaining roughly two-thirds of each drop. Trend shifts and post-shock trend slopes are indistinguishable from the counterfactual after both 2002 and

2008, showing that the effects of a severe bear market are plainly unidirectional (there are no sharp increases in risk-taking when the stock market rises comparably) and long-lasting (the new trend lines stay well below the simulation with slopes parallel to it). In fact, what this set of results suggests is that shocks encourage people to re-allocate their 401(k) portfolios to more conservative holdings, and then they return to business as usual. The non-disjoint, gradual upward risk slopes during non-treatment years are not statistically different from the simulation, again suggesting that post-treatment up-trends are merely described by the mechanical response of stocks recovering in value over time.[18]

In bear market years (i.e., 2002 and 2008) the decline in portfolio risk exceeds that of the simulations, ruling out mechanical effects. If it is not mechanical effects, then it must be the retirement savers themselves who alter their own mix of stocks, bonds, and cash. It is not plausible that another actor would be making these decisions – it would not be portfolio managers since they are required to follow the stated strategy of the mutual fund they supervise; and it would not be the financial advisors (if there were access to one), who in fact implore investors not to panic sell during a crisis, but to stay the course and take advantage of the opportunity to buy stocks when they are low. Although portfolio risk does recover gradually after a shock, this rise is attributable to mechanical effects corresponding to a rising stock market and not to a change in behavior geared toward more aggressive portfolios – an asymmetry where market downturns produce a striking effect, but equivalent positive years do not elicit the converse. This is confirmed by the fact that post-shock trends share similar slopes with the simulations.

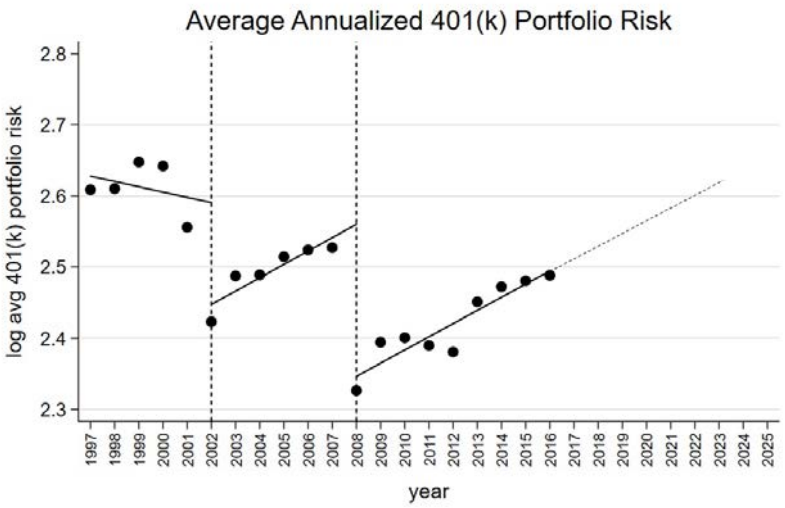


Figure 2. 401(k) Retirement portfolio risk trajectory.

This figure extrapolates the trendline estimates from 2008-2016 onward. Based on the observed 2008 risk level and trajectory, it would take until approximately the year 2022 for 401(k) retirement portfolio risk to return to its pre-2002 levels, barring any intervening contingencies. This figure further illustrates that risk-taking attenuates markedly after the 2002 and 2008 bear markets. However, many positive years do also occur in the non-treatment years (see Table 2). Despite many more positive years than negative years, even when some of these positive years are quite substantial, risk-taking remains subdued.

Shifting out of stocks following a severe bear market reinforces the steadiness of 401(k) plans, but this can also lead to underinvestment in stocks for retirement savers. In finance, the antithesis of risk is return, and so by shunting portfolio risk, expected return is also

diminished. The upshot is that many retirement savers might find that their 401(k) accounts have not generated sufficient returns to maintain their standard of living at retirement, leaving them with a difficult choice: compromise consumption habits or else work longer into old age. Ultimately, the social meaning of retirement funds could unfortunately serve to exacerbate the retirement readiness crisis and create more danger than it hoped to avoid, with the youngest of savers (who have the longest time horizon) most vulnerable. Extrapolating the 2008 level and trajectory of aggregate portfolio risk past the end of the study period, it would take until the year 2023 to return to pre-2002 levels, barring any intervening contingencies.

Limitations in the data and its analysis

Some limitations of the empirical study above are worth mentioning. First, the aggregate-level data employed, although appropriate for this analysis, precludes any further investigation using individual-level data. Such granularity could paint a much richer picture and bring out potential differences in behavior based on ascribed characteristics such as race or gender. Because the interrupted time series analysis here evaluates differences between observed and counterfactual controls, the aggregates used would not be subject to an ecological inference problem that could presumably arise in correlational inference. Put differently, any ecological fallacy that would exist in the observed aggregate data would reproduce itself in the simulations, and thus cancel each other out. The data is segmented broadly by income group and age decile; however, carrying out similar analyses as above on these sub-groups yielded no significant results.

