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WHAT DRIVES INVESTORS TO CHASE RETURNS?

by Jonathan Huntley*, Valentina Michelangeli§, and Felix Reichling*

Abstract

We use data on one-participant retirement savings plans to identify a behavioral bias in savings decisions. Investors who earn top-decile returns increase contributions to their accounts more than other investors. Accounting for the characteristics of the investors and of their retirement savings accounts within a multivariate regression analysis, we first show that such 'return chasing' behavior is robust to controls for financial illiteracy, macroeconomic conditions, learning, transaction costs, housing prices, and informational frictions. We then use a structural two-asset model with tax-deferred and taxable assets to show that a permanent increase in expected returns produces investment responses for younger or liquidity-constrained investors that are consistent with our data. Our results provide evidence that younger investors' recent portfolio experiences have highly persistent effects on their expectations.

JEL Classification: D14, G40.
Keywords: household finance, retirement saving, life-cycle.
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Contents

* Penn Wharton Budget Model, The Wharton School, University of Pennsylvania; § Bank of Italy, Economic Research and International Relations.

1 Introduction[1]

Do investors' past experiences influence their investment decisions and expectations of returns in a way that causes them to diverge from rational behavior? Many papers present evidence that experiences do affect investment decisions in the form of "returns chasing," where investors follow price increases with additional investment.[2] This bias is referred to as "chasing trends" and has been used to explain the technology stock bubble of the late 1990s and early 2000s (Greenwood and Nagel, 2009). Numerous empirical studies document returns-chasing in mutual fund choices (Choi, Laibson and Madrian, 2010*b*). Some argue that "trend chasing" is tied to behavioral biases (Bailey, Kumar and Ng, 2011). Choi et al. (2009) observe a positive correlation between returns and contributions among participants in large-employer 401(k) plans and conclude that returns chasing "indicate[s] that savings decisions are affected by random accidents of personal financial history that should not matter to a rational agent."Similarly, Bender et al. (2020) survey higher-wealth investors, of whom 24 percent report that personal experiences in the stock market are important for determining the equity share in their portfolios.[3]

In our work, we define returns chasing as the correlation between high returns in a financial account and additional investment in the same account, which we observe in Solo 401(k) retirement accounts.[4] Following similar work by Choi et al. (2009), we contribute to the existing literature that seeks to identify the micro-foundations of returns chasing by exploring a dataset

[1]This paper has not been subject to review by the Penn Wharton Budget Model. The analysis and conclusions expressed herein are those of the authors and should not be interpreted as those of the Bank of Italy or the Penn Wharton Budget Model.We would like to thank Alex Michaedelis, Efraim Berkovich, Francesco Columba, Paolo Finaldi Russo, Daniel Kirsner, Jason Levine, Silvia Magri, Damien Moore, Sabrina Pastorelli, Richard Prisinzano, Tarun Ramadorai, John Sabelhaus, Martino Tasso, the participants and discussants at several seminars, and two referees for helpful discussions. We thanks Claire Sleigh and Shiqi Zheng for their excellent research assistance. We also gratefully acknowledge the organizers of the CFP Board Academic Research Colloquium for Financial Planning and Related Disciplines for awarding the 2019 TD Ameritrade Institutional Best Paper Award for Behavioral Finance for an earlier version of this paper, which was titled "Chasing Investment Returns: Do Learning, Literacy, and Experience Really Matter?".

[2]Many studies investigate circumstances in which returns chasing may be a rational behavior. In some model frameworks, it is optimal for traders to follow the crowd anticipating that uninformed investors will subsequently enter the market (De Long et al., 1990).

[3]Similarly, personal economic experiences can shape macroeconomic expectations (Das, Kuhnen and Nagel, 2020).

[4]In the literature cited above and many other studies, the term returns chasing is also used to describe similar behaviors in portfolio allocation decisions.

on retirement savings and by building a structural model. Using our data and model, we narrow down a set of common explanations to one: an increase in expectations regarding future returns, restricted to younger investors, explains the key empirical regularities we observe in our data.

We start with a list of causes that are commonly hypothesized to explain the returns chasing we observe and that is documented by Choi et al. (2009): 1) financial literacy (Van Rooij, Lusardi and Alessie, 2011); 2) information acquisition costs (Sims, 2003; Reis, 2006; Abel, Eberly and Panageas, 2013; and Moscarini, 2004); 3) transaction costs (Kaplan and Violante, 2014); 4) reinforcement learning (Choi et al., 2009; Kaustia and Knupfer, 2008; and Anagol, Balasubramaniam and Ramadorai, 2019); 5) experience (Greenwood and Nagel, 2009); and 6) changes in expectations (Vissing-Jorgensen, 2003; Greenwood and Shleifer, 2014; Briggs et al., 2015; and Gennaioli, Ma and Shleifer, 2016).[5]

We conclude that, among those hypotheses, changes in expectations limited to young investors are the best fit for the returns chasing behavior we observe in a publicly available administrative dataset that contains information on 18 years worth of one-participant retirement plans (also known as Solo 401(k) plans). This conclusion supports two important findings from recent works on expectations formation: Experiences in early life have a much larger impact than experiences later in life, and the impact of such experiences is permanent or highly persistent (Malmendier and Nagel, 2011; Malmendier, Tate and Yan, 2011; Cronqvist and Siegel, 2015; and Malmendier and Nagel, 2015). We make six observations to support our conclusion by documenting the stylized facts about these business owners, using regression analysis, and simulating investor behavior in a buffer-stock type model (Carroll, 1997) with tax-deferred and taxable assets (Gomes, Michaelides and Polkovnichenko, 2009; and Huntley and Michelangeli, 2014).

First, we observe that the investors in our sample self-identify as financially literate or employ financially sophisticated advisors because of the start-up costs associated with Solo 401(k) accounts.[6] Moreover, they tend to be more educated than the typical large-company 401(k) in-

[5] There are many mechanisms through which expectations could be influenced. In addition to the mechanisms discussed in the papers cited here, others cite overconfidence as a source of changes in expectations (Bailey, Kumar and Ng, 2011) or the role of social interaction in disseminating information and changing expectations (Ambuehl et al., 2018 and Duflo and Saez, 2003).

[6] Establishing such accounts requires a significant degree of financial sophistication or the assistance of a

vestor. Although households with less education are more likely to make errors than better educated households (Campbell, 2006), our highly educated investors—a huge fraction of whom are doctors, lawyers, engineers, and other professionals with substantial educational requirements—exhibit the same behavioral biases documented by Choi et al. (2009). This suggests that financial literacy and education are not the proximate cause of returns chasing, a conclusion that fits with previous research on the relationship between investment decisions and financial literacy (Choi, Laibson and Madrian, 2010*a*; Choi, Laibson and Madrian, 2010*b*; and Lusardi and Mitchell, 2014).

Second, we observe that our agents actively manage their accounts by changing their contributions each year. Less than 20 percent of contributors keep their contributions fixed at nominal levels from one year to the next.[7] Investors are free to make these changes because Solo 401(k) plans offer a wide variety of investment options with extremely low transaction costs. Although there may be pecuniary and non-pecuniary transaction costs for making changes to large-company 401(k) elections, these are not common to Solo 401(k) plans. Thus, this activity likely reflects the plans' low transaction costs, as well as the requirement that investors or their advisors monitor their account at least once per year to file their tax returns and make contribution decisions. Since investors are required to pay informational and transaction costs each year, and we continue to observe returns chasing, we conclude that information and transaction costs do not contribute to this behavioral bias.

Third, we find that returns chasing is concentrated among investors who realize top decile returns.[8] Indeed, investors in the top decile of annual returns typically contribute roughly 1.5 cents for each additional dollar of investment income, or almost three times as much as those receiving average returns. This result is similar to that derived from experimental data (Kuhnen,

financial planning professional. For example, an E*TRADE individual 401(k) plan application is 20 pages long: `https://content.etrade.com/etrade/estation/pdf/Qualified_Retirement_Plan_App.pdf`

[7]Unlike large company plans, there is no easy way to elect contributions as a proportion of income. Solo 401(k) participants typically wait until the end of the year or tax-filing to elect a contribution denominated in nominal dollars, which can be a function of cash-flow, earnings, expected income, liquidity needs, and other factors.