A potential concern could be that many retirement savers simply cashed out their 401(k) plans early in times of great losses, despite penalties due, which may reasonably occur with a greater frequency among those who experience financial pain in other areas of their lives during these periods, such as those experiencing falling home prices or increasing credit card debts. If retirement savers on the lower end of the socio-economic distribution are most affected by multiple financial harms, and if that demographic is also the most naturally risk averse, their absence could bias the results. However, this is unlikely: changes to both mean and median end-of-year 401(k) account balances before and after treatment years correspond to the average losses experienced by stocks at those times (Holden et al., 2013: 11). This tells us that there were not widespread withdrawals from 401(k)s in 2002 and 2008, just a reallocation of existing funds. Moreover, controlling for changes in housing wealth, unemployment, and the savings rate did not alter the results in a meaningful way.

Discussion and conclusion

The utilitarian approach to money, that all dollars are interchangeable with one another, is an idea that has only been challenged in earnest since Viviana Zelizer's program to uncover the social meaning of money. Rather than being fungible, Zelizer (1989: 343) argues that people "assign different meanings and designate separate uses for particular kinds of monies", suggesting "not all dollars are equal". The meanings we ascribe to different monies depend on the context from which they are obtained and from whom they are received (i.e., how different money is 'earmarked'). Writing some time ago, she also commented that "[M]oney remains confined primarily to the economists' intellectual domain; its noneconomic aspects have not been systematically explored" (Zelizer, 1989: 343). Zelizer's agenda has since gone on to produce a wealth of empirical and theoretical contributions that have increased our understanding of money as a sociological object. This article extends that program to an

adjacent object of study whose noneconomic aspects remain yet to be explored – what I am calling *loci* of financial wealth – and evaluates the specific relationship with financial risk associated with these locations by moving away from a purely economic or cognitive viewpoint.

By locus, I mean to address the type or context of a financial product as it relates to a household's overall portfolio of wealth. Rather than asking about money, I challenge the dominant assumption that *wealth* is fungible; not all accounts are equal. The semantic contrast between money and wealth is of increasing importance as financialization encroaches upon households through a plethora of offerings, from mortgages and home equity loans (Aalbers, 2008) to mutual funds, trading accounts, student debt, car loans, and various forms of retirement products (Fligstein and Goldstein, 2015). Wealth is not merely money in and of itself, but is segregated into these various products and investments. Indeed, Davis (2009: 193) argues that households are adapting to a 'portfolio society' where "investment becomes the dominant metaphor to understand the individual's place in society". More recently, Aalbers (2017: 2) describes a financialization of the household itself, where "financial motives, rationales, and measures become increasingly dominant, both in the way individuals and households are being evaluated and approached, and in how they come to make decisions in life". It is thus appropriate to begin exploring the social meaning of household wealth, invested in financial loci that serve various symbolic goals.

A particular financial locus (account) has meaning related to its specific history, corresponding to the institutions and other social structures that support and interact with it. For instance, an individual retirement account like a 401(k) plan will be bound up with the institution of retirement, which is itself enmeshed with values attached to work, family, and the life course. A child's college savings account will similarly be tied to expectations of educational attainment, parental responsibility, and consequent employment. An inter-vivos trust will involve intergenerational transfers of wealth and establishing a legacy. Dependent to all these are the past interactions – political, social, and economic – that have shaped the worldview of what retirement, college, and legacy mean in contemporary society. Each of these accounts, moreover, is referential to some culturally salient and socially recognized milestone in a person's life that engages shared systems of meaning.

Because of this, the meaning of a retirement account will be subject to the social meaning of retirement itself. The brief history presented earlier in the article underscores the fact that expectations of a conspicuous period of retirement in the life cycle is a fairly recent development, and one that is socially constructed and re-constructed. Even more recent is the common expectation that individuals are meant to save for their own future, make their own allocation decisions, and shoulder all the investment risk that their chosen portfolio will bear. The 401(k) renders financial what has become a ritualized transition from work to retirement, a rite of passage that is accompanied by some degree of economic uncertainty. According to Weiss (2005: 2), you are retired only if others see you as such. So, while retirement is decidedly a personal affair, it is also a socially affirmed one – and so too are the funds appropriated for that purpose.