[8]We selected deciles because this was the level of disaggregation at which we could most clearly observe returns chasing in the empirical distribution. Moreover, other studies (Barber, Odean and Zheng, 2005) document returns chasing in financial flows into high performing mutual funds also break down their samples into deciles for analysis.

2015). The fact that returns chasing behavior is concentrated asymmetrically among investors earning top-decile returns suggests that reinforcement learning (Kaustia and Knupfer, 2008), which more heavily weights personal experience, does not explain all of investors' decisions in the sample of Solo 401(k) investors.

Fourth, among those top-decile investors "chasing returns," we observe a permanent (or highly persistent) level shift in investors' lifetime contribution profiles. When investors receive top-decile returns, they increase their contributions for that and subsequent periods, a behavior similar to the empirically observed long-term effects of personal experiences (Malmendier and Nagel, 2011).

Fifth, the propensity to chase returns decreases with wealth and account age, which are highly correlated with each other, which is a result consistent with other empirical studies (Choi et al., 2009).

Sixth, in a structural, life-cycle, two-asset model with tax-deferred and taxable assets based on those of Huntley and Michelangeli (2014) and Gomes, Michaelides and Polkovnichenko (2009), only a permanent change in expectations (not a transitory one) can generate responses that match key observations from our sample. The results of our simulations indicate that a permanent change in expectations can generate investment behavior for younger and liquidity-constrained investors that is similar to that observed in the data—that is, a long-lived or permanent shift in the level of tax-deferred contributions. However, temporary changes in expectations fall short of explaining behavior for every subgroup of agents. A short-term increase in expected returns leads to a drop in contributions in subsequent periods, as individuals revert to a contribution profile similar to that of agents who did not experience exceptionally high returns.

In our model, permanent expectations generate responses similar to those we observe in the data for agents who are more than a decade from retirement. Agents nearing retirement face comparatively little lifetime idiosyncratic labor income risk and thus have less of a need to save in their liquid account. When these agents expect a higher, permanent change to returns, they do two things. First, they increase their contributions in a manner similar to younger agents. But second, they also move a large fraction of their liquid assets into illiquid, tax-deferred accounts. This behavior generates a large increase in tax-deferred contributions as they reallocate their savings, followed by a large decrease in tax-deferred contributions once they are done reallocating their savings portfolio across taxable and tax-deferred accounts. Those older individuals still permanently increase their tax-deferred contributions, but that increase is dwarfed by the effect from asset reallocation, which we do not observe in the data.

The results from our simulation are aligned with the conclusions from a number of recent papers that provide empirical evidence that personal experience may result in permanent or highly persistent changes in expectations, but that this effect is limited to younger or less experienced investors. Malmendier and Nagel (2011) show how personal experiences have life-long effects on investment patterns and risk taking, especially for young investors. Malmendier, Tate and Yan (2011) show how early life experiences are correlated with CEOs' investment decisions much later in life.[9] Malmendier and Nagel (2015) find that "young individuals update their expectations more strongly than older individuals since recent experiences account for a greater share of their accumulated lifetime history." And Cronqvist and Siegel (2015) demonstrate that "Parenting contributes to the variation in savings rates among younger individuals in our sample, but its effect has decayed significantly for middle-aged and older individuals." Finally, Giuliano and Spilimbergo (2013) show that recessions have lifetime effects on political outlooks.

The remainder of the paper is structured as follows. In section II, we describe the data sources and provide graphical evidence for investors' changes in contributions. In section III, we present the results of the regression analysis. In section IV, we introduce our model, and we evaluate the simulation presented in section V. We offer conclusions and direction for future work in section VI.

2 Data

2.1 Administrative Data: Form 5500

This section summarizes the main features of the Solo 401(k) defined contribution plans that form our sample; a more detailed treatment of the plans and their differences from the typical

[9] Similarly, Kuhnen and Miu (2017) document many instances when early-life experiences can affect decisions among people with lower socioeconomic status.

large-employer 401(k) is provided in Appendix 6.

The Employee Retirement Income Security Act of 1974 (ERISA) requires that retirement plan sponsors—in this case, the individual filers and owners of the Solo 401(k) account—file Form 5500 or one of its derivatives for a wide variety of retirement benefits.[10] Starting from these forms, we construct a dataset on single-employee businesses that sponsor their own defined contribution plans. Each year from 1999 to 2017 contains some 15,000 to 20,000 records of these Solo 401(k) accounts. We link individuals' records across years using their employer identification numbers (EIN) and the plan number, in the event that the filer maintains more than one Solo 401(k) account. Although a number of filers enter and drop out of the sample—depending on whether or not their assets meet the filing threshold or they roll their assets into or out of other retirement plans—we are able track many filers over several years.

For single-participant plans, the business owner or plan sponsor picks a plan administrator (often him or herself) and a custodian (typically a bank or brokerage that holds the plan's assets). Most major brokerages provide custodial services and offer a suite of options covering potential plan features such as loan availability, investment options, hardship withdrawal availability, plan fees, and more. Plan sponsors can establish accounts with features important to them using any of the major brokerages.

2.2 Filer Characteristics

Compared to investors in typical large-company 401(k) plans, investors in Solo 401(k) plans:

- are considerably more financially sophisticated or are more likely to directly employ a financial advisor;
- are typically highly educated individuals, as shown in shown in Table 1;

[10]The large majority of Form 5500 and 5500-SF filings are for businesses with multiple employees, ranging from local businesses to large multinational conglomerates. Regardless, any business that sponsors a retirement plan under ERISA is subject to the reporting requirement. For the defined contribution plans in our sample, filers with Solo 401(k) accounts exceeding an aggregate value of $250,000 from 2007 on and $100,000 before 2007 are required to file. Many filers in our sample do not meet the filing threshold. These filers may have external accounts that count toward the filing requirement; they may submit forms provided by organizations that service the plans and are delivered nearly complete; or they may submit filings to minimize exposure to audits.

- can select plan custodians to access low or no transaction costs;
- generally have higher contribution limits;[11]
- have access to a wide range of investment options;[12]
- pay any possible observation costs at least once per year, as they are required to file their income tax returns and make contribution decisions.

Overall, 5500 filers have the option to contribute more than can be paid into traditional large-employer 401(k) plans. They are generally allowed to make up to three types of contributions to their Solo 401(k) accounts: a base amount (up to $18,000 in 2017); an employer contribution of up to 20 percent of pre-contribution compensation, the sum of which cannot exceed the inflation-indexed amount (up to $54,000 in 2017 before any applicable catch-up contribution); and catch-up contributions for older filers ($6,000 in 2017).

Most plan sponsors make large contributions at the end of the year, or even in the subsequent fiscal year, to optimize their cash flow and tax efficiency.[13]

Moreover, 5500 filers have the flexibility to choose from a larger choice set. Modal large-employer 401(k) plan participants may be constrained by administrative processes as well as time and pecuniary transaction costs, which may discourage them from updating savings decisions when faced with income or wealth shocks. In contrast, 5500 filers and their advisors are already familiar with these processes, which should make them no less likely to respond to wealth and income shocks than modal large-employer plan participants.

[11] Contribution limits for individual 401(k) plans were $55,000 in 2017 (or $61,000 for people age 50 and older), considerably more than regular 401(k) participants are allowed to contribute ($18,000 plus employer's match or contribution in 2017, $24,000 plus an employer's match or contribution for people 50 years of age and older). For more details, see Internal Revenue Service Publication 560 at `https://www.irs.gov/pub/irs-pdf/p560.pdf`. Large-employer plans have the option of setting the same high level of employer contribution limits, but rarely do.

[12] Personal retirement accounts can contain a huge variety of assets; however, there are several restrictions, mostly intended to arrest self-dealing behavior. See `https://www.irs.gov/retirement-plans/plan-participant-employee/retirement-topics-prohibited-transactions` for some examples of disallowed investments.

[13] An informal survey of financial planning professionals attending the 2019 Certified Financial Planner Board Academic Colloquium suggests that most Solo 401(k) account holders time their contributions with preparation of their income and 5500 tax returns, which occur in the subsequent calendar year.

Taken together, these requirements make Form 5500 and 5500-SF filers qualitatively different investors from studied participating in large-employer 401(k) participants (Madrian and Shea, 2001; Agnew, Balduzzi and Sunden, 2003; Choi, Laibson and Madrian, 2004; and Choi et al., 2009) or from more representative samples of households (Calvet, Campbell and Sodini, 2009).

Like most studies of retirement accounts, we are unable to observe filers' entire portfolios. And, unlike many of the investors contributing to large-employer 401(k) plans, investors in our sample may have external, liquid assets on which they can draw when necessary.[14] Nonetheless, the investors in our sample are likely to have higher personal income and, as a result, high marginal ordinary income tax rates, which makes these tax-deferred accounts particularly attractive.[15]

To focus on financial instruments that are (almost certainly) filers' primary vehicles for employer-based tax-deferred retirement savings, we restrict the dataset to active accounts, defined as those for which the filer made a contribution in the current year or makes a contribution in a future year. Many accounts in our sample may be inactive—they may still meet statutory filing thresholds even though the business has been dissolved or suspended, or the account has been superseded by an alternate tax-deferred instrument. When analyzing the empirical distribution of the changes in contributions, we exclude the observations censored by statutory maximums. We do include these observations in the regression analysis and specify a censored regression to account for contribution limits.

We present descriptive account data in Table 2. The Form 5500 filers in our data have, on average, more savings in these accounts than the typical U.S. household. The median household actively contributing to an account in 2013 had a balance of \$109,000, with an average balance of \$450,000 (see Table 2). By contrast, the median balance in 2013, as computed by Vanguard and reported by the Center for Retirement Research (CRR) at Boston College, was \$31,396; the value for older individuals aged 55–64 was about \$76,000.[16] Over the sample period, median and

[14] Most households that hold tax-deferred assets also hold some taxable assets as well. For example, in the 2001 Survey of Consumer Finances, Huntley and Michelangeli (2014) find that about 65 percent of households have tax-deferred assets, and of those, 86 percent have both tax-deferred and taxable assets.

[15] Phaseouts for exemptions, deductions, and credits may make the effective marginal tax rate on labor income even higher than the statutory rates for each income bracket for high-income filers.

[16] The Vanguard/CRR report is available at http://crr.bc.edu/wp-content/uploads/2017/10/$\mathrm{IB}_1 7 - 18.pdf$

mean values of the accounts for holders who have taken a distribution are typically considerably larger than the mean and median of accounts whose holders have made a contribution.

2.3 Other Data: House Prices, Industry, and Employment

The data from Form 5500 and Form 5500-SF can be matched with indicators from other sources to control for the effects of changes in real estate prices and in local economic conditions.[17] Kuchler and Zafar (2019) find that changes in local house prices affect investors' perceptions of other macroeconomic variables. Therefore, we pair the sponsor's business zip code with data on house prices from Zillow and include it in our analysis.[18]

Forms 5500 and 5500-SF do not contain data on labor income. However, the plan sponsor provides a six-digit NAICS industry code for the business, which, combined with the zip code, allows us to use to pair each observation with industry- and county-specific information from County Business Patterns (CBP).[19] The CBP dataset provides employment and payroll statistics at both the countywide and industry-specific level and uses the same NAICS codes reported in Form 5500 filings. We match employment statistics' two- and four-digit NAICS classifications.[20]

2.4 Descriptive Evidence of Changes in Contributions

To document how investors use their Solo 401(k) accounts, we start by showing (in Table 3) changes in account contributions from one year to another for filers with active accounts whose

The authors note that the Survey of Consumer Finances shows increasing values for 401(k) balances for older participants, but still well below the median of our filers.

[17]Unlike employees of larger business, self-employed business owners may be able to sell their businesses. Therefore, to the extent that local economic conditions affect the value of the business, they may have a significant effect on the plan sponsors' savings decisions.

[18]Zillow maintains a dataset of median house prices for single family homes by zip code, which is available back to the beginning of our Form 5500 dataset for the majority of the zip codes in our sample. Zillow data is available at `https://www.zillow.com/research/data/`.

[19]CBP data is available at `https://www.census.gov/programs-surveys/cbp/data/datasets.html`.

[20]The 2017 NAICS manual describing the classification system is available at `https://www.census.gov/eos/www/naics/2017NAICS/2017_NAICS_Manual.pdf`. We match the NAICS level across the Form 5500 filings and the CBP at the least granular (one digit) to most granular (six digit) classification. We find, however, that percent change in the indicators at the five- and six-digit NAICS levels is exceptionally noisy, especially for small industries and in small counties. Therefore, our analysis is based on four- and two- digit industry categories.

contributions were not constrained by statutory limits.[21]

In our sample, plan sponsors make frequent changes to their annual contributions, and some of those changes are quite substantial. One reason for this behavior is that, unlike participants in large-employer 401(k) plans, these investors may not be able to compute income at short enough intervals to serve as a metric on which to base regular contributions. Over most years, even if the median change in contributions is zero, around 80 percent of filers make a change to their annual contributions. Of those modifying their contributions, approximately half make fairly modest changes, in a range of $2,000 around the median. The remaining investors make much larger changes to their contributions: Typically just over a quarter of filers make changes in excess of $5,000 in a given year.

There is some evidence of time-varying effects on moments of account contributions, similar to the effects observed by Guiso, Sapienza and Zingales 2018. The distribution is shifted toward negative changes during the 2008 and 2009 recession compared to 2007 and 2010, the years that bookend the recession. The 25th percentile in 2008 is more than $1,000 lower than in 2007 and 2010. The 75th percentile in 2008 is about $800 lower than 2007, and $900 lower than in 2011. In years outside the recessions, the percentiles appear remarkably alike: For example, the percentiles in 2013 are quite similar to the percentiles in 2005.

All of this activity points to accounts that are actively managed, which raises the likelihood that these accounts will reflect marginal changes to investors' savings. The accounts in this sample are rarely put on autopilot, as is typical for large-employer 401(k) participants (Madrian and Shea, 2001)). This leads to a much greater degree of overall variation (shown in Table 3) than is observed in studies of traditional 401(k) participants (Choi et al., 2009 and Madrian and Shea, 2001).

We present a visualization of the empirical distribution of dollar changes in contributions in active accounts in Figure 1. Specifically, the bars show the middle 50 percent (middle two

[21] Filers who report inactive accounts—defined as accounts that are specified as closed on the Form 5500 or inferred as closed from a lack of subsequent contributions in any future filings—may have closed the business, retired, or may be making contributions to other accounts. In all of these cases, the lack of contributions may not reflect the filers' savings decisions. Of the approximately 150,000 observations of changes in contributions, about 135,000 were unconstrained by the annual maximum contribution limit ($54,000 in 2017, plus potential catch-up contribution) in both the current and previous years.

quartiles) of filers sorted by decile of returns. We compute each account's annual return by taking 401(k) income, which is directly reported in dollars on Form 5500, and dividing it by the beginning-of-year balance. For all subsequent empirical analysis, we discard two additional types of observations: investors who rolled over external funds into the account and investors whose beginning-of-year account value was zero. In the former case, we do not know the date on which the rollover occurred, and since some of the rollovers are quite large, our computed return will likely be quite inaccurate. In the latter case, investors likely established the account during the year, which presents similar challenges.[22]

If all contributions were made on December 31, the basis will equal the beginning-of-year balance in the account. If the contributions were made significantly in advance of the end of the calendar year, computed returns will incorporate income from these mid-year contributions. Although contributions almost always come at the very end of the year, or in the subsequent calendar year before Form 5500 is filed, it is possible that large and increasing contributions made early in the year could select some investors into higher deciles.[23] For robustness, we try a regression analysis that adjusts the basis on which 401(k) returns are calculated using a fraction of the plan year contributions. Although the estimates change slightly, the qualitative results remain the same.