In recent years, new research exploring the concept of relational accounting has emerged that extends Zelizer's original project beyond money (Wherry, 2016, 2017; Bandelj et al., 2017). Rather than earmarking monies based on their source and intended use, financial accounts that are earmarked for collectively endorsed life stages or ceremonial purposes come to embody shared social and symbolic importance. The meaning of retirement savings makes this a guarded locus of financial wealth, revealed by the fact that market shocks cause 401(k) plan participants to actively engage in a strategy of conservation – the disposition to realize losses and subsequently reduce risk exposure for a prolonged period of time. This

constitutes a unique pattern of behavior that does not conform to prevailing theories from economics or behavioral economics; indeed, the observed pattern of risk behavior is more closely situated within a relational accounting or social meaning of money framework. Relational accounts are not simply designated for certain life events but moreover come to crystalize those very milestones in definite forms of financial wealth. Such a conclusion not only provides a rival explanation to behavioral economics in terms of what monies are used for which purposes, but additionally in terms of *how* different forms of wealth are treated with respect to risk. We should therefore expect people to interact with these accounts in ways that deviate from purely economic predictions – not only with respect to one's reticence to withdraw monies from them, but also in how risk decisions are made within the boundaries of the account itself, even as the money is kept in its place. Put differently, relational accounting may be able to reveal a social-symbolic dimension of certain types of financial behavior that would be invisible to both mainstream and behavioral economics.

We know from prior studies that durable conservatism does not present itself in the case of general investment funds. We also know from an abundance of empirical evidence that investors demonstrate loss aversion (in the form of the disposition effect), which actually increases in intensity during a market crisis. But what we see here is quite the opposite – rather than maintaining or increasing exposure to stocks, retirement savers lock in losses and decrease their stock allocation weights. Retirement wealth is not treated with loss aversion but with *loss prevention*. Interestingly, Benartzi and Thaler (2007) seem to stumble across this same behavior in their now classic study of various retirement account heuristics, but they do not go on to pursue the finding in any depth. In fact, their data describes exactly what I find for the 2002 bear market, and that which will repeat for retirement savers in 2008.[19]

Strategies of durable conservatism correspond with contemporary dispositions toward retirement, and so retirement savers may believe they are acting in a morally responsible fashion. However, a looming unintended consequence is the potential for underinvestment in stocks. As long-term portfolios, both one's ability and willingness to bear risk should reflect a high degree of tolerance in order to generate sufficient returns and avoid a financial shortfall later in life. Paradoxically, adhering to social forces rather than psychological errors may here create a discrepancy between the objective chances of retirement security and the subjective aspirations of 401(k) savers. This suggests an interesting irony, where cultural meanings may actually undermine their own fulfillment.

The fact that sociological theory can produce a compelling alternative – or at least a persuasive complement – to the dominant force of behavioral economics, which is firmly grounded in cognitive psychology, opens doors to exciting new lines of empirical research and theory development. Most obvious is to continue the emergent work in relational accounting in juxtaposition to mental accounting, as well as further examining the symbolic meanings attached to various other types of earmarked financial accounts. As suggested previously, a child's college savings account, a trust account meant to endow a charity, a permanent life insurance policy with a spousal beneficiary, or an account set aside for the down payment on a first home are all examples of relational accounts yet to be explored. Various types of household debts as well, which are enumerated as negative balances earmarked in specific accounts, are also likely to be subject to relational accounting. While economic logics would predict repayment of different debts by order of highest interest rate to lowest, social logics may prioritize repayment of student loans or home mortgages – both of which correspond to symbolic and culturally important milestones – despite carrying objectively lower rates than, say, general purpose credit cards. Empirical work could reveal such a moral ordering of debts.

Still, several other directions can be followed that draw on the (non-economics) social sciences to explain how economic actors behave in reality: to illuminate patterns unexplainable by cognitive factors alone; or to provide rival explanations for phenomena already explained psychologically. For instance, Bourdieu's conception of habitus might be operationalized as a way of explaining variations in phenomena such as loss aversion or time inconsistency bias based upon one's composition of capitals relative to their position in a particular field. This may help explain why Bernheim et al. (2015: 3), among several others, find that the poor are much more likely to be present-biased and seek instant gratification – or as they put it, that "poverty perpetuates itself by undermining the ability to exercise self-control". We can no longer simply take for granted that "[t]he preference for immediate gratification captured in these studies appears to have identifiable neural underpinnings" (DellaVigna, 2009: 318). At the very least the underpinnings are often socio-cognitive.