The number above each bar is the number of observations in the decile; the bar thus represents the range of the middle half of those observations.[24] The left bar (about -\$800 to \$2,200) represents the middle half of the range of changes for investors who earned returns in the lowest decile of the sample in each year. The next bar (about -\$1,000 to \$2,200) is the middle half of changes to contributions for investors who realized returns in the second decile in that year. Most

[22]Accounts must be established by the end of the calendar year, and may be seeded with a contribution in advance of actual contribution deadlines.

[23]Based on informal conversations with professionals and practitioners at the Certified Financial Planners 2019 Academic Research Colloquium, nearly all contributions come at the end of the year or in the subsequent year. According to literature from the New Direction Trust Company and other sources, the employee contribution is due on December 31st; however, employer profit-sharing contributions to Solo 401(k) accounts are due no later than the time the tax return is due.

[24]We compute the thresholds for the deciles of returns from all investors filing a return for that year. To compute the change in contributions, we also need to observe the same plan in the previous year. As a consequence, there is some variation in the number of observations used to construct the empirical distribution by decile of returns.

bars span a range of about $3,000, which indicates that about half of the filers make changes in a $3,000 range located asymmetrically around zero.[25]

The filers in the top decile of returns for each year show changes to their contributions that are qualitatively and quantitatively different from those of investors who earned lower returns. Specifically, we find that the 75th percentile is associated with contributions higher by about $1,000 or slightly more compared to the 75th percentile of the nine decile of returns; the bottom 25th percentile exceeds by about $800 the average of the rest of the deciles of returns. This represents a substantial shift in behavior for investors earning exceptional returns and suggests that a fraction of the population earning returns in the top decile may be chasing returns.

To evaluate whether returns chasing depends on macroeconomic conditions, we present investors' behavior in three years representative of different financial market conditions—2001, 2007, and 2017—in Figure 2. In spite of the greater variance in the range of these smaller samples' middle 50 percent, these three years illustrate that investors in the top decile appear to contribute more than their contemporaries regardless of actual returns in a specific year.

In 2017, the S&P 500 increased by a healthy 19.4 percent, and investors who realized returns in the top decile increased their contributions substantially more than investors in any other decile, as shown in the top panel. By contrast, 2007 generated much more modest returns in equities markets. In this year the S&P 500 had a return of about three percent. Nonetheless, the middle panel illustrates that investors in the top decile continue to show the same behavior, with the 75th percentile contributing nearly $2,000 more than investors in the other nine deciles. In 2001, when the S&P 500 lost about 13 percent of its value, investors needed to earn only six percent to get to the top decile of returns. As shown in the bottom panel, investors at the 75th percentile in the top decile still increase their contributions by about $600–$700 more than their peers in each of the other nine deciles of returns. In all three of these cases, investors earning top-decile returns appear to be chasing returns. This indicates that the relationship between top returns and contributions is common to all types of aggregate conditions in equities markets.

We evaluate changes in contributions against returns by account age. The results are similar

[25] Although not shown, there is typically a significant mass of about 15 percent of the population exactly at zero, consistent with what was reported in Table 3.

to the changes in contributions evaluated by changes in account size, probably because the two variables are highly correlated, especially in retirement accounts. A 5500 filer is not required to divulge the plan sponsor's age; however, the sponsor does provide the date on which the account was established, which is highly correlated with both the age of the account holder and the account holder's investing experience.

Figure 3 has three panels with sub-samples sorted by account age. The ranges for the account age are selected so that each sub-sample represents approximately one-third of the entire population of filers. The upper panel shows accounts that have existed for four or fewer years; the middle panel contains accounts open between five and 12 years; and the bottom panel contains accounts open for more than 12 years. All panels indicate that investors earning top returns choose to make some additional contributions in tax-deferred accounts. In the top panel, we show a $1,500 higher 75th percentile contribution for the top decile of returns relative to the ninth decile. Similarly, in the middle panel, investors in the top decile of returns make contributions higher by about $1,000 than those receiving returns in the lower deciles. In the bottom panel, the account holders (who are among the most experienced investors in the sample) also appear to chase returns, but to a lesser degree than their younger counterparts. The 75th percentile of contributions for investors with returns in the top decile is higher than it is for investors in most of the middle deciles. Nonetheless, the distribution of contribution increases is similar among the top and bottom deciles.

In Figure 4, we take a deeper look at the effects of prior top decile returns on the distribution of leading and lagging contributions. The dashed lines define the middle two quartiles for the entire distribution. Each bar shows the change in contributions for investors who earned returns in the top decile at different time horizons. For example, the first bar shows the change in contributions for investors who earned returns in the top decile two years after this contribution, and the far right bar shows the middle two quartiles of changes in contributions for investors who earned returns in the top decile four years earlier than the contribution. From the top panel of this figure, which includes all Form 5500 filers, we can identify two clear features of the dataset. First, on average, investors increase their contributions in the plan year during which they make returns in the top decile. The 75th percentile is about $1,300 higher for those two periods than it is for any other periods represented in this graph. The 25th percentile is also a few hundred dollars higher than the threshold for the bottom quartile for any of the other periods represented in this graph. Second, some fraction of the investors earning high returns appear to permanently shift the level at which they make those contributions. Indeed, the figure shows a strong contemporaneous correlation between high returns and changes in contribution, but there is no offsetting decline that would indicate that these investors return to their previous level of savings in subsequent periods.

In the bottom two panels, we show the same results conditioned on account age. In the bottom left panel, we show the middle two quartiles of changes to contributions for accounts that have been open for fewer than 10 years. In this case, the effect is quite strong; the 75th percentile in the year of the high return is about $1,700 higher than it is in any other year, and the 25th percentile is slightly higher than the preceding and subsequent years. As for the upper panel, this suggests that some investors significantly increase their contributions, and maintain their contributions at this higher level. By contrast, in the bottom right panel, we show the middle two quartiles of changes to contributions for accounts that have been open for a decade or longer. In this case, the 75th percentile of changes in contributions in the same plan year as top-decile returns are higher than the adjoining years by about $1,000, but still only about $500 higher than the entire sample's 75th percentile, denoted by the horizontal dashed line. These two bottom panels show that the relationship between top-decile returns and changes with investing experience, reflecting the empirical distribution seen in Figure 3.

In the next section, we attempt to quantify the effects of high returns by estimating a censored regression model. After that, we develop our two-asset, life-cycle model with taxable and tax-deferred assets to evaluate conditions under which changes in expectations can be reconciled with these qualitative and quantitative observations.[26]

[26]Additional analysis of the empirical distribution of changes to contributions conditional on account size is available in Appendix 6.

3 Regression Analysis

We use the preceding graphs to motivate our regression analyses, which we use to quantify the relationship between returns and contributions. As before, the observations are drawn from active accounts, defined as those into which the sponsor makes contributions contemporaneously or in the future. Contemporaneous or future activity is a good indicator that the account is accessible for additional contributions (as opposed to inaccessible due to changing jobs, closing the business, or retiring). Overall, the results from our regressions mirror the trends and observations shown in the figures.

Our specification accounts for the possibility that filers' contributions may be censored—that is, equal to the maximum employee plus employer contributions allowed by law.[27] We consider several specifications and include a set of controls, such as employment changes at the two- and four-digit NAICS level, both at the county and the national level, and employment changes for the entire county over all industries.[28]

We estimate the following system:

[27] There is a maximum employee deferred compensation component to the contribution and maximum employer profit sharing component to the savings. In 2015, the deferred compensation component is $18,000. In 2015, the "profit sharing" component is 20 percent of pre-contribution income, up to $35,000. For an individual over the age of 50, there is an additional employee "catch-up" contribution allowed. In 2015, the maximum allowable catch-up contribution was $6,000. If the filer is at the deferred compensation and profit sharing maximum for his or her contribution—equal to $53,000 in 2015, for example—we assume that the observation is censored. If the filer is above that threshold, but below the threshold plus the catch-up contribution ($59,000 in 2015), we assume that the observation is uncensored. If the filer claims contributions equal to the deferred compensation, profit sharing, and catch-up combined—$59,000 in 2015—we assume that the filer is censored. If the filer is above all three, we assume that the filer either made an error or followed the contribution with a recharacterization, either of which necessitates discarding the observation. The actual limit to contributing to the account may be lower than the $53,000 in 2015; however, the majority of contributions below that limit are small enough that the contribution limits based on income almost certainly do not apply. Moreover, as shown in Table 1, the vast majority of businesses in the sample employ high-income professionals.

[28] We run a number of specifications using countywide and industry-specific tax return data from the Statistics of Income (SOI) and and found nearly identical results. We use changes in aggregate wages and salaries to measure the economic growth at a county level, and aggregate wages from the business SOI data at the national level with industries matched at the most granular NAICS classification available. The regression results using variables drawn from the SOI for businesses and households are sometimes statistically significant but rarely economically significant. Lastly, we try a number of different specifications involving different combinations of county and industry employment data and found nearly identical results.

$$C_{i,t} = \begin{cases} 0 & \text{if } \Pi(i,t) \leq 0 \\ \Pi(i,t) & \text{if } 0 < \Pi(i,t) < \overline{m}_{i,t} \\ \overline{m} & \text{if } \Pi(i,t) > \overline{m}_{i,t} \end{cases} \tag{1}$$

where

$$\Pi(i,t) = \alpha_0 + \alpha_1 \boldsymbol{W_{i,t}} + \alpha_2 \boldsymbol{E_{i,t}} + \alpha_3 \boldsymbol{X_{i,t}} + \alpha_4 C_{i,t-1} + \epsilon_{i,t} \tag{2}$$

The variable $C_{i,t}$ is the contribution made by investor i at time t. Contributions are bounded below by 0 and above by $\overline{m}_{i,t}$, which we set to the statutory employer plus employee limit, adjusted by the catch-up contribution limit if the level of contributions indicates that the individual is eligible to make a catch-up contribution.[29]

The vector $W_{i,t}$ is populated with the variables related to wealth: the dollar change in the median house price for the same zip code as the investor, the investment income in dollars, and interactions with other indicators.[30] Investment income comes directly from Form 5500.[31] Given the typical size of these accounts, investment income can be quite substantial.

To quantify the effect of high returns on contributions illustrated in Figure 1, we include interaction variables in $W_{i,t}$. We specify an indicator that is equal to one if the returns are in the top 10 percent of all returns from that year, and zero otherwise. As shown in Figure 1, the propensity to contribute increases when returns are high; this interaction term quantifies that relationship. In various specifications, we interact the high returns indicator, the lagged high returns indicator, and a low returns indicator with investment income. We also interact the investment income with the age of the account and the natural log of the beginning-of-year

[29]We included all observations for which the investor made contributions above the non-age-adjusted maxima but below or equal to the age-adjusted maxima. Even if the filer made a mistake and contributed a catch-up contribution, this decision still reflects their savings decision. The vast majority of individuals in this range are at the age-adjusted maxima.

[30]We specify our dependent variable (contributions) and investment income in dollars. Choi et al. (2009) use percent returns as a regressor and contributions as a share of income as the dependent variable. We do not have income, so this specification is unavailable to us. We considered other specifications such as natural logs, however, using levels in dollars was most consistent with the censored regression specification, accommodated a sample in which a sizable percentage contributed zero dollars, and has an straightforward economic interpretation.

[31]Participant loans are not included in income; following Form 5500, participant loans are treated as an asset. Therefore, obtaining a loan would not affect our measure of income.

value of the account to see whether any relationship abates with experience.

In addition to changes in asset values, we include a number of variables that may characterize potential health of the business, summarized by the vector $E_{i,t}$. This vector includes percent changes in employment in the entire county. It also includes changes in employment in the filers' industry at a county and a national level. Finally, the vector $X_{i,t}$ includes time-dummy variables. We removed the top and bottom one percent of observations sorted by income.[32] Clustering was applied at the county level; we applied clustering at the state level and found only small differences in the standard errors.

We present the main results in Table 4.[33] The first column shows the baseline specification containing no interaction variables, and is closest to the analysis presented by Choi et al. 2009.[34] The coefficient on investment income is positive and significant; on average, for every dollar of returns, contributions to the account increase by about 0.8 cents. These coefficients may seem small; however, they are applied to large regressors. Some investors make very large returns in dollar terms, which are correlated with significant changes in total contributions. Moreover, since there is a good deal of persistence in these savings decisions, even moderate changes in savings decisions early in life can have very large effects on the size of investors' savings at retirement. For example, an investment income of $50,000 correlates with a $400 increase in yearly saving, leading to a change in behavior that could result in tens of thousands of dollars in additional savings at retirement.

Several local employment or industry-specific employment indicators are correlated with changes in contributions. Change in employment at the county level has a small effect on contributions: A one-percent change in this variable leads to about a $33 increase in contributions,

[32] In many of these cases, the income from these assets listed on Form 5500 likely does not reflect actual year-to-year changes in the market value of the investment.

[33] We excluded the top and bottom one percent of observations by total investment income. In many cases, these incomes were extraordinarily unlikely to represent actual income generated by their assets. In some cases, these numbers were the result of filing errors or other behavior that did not reflect or underlie any deliberate life-cycle savings decisions.

[34] All specifications include the following controls: constants, year dummies, change in employment for the filers' industry classification at the county level by two- and four-digit NAICS codes, change in employment for the filers' industry classification at the national level for the two- and four-digit NAICS codes, and change in total county employment. Clustering is applied at the county level; applying clustering at the state level does not materially change the results. For brevity, we omit reporting some variables that do not have statistically significant effects.

which is significant at the 10-percent level. A one-percent change in the two-digit NAICS employment category at the national level leads to an increase in contributions of about $106. The coefficient on lagged contributions is about 0.943, which indicates that the increased contributions from a high-return year persist for several years.

All time dummies are included in the regressions, but we limit reporting to years around the two recessions in our sample. The coefficients on these dummies indicate that there is a fairly sharp change in behavior at the onset of recovery. The coefficient jumps by nearly $3,000 from 2001 and 2002 to 2003, a result that is common to all regression specifications. Nonetheless, after 2003, the year dummy returns to levels that are stable between 2005 and 2008. By contrast, between 2008 and 2010, the coefficient drops by about $800 to $900, and remains statistically indistinguishable from zero in every subsequent year through 2016.

In the second column on Table 4, we interact investment income in dollars with a dummy variable indicating that the investor earned contemporaneous top-decile returns. This specification admits the possibility that the effect of returns on contributions is non-linear, and is meant to allow for the possibility that investors who realize top returns have qualitatively different behavior, as shown by Figure 1. The coefficient on the indicator indicates that higher contributions among the filers with higher returns explains a large fraction of the effect of higher returns. A dollar of additional investment income is correlated with 0.6 cents of additional contributions to Solo 401(k) accounts. Investors in the top decile of returns contribute an additional 0.9 cents for each additional dollar of investment income, for a total of about 1.5 cents for each additional dollar of income. The other covariates remain similar in both magnitude and statistical significance.

The third column of Table 4 shows the same specification, but with the interaction of prior-year, top-decile returns. If investors are learning, we would expect the effects of high returns on investor behavior would begin to dissipate in subsequent years. Although a point estimate of the coefficient is slightly negative, we are unable to reject the null hypothesis that the coefficient is zero. This result is consistent with the investor behavior over time documented in Figure 4. Moreover, the coefficient on lagged contributions is close to one, which confirms the observation from Figure 4 that investors receiving high returns shift their levels of contributions. All other coefficients are similar to their values in the second column.