Another potential point of interest could be to merge sociological and cultural approaches to the risk literature that elaborates the collective response to manmade and natural disasters, and then map these onto financial crises and deep economic downturns. For instance, the social amplification of risk framework (SARF), following Kasperson et al. (1988), could provide a useful way of re-interpreting how people experience and respond to market crashes, hyperinflation, or the displacement of populations due to failures in the credit market by framing these shared economic calamities as disasters in their own right. And of course, returning to the classic themes of new economic sociology, we could link social networks analysis and theories of social capital to the so-called emotional or affective biases (as opposed to what have been identified as cognitive errors) observed in behavioral finance. Each of these potential strands would certainly transcend behavioral economics and make for a more inter- or even post-disciplinary approach to explaining the way people actually behave in financial and economic situations.

Notes

1. <https://www.nobelprize.org/nobel_prizes/economic-sciences/laureates/2017/press.html/>.
2. To be clear, I am not arguing that cognitive or psycho-emotional factors play no part in 'irrational' patterns of economic action; instead, I maintain that top-down influences from culture and society also contribute to the way economic actors actually behave. Nor am I arguing against the importance of the 'embeddedness' approach in economic sociology, where one's social network ties can be crucial in explaining objectively sub-optimal financial decisions (Granovetter, 1985; Uzzi, 1999). Rather, I develop Zelizer's (1989) social meaning of money principle as a rival explanation to behavioral economics in cases where the social overrides the psychological.
3. While the 401(k) account is specific to the American context, defined-contribution individual retirement accounts are becoming increasingly the norm in many parts of the world, and so the symbolic value of these retirement accounts is indeed a global concern.
4. A bear market is typically defined as an annual decline in price of 20% or more.
5. 'Saving' is a bit of a misnomer since retirement assets are primarily invested in risky assets. For consistency, however, I stick with the commonly used savings terminology.
6. The tradition of giving gold watches for retirement supposedly originated in the 1940's with PepsiCo; the concept was "you gave us your time, now we are giving you ours".
7. <http://www.gallup.com/poll/182816/little-change-percentage-americans-invested-market.aspx/>.
8. US Dept. of Labor 1979-1998, Employee Benefit Research Institute (EBRI) 1999-2013.

9. <https://www.federalreserve.gov/econresdata/2015-economic-well-being-of-us-households-in-2014-retirement.htm/>.
10. Repeated cross-sections are likely to capture changes to the distribution of wealth in the population over the study period.
11. For 2016, the EBRI/ICI database included 27.1 million individual 401(k) plan participants at 110,794 employer plans, totaling $2 trillion in assets.
12. From available asset classes in the EBRI/ICI 401(k) data, I exclude those 401(k) plans that include any allocations to company stock and/or guaranteed investment contracts (GICs). Company stock is too idiosyncratic and cannot simply be lumped together with broadly diversified stocks. I add 60% of balanced fund assets to stocks and 40% to bonds. A balanced fund is a mutual fund strategy generally consisting of 60% stocks and 40% bonds. Target-date funds are combined with balanced funds in the data prior to 2007, so I continue to combine target-date funds with balanced funds from 2007-16 to maintain consistency across the study period.
13. The Vanguard Total Stock Market Index is designed to provide investors with exposure to the entire US equity market, including small-, mid-, and large-cap, growth and value stocks.
14. I use the terms 'cash' and 'money market' interchangeably. Money market funds invest primarily in risk-free short-term government securities, which can be represented by 3-month US Treasuries.
15. The simulation portfolio allocations are slightly different from observed since observed allocations may not add up to 100%. The initial $\ln(\sigma_p) = 2.654$ for both the observed and simulation.
16. <https://www.psca.org/401-k-plan-research/>..
17. The active simulation by itself is thus represented as a horizontal line corresponding to the portfolio risk of the baseline allocation.
18. A question arises regarding the initial asset allocations for the simulations: What would happen if we began the study a year or two before or after? The passive simulation, since it reflects only changes in asset prices would see no difference, as it is agnostic to starting point so long as the simulation's initial allocation matches the observed. The active simulation, however, would shift up or down depending on the starting observed portfolio risk, where starting with a lower initial risk level would increase the standard errors of the level shifts in column (5). A sensitivity analysis shows that statistical significance for the year 2002 at $p < 0.10$ is lost when the initial risk target for the active simulation is $\ln(\sigma_p) = 2.52$, a risk level that is surpassed in all years prior to 2002. So long as the study begins before that year, all findings are consistent. If the study were to start after 2002, the 2008 results would still be significant compared to the passive simulation, and since that is the more conservative counterfactual, those results too would remain consistent.
19. Benartzi and Thaler (2007) had unique access to Vanguard 401(k) plan allocation data covering the period 1992-2002. In their words, "participants were already allocating 58 percent of their [retirement] assets to equities in 1992, and that percentage rose to 74 percent in 2000. In the next two years, however, the allocation to equities fell back to 54 percent. The market timing of … participants in their exposure to equities was exactly wrong. *They bought high and sold low*" (Benartzi and Thaler, 2007: 92, emphasis added).

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