We try several specifications to determine how age, wealth, low returns, and house prices interact with investor behavior, and report the results in Table 5. The coefficients and significance of all geography-specific indicators and time dummies are extremely similar to their analogues in Table 4, and so we do not report them. In the first column, we introduce the dollar change in the median single family house price as a regressor. For every dollar increase in median single-family house price in the same zip code, investors increase their contributions by about 0.5 cents; however, we fail to reject the hypothesis that this coefficient is zero. The remaining coefficients are extremely similar to all of the specifications reported in Table 4: A dollar of income tends to increase contributions by about 0.6 cents, but having a top-decile return increases the contribution to about 1.5 cents for each additional dollar of income.

In the second column in Table 5, we interact the natural log of the account size with investment income and a high returns indicator. This will allow us to see whether the propensity to chase returns diminishes with account size. We see a clear negative correlation between the natural log account size and contributions. This indicates that the effect is quite strong for investors with small accounts, and abates as their accounts grow.[35] Specifically, if the account size roughly doubles (the log value increases by one), the estimates suggest that investors in the top decile reduce their contributions per dollar of investment income by about 0.5 cents.

In the third column, we add account age, which we interact with high returns and investment income. We find that account age, which is correlated with investor age, has a negative sign significant at the five percent level. For the investor with a brand new account, high returns are correlated with a 2.3 cent increase in contributions for each dollar of income, a relationship that abates at a rate of 0.06 cents for every additional year that the account is open.[36] This finding is similar to what we observe in Figures 3 and 4, both of which seem to indicate that the propensity to chase returns is lower for more experienced investors.

In the fourth column, we evaluate a specification with low returns to see whether investors

[35]We also tried specifications where we broke the sample into tertiles or quartiles by account size, but we did not identify any statistically significant coefficients on the account size indicators among these specifications.

[36]We tried specifications with both account size and account age; those variables are highly correlated. Although we saw the expected signs in each case, there was no statistical significance attached to either coefficient individually.

earning low returns show different behavior. Specifically, we interact an indicator that is one if the investor received returns in the bottom decile with investment income in dollars.The interaction variable has a negative sign, indicating that individuals with bottom returns decrease their contributions with respect to the average. Combining the coefficient on $InvestmentIncome$ and $InvestmentIncome * LowReturnsIndicator$ gives us an estimate of the total change in contributions for investors earning returns in the bottom decile. The combined point estimate for this effect is about 0.5 cents per dollar of income, which is significant only at the 10 percent level. This suggests a small increase in contributions in the bottom decile as income declines, which is broadly consistent with the behavior we might expect to see from an agent in a canonical life-cycle model who was impacted by a negative wealth shock.

Overall, although returns are correlated with higher levels of contributions, exceptionally high returns explain a large share of increases in contributions. Moreover, high returns affect the contribution decision in the year in which those returns are made and in many subsequent years. In the next section, we develop a model with taxable and tax-deferred assets to explain how and under what conditions changes to expectations can generate this type of persistent response to high returns.

4 The Model

In this section, we outline the two-asset model with portfolio choice over taxable and tax-deferred assets, which is based on Huntley and Michelangeli (2014) and similar to the model with taxable and tax-deferred assets used to study equities ownership by Gomes, Michaelides and Polkovnichenko (2009). We use this model to illustrate how wealth shocks and changes in expectations affect individuals' financial decisions and compare the model's predictions with our data across different demographic groups. We calibrate the model to a yearly frequency and choose parameter values to mirror the main features of the U.S. economy. We then simulate a sample of investors and show that only a persistent change in expectations for returns can generate a response that is consistent with our empirical findings.

The economy is populated by a continuum of heterogeneous investors who enter the economy at age 20, retire at age 65, and can live to a maximum age of 99. The state variables are individual age, j; tax-deferred assets, k^d; taxable assets, k^t; and labor productivity, θ.

Preferences over consumption c are described by the constant relative risk aversion utility function $u(c)$, which takes the following form:

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma} \tag{3}$$

Upon receiving news of its labor productivity status, the individual chooses consumption, next-period tax-deferred assets $k^{d\prime}$, and next-period taxable assets $k^{t\prime}$. The problem can be written as follows:

$$V(j, k^d, k^t, \theta) = \max_{c, k^{d\prime}, k^{t\prime}} u(c) + \beta E S(j+1)[V(j+1, k^{d\prime}, k^{t\prime}, \theta')] \tag{4}$$

where $S(j+1)$ corresponds to the likelihood that the agent survives to age $j+1$ conditional on survival to age j.

The budget constraint is given by:

$$\begin{aligned} c(1+\tau^c) + k^{d\prime} + k^{t\prime} + \phi(j, k^{d\prime} - k^d) \leq \\ (1 + r(1-\tau^{kt}))k^t + (1 + r(1-\tau^{kd}))k^d + w\theta(1-\tau^l) \end{aligned} \tag{5}$$

where r is the real pre-tax return on individual investments; τ^c is the effective tax rate on consumption; τ^{kt} is the effective tax rate on taxable capital income; τ^{kd} is the effective tax rate on tax-deferred income; and τ^l is the effective tax rate on labor earnings, which includes both labor income and payroll tax rates. The penalty function, $\phi(j, k^{d\prime} - k^d)$, indicates how much the individual must pay (or receives because of tax deductions) when modifying its stock of tax-deferred assets.

Tax-deferred assets, k^d, earn income at the rate of $(1-\tau^{kd})r$, which is the return on income after business taxes are applied. Agents do not pay ordinary income tax on the income earned on those assets as long as the earnings remain in the accounts; however, they pay taxes on the assets when they are withdrawn.

The individual's age, j, determines the cost for changing the stock of tax-deferred assets. A working-age individual younger than 59.5 pays taxes on the withdrawal and a 10-percent early withdrawal penalty.[37] Conversely, if the agent increases its tax-deferred assets, it gets to take a tax deduction. Individuals older than 59.5 but younger than 66 years can take withdrawals without triggering a penalty, but pay the same ordinary tax rate as younger individuals. Individuals older than 65 taking withdrawals do not pay a penalty; however, they do pay taxes on the withdrawal. Withdrawals for these individuals are taxed at a lower ordinary rate, reflecting the decline in labor income realized upon retirement.[38]

To account for these features, we use an asymmetric penalty function $\phi(j, \Delta k)$, which depends on the agent's age j and the individual's change in the tax-deferred assets $(k^{d'} - k^d)$. Unlike the agents modeled in Huntley and Michelangeli (2014), the types of individuals we're modeling have much larger contribution limits, so we do not limit the tax deduction for the working-aged. We have separate penalty functions for different ages: agents up to age 60, and agents age 61 to 65. Agents over 65 do not put money into the accounts. The only source of risk in the model for retired agents is their survival, and they draw down their accounts and pay a tax rate of ξ^{66+} on the withdrawals. The penalty function for the first group has a kink; that is, it is continuous but not differentiable. To approximate it, we use a smoothing function (Chen and Mangasarian, 1996). The function for agents below 60 years old is:

$$\phi^{60-}(\Delta k) = \xi^p[(\Delta k + \log(1 + \exp a(-\Delta k)))/a] - (\xi^{65-} + \xi^p)\Delta k \tag{6}$$

In this equation, the penalty on withdrawals, ξ^p, is typically set to 10 percent. The curvature of the function is determined by the parameter a.[39] The function for agents 61–65 years old does not have the kink; it is a simple linear function because there is no penalty, and agents can still

[37] Assets withdrawn from such accounts are taxed at the ordinary income tax rate, excluding payroll taxes, not at the capital tax rate.

[38] After retirement, individuals often must withdraw funds from tax-deferred assets. For example, after age 70, a person with a traditional IRA must start withdrawing funds to avoid paying a penalty. We do not explicitly model that after-retirement contribution limits because, in our model, it is optimal for an individual to start withdrawing assets, and the constraint would not bind in equilibrium.

[39] Higher levels of a make the approximation closer to the true kinked function, but reduce the likelihood that optimization routines are able to find a solution.

contribute to their accounts and can withdraw without penalty.

$$\phi^{61-65}(\Delta k) = \xi^{65-}\Delta k \tag{7}$$

In both of these cases, all agents pay a tax rate of ξ^{65-}, which applies positively to withdrawals and negatively to contributions.

After-tax consumption, next-period tax-deferred assets, next-period taxable assets, and penalties must be no greater than the net rental earned on capital, net wage income, and the total value of tax-deferred and taxable assets.

Furthermore, the agent is subject to the following borrowing constraints:

$$k^{d'} \geq 0; k^{t'} \geq 0 \tag{8}$$

The lifetime labor earning process evolves as follows:

$$\ln \theta_j = f(j) + z_j + \epsilon_j \tag{9}$$

where

$$z_j = \rho z_{j-1} + \eta_j \tag{10}$$

The function $f(j)$ is a polynomial in age drawn from Cocco, Gomes and Maenhout (2005); it represents the typical life-cycle earning profile and is entirely known to the agent at the time of entry into the labor force. In addition to this deterministic component, we account for two random components into Equations 9 and 10: a persistent component z_j that evolves as an autoregressive process with persistence ρ, and a transitory component ϵ_t. η_t and ϵ_j are i.i.d. with variance σ_η^2 and σ_ϵ^2, respectively. At age 65, the individual retires and receives a constant retirement income.

We simulate 5,000 separate individuals for each age 20 through 100, which leads to a sample of 400,000 individuals starting in year one. We then simulate each of those individuals for six years, with wealth and expectation shocks realized in the third year. From those 400,000 simulated agents, we draw a sample of 50,000 to match the age profile in the United States. For the model's computational solution, see Appendix 6.

4.1 Parameterization

The model's parameters are chosen to mirror the main features of the U.S. economy and are consistent with related literature using life-cycle models and key indicators in U.S. data such as the asset-to-income ratio (Table 6). The discount factor β is chosen such that the average median wealth-to-income ratio is consistent with the empirically observed asset-to-income ratio from Huntley and Michelangeli 2014, 0.945.

Following Carroll (1997), we set the coefficient of relative risk aversion, γ, to two. The parameters for the age-polynomial $f(j)$ in Equation 9, which describes the life-cycle component of the income process, are taken from the analysis of Cocco, Gomes and Maenhout (2005). The persistence of the persistent shock to the income process in Equation 10 is adopted from Storesletten, Telmer and Yaron (2007) and the variation for the persistent shock is taken from Fernandez-Villaverde and Krueger (2011). The estimated income process is based on annual data, and in our model, agents receive these shocks annually. We set the replacement ratio for retirement income equal to 0.6 of the median labor income realization in the final year of working, following Bernheim, Skinner and Weinberg (2001).

In the model, we assume that the annual real gross return on assets is about 1.5 percent.[40] Corporations and businesses pay taxes, τ^{kd}, equal to 13.4 percent of income before the investor receives any investment income. We set tax rate on taxable assets at 35.2 percent, which encompasses both personal and business taxes.[41]

5 Simulation Results

To provide intuition for the individual behavior that underlies the aggregate results, we present select simulated individuals in Figure 5. This figure shows the effects of shocks to wealth and

[40] This return is calculated net of business and corporate taxes, but before personal income taxes.
[41] Source: Staff estimates from the Congressional Budget Office.

expectations on four types of simulated individuals, which differ with respect to their age and their holdings of liquid and tax-deferred assets.

We selected individuals with the same labor productivity realizations over the four periods displayed ($t = -1, 0, 1, 2$) in order to abstract from the effects of changes in labor earnings. In each of the panels, we present four series of changes in contributions to tax-deferred assets, which capture behavior in response to different shocks. The first scenario ("Baseline") is represented by a black solid line: This is the standard life-cycle behavior for the individual in a model without shocks to wealth or expectations. The second scenario ("Wealth Shock") is identified by the dotted line, and illustrates the agent's behavior when it receives an extra 15 percent return in the tax-deferred account in period $t = 0$. In the third scenario ("Wealth and Tmp Exp Shock"), indicated by the long-dashed line, the individual receives an extra 15 percent return in the tax-deferred account in period $t = 0$; at the same time, the agent increases its current-period expectations over returns in the tax-deferred account by one percent. This shock to expectations is temporary, as the investor reverts to its original expectations in period $t + 1$. The fourth scenario ("Wealth and Perm Exp Shock") is illustrated by the dotted-and-dashed line. It is similar to the third scenario, with the difference that the investor permanently reformulates its expectations in period 0 and never revises them, regardless of future outcomes.

In the upper-left panel, we focus on individuals that have neither taxable nor tax-deferred assets. Households without taxable or tax-deferred assets made up about 16 percent of the population according to the 2001 Survey on Consumer Finance (Huntley and Michelangeli, 2014). In the panel, we show the individual starting at age 31 in period $t = -1$. This type of agent is not widely studied in the household savings literature because they have minimal savings, but its behavior nonetheless provides a baseline against which to evaluate the behavior of other types of individuals. This individual is at the beginning of its career and, until now, has been borrowing-constrained and unable to accumulate significant assets. Consequently, the impact of a wealth shock is null: Its behavior is close to unchanged between the baseline and the wealth shock scenario. When hit by a temporary shock to expectations over returns, the individual increases its savings in the tax-deferred account by about \$500 in period $t = 0$—which is about \$500 more than the contribution at baseline. In the subsequent period, the agent decreases its contribution by a similar, if slightly larger amount. Only upon receiving a permanent shock to its expectations do the individual's contributions remain persistently higher than in the baseline scenario. Only the permanent change in expectations generates investor behavior that is in line with the empirical evidence from our sample of 5500 investors.

The upper-right panel and the lower-right panel show individuals who have both taxable and tax-deferred assets; this group accounts for about 56 percent of the U.S. population. The upper-right panel focuses on a comparatively wealthy individual beginning at age 31. The individual in the upper-right panel, while relatively young, has amassed above-average holdings of both taxable and tax-deferred assets in period $t = -1$ (the median values of tax-deferred and taxable assets for households in this group are equal to 16,000 and 6,000 dollars, respectively) and it is a good representative of the type of individuals in our sample, as well as of the type of investors studied by Malmendier and Nagel (2011). In spite of being wealthier, this individual's behavior resembles its less-wealthy counterpart in the upper-left panel. A wealth shock alone is not sufficient to induce an increase in contributions to tax-deferred accounts. Combining the wealth shock with a temporary change in expectations induces a strong positive response to savings. This deviation from baseline, however, is reconciled as expectations return to pre-shock levels. Only a permanent change in expectations, similar that documented by Malmendier, Tate and Yan (2011), and consistent with the behavior described by Greenwood and Shleifer (2014), can induce a level shift in the agent's savings profile.

The lower-left panel illustrates the behavior for an individual that has only tax-deferred and no taxable assets, which constitute about nine percent of the population. In particular, it shows a 43-year-old with retirement savings in its tax-deferred account but very low assets in its taxable account. This individual is representative of the agents from large-company 401(k) plans (Choi et al., 2009; Madrian and Shea, 2001; and Agnew, Balduzzi and Sunden, 2003). Although some of these individuals undoubtedly save, many of these are salaried individuals whose primary vehicle for saving is their employer-sponsored tax-deferred accounts. Many individuals in our sample likely fit this profile, particularly young professionals paying off professional school loans (see Table 1) who have not had enough time to accumulate significant assets in their taxable savings accounts. Like the younger, wealthier individuals, this agent's savings profile fits the same pattern as the individuals in the upper panels: A permanent change in expectations induces the investor to contribute a greater share of labor income to savings in tax-deferred retirement accounts.

The lower-right panel shows an individual closer to retirement, who has both tax-deferred and taxable assets. About half of U.S. households have some positive savings in both tax-deferred and taxable assets (Huntley and Michelangeli, 2014). These households are similar to the older individuals in our sample. Many of our sole proprietors have millions of dollars in their tax-deferred accounts, and many of them contribute the maximum allowed by law. Therefore, it follows that such investors would likely have accumulated a stock of taxable assets over their lives. Such wealthy, older investors are the subject of study in papers such as those from Malmendier and Nagel (2015) and Malmendier and Nagel (2011). These individuals behave differently than those depicted in Figure 4. In period $t = -1$, this agent is age 54 and has amassed fairly large holdings of tax-deferred assets and taxable assets, which can be used to smooth consumption over bad labor income realizations. As before, a wealth shock, by itself, prompts the individual to slightly lower its contribution relative to baseline.

Temporary or permanent changes of expectations, however, generate a substantially different savings response in this case. This individual does not increase savings in the tax-deferred account out of labor income as the age 31 and age 43 individuals do. In this case, the individual transfers a large share of savings out of the taxable account and into the tax-deferred one. In period $t = 0$, the individual's contributions increase by about \$6,000. This behavior reflects the fact that, as agents gets closer to retirement, there are fewer idiosyncratic productivity shocks, and the age at which they can make penalty-free withdrawals is much closer. Therefore, the motivation to keep a large stock of liquid assets to smooth consumption is less important than the motivation to earn high returns. In period $t = 1$, we observe an approximately \$4,000 drop in tax-deferred contributions, reflecting the fact that the agent's stock of taxable assets has been exhausted and it has no more assets to transfer to the tax-deferred account.[42]

[42] We considered an experiment when expectations increase across both accounts. The only difference is the smaller initial transfer from the taxable to the tax-deferred account. In the case when the earnings expectation shock is applied equally to both accounts, the increase in contributions is a little less than \$13,000, slightly below the \$15,000 increase in contributions observed when the expectations change only for the tax-deferred account. In this two-asset model, the main way to induce older individuals to not move their assets from the more liquid

We conclude that younger agents, on average, exhibit simulated behavior that is similar to the behavior we observe among Form 5500 filers. Even younger agents in the model with a significant stock of liquid assets, like the example in the upper right panel of Figure 5, permanently raise their tax-deferred contributions as their expectations change. The model predicts that agents closer to retirement who have significant liquid assets, however, are likely to reallocate their portfolios in ways that are inconsistent with the behavior we observe in our sample.

However, if these agents do not change their expectations, older agents' behaviors will look more like the dotted line in the bottom right panel. A wealth shock, absent a change in expectations, will generate minimal deviations from agents' anticipated contribution plan for their tax-deferred accounts. For more experienced investors, a response to a wealth shock absent any change in expectations is far more consistent with the distribution of contributions for older, wealthier investors shown in Figure 3, Figure 4, and in the estimates from Table 5.

In Figure 6, we show moments of the distribution of agents in the model and show their savings decisions in a format comparable to the panels in Figure 4. Specifically, we show the middle two quartiles of the change in contributions for all agents making positive contributions in period $t = -1$. Overall, our model generates considerably less variation than we observe in the empirical data, reflecting the limited number and types of shocks we are simulating in our experiment.

In the upper-left panel, we show the distribution of savings behavior when agents earn a 15 percent excess return in period $t = 0$, coupled with a one-period change in the path of their expected returns. As we observed with the illustrative examples, the model indicates a significant increase in contributions in period $t = 0$, which is followed by a drop in the following period, $t = 1$. This behavior is not consistent with what we observe in our data: Figure 4 shows individuals who shift their savings profile without a subsequent rebound.

In the upper-right panel, we show the results of the same experiment, assuming that individuals permanently change their expectations of future returns in the tax-deferred accounts. In the aggregate, there is a drop in contributions in period $t = 1$, though it is smaller than the

taxable accounts to the less liquid, higher return tax-deferred accounts is by removing the incentive to accumulate assets in the taxable account. With lower uncertainty with respect to labor income, individuals accumulate fewer assets, particularly in taxable accounts.

drop projected when the change in expectations was temporary. To illustrate how age affects how agents respond to this type of shock, we split the sample.[43]

Individuals 45 years and younger—shown in the bottom-left panel and exhibiting changes to investors' expectations similar to those studied by Malmendier and Nagel (2011) and Malmendier and Nagel (2015)—behave very similarly to those in the empirical sample. They increase their contributions at the time of the shock and do not revert their savings habits after one period. This empirical distribution of simulated changes to contributions qualitatively mirrors the analogous measure of investor behavior shown in the bottom-left panel of Figure 4. In both cases, we see investors increasing their contributions and then generally maintaining that higher level of contributions in the years subsequent to the shock.

In the bottom-right panel, we consider individuals who are 46 years and older in period $t = -1$. These agents move a large quantity of assets into their tax-deferred accounts upon receiving a wealth shock and then lower their contributions in the subsequent period. These older individuals exhibit behavior that is inconsistent with our empirical findings in two ways. First, these investors show a much stronger reaction to the shock than the investors shown in Table 5. The model predicts the strongest response to this shock among these older investors. By contrast, the empirical evidence summarized in the lower right panel of Figure 4 suggests a more modest correlation between positive changes to contributions and high returns. In addition, the model predicts that these older investors will exhibit a negative change in contributions in the following period, the year after they are done relocating assets from the taxable to the tax-deferred accounts. This is clearly not consistent with the behavior of investors with accounts 10 years or older. There is clearly no "rebound" in contributions in the bottom right panel of Figure 4.

A life-cycle model with tax-deferred and taxable assets is able to generate simulated results that are similar to observed choices among Form 5500 filers, but only if the shock is accompanied by a permanent or highly persistent change to expectations, and if that shock is limited to younger investors.

[43]Investor age is also extremely highly correlated with account size and exhibits the same relationship with contributions, which we show in Appendix 6.

6 Conclusion

We use 18 years of data from single-employee businesses that file 5500 returns to help identify the causes of returns chasing. Compared to the large-employer 401(k) investors analyzed in other studies, our sample is populated by more highly educated, wealthier individuals who are more financially educated and have more resources. Moreover, the investors in our sample are required to engage with their retirement savings plan on a yearly basis to file tax forms and make contribution decisions. They are also beset by fewer administrative, informational, and transaction costs than their contemporaries investing in large-employer 401(k) plans.

Because the 5500 filers are closer to the canonical agent in the rational expectations literature, we would expect that these investors would be less likely to chase returns. Instead, we find that our investors display a similar behavioral bias, but concentrated in response to exceptionally high returns—that is, in the top decile of the sample. This investment behavior drives level shifts in filers' savings plans, which do not revert in subsequent years. The propensity to chase returns appears to be uncorrelated with aggregate economic conditions or equity market performance, but is correlated with age and account size.

We evaluate the extent to which a life-cycle model with wealth and expectations shocks could mirror these empirical facts. We find that these wealth shocks combined with permanent shocks to expectations produce simulated results that best fit the empirical data. In our model, younger agents, and agents with few liquid assets, react in a way that is consistent with observed investor behavior. The older agents approaching retirement age, when tax-deferred accounts become considerably more liquid, typically over-react to these shocks with a single large wealth transfer from taxable to tax-deferred accounts.

Numerous papers (Malmendier and Nagel, 2011, and more) cite evidence that less-experienced investors are more likely to respond to personal experiences, and that investors' responses reflect highly persistent or permanent changes to expectations. We find that this literature offers a compelling explanation that bridges the inconsistency between our model's predictions and what we observe in Form 5500 filings for more experienced investors. In our model, older agents who realize wealth shocks without changes to expectations fit our observed data on older, wealthier individuals.

We look forward to continuing research to determine whether changes in investors' expectations in response to high returns are, in fact, persistent enough to generate the types of responses we see in our model and in our dataset. In particular, we are interested in ongoing research by Bender et al. (2020), who demonstrate that financial advice plays an important role in many wealthy individuals' investment decisions. Our findings could reflect financial advisors taking advantage of clients' idiosyncratic above-average returns to convince them to invest more. More skilled advisors could be more successful in convincing their clients to increase their contributions, and that mechanism may contribute to how returns affect expectations asymmetrically, particularly among less experienced investors.

Appendix: Details on the Data

Our data is based on sponsors of one-participant, defined contribution plans who file Form 5500 or Form 5500-SF.[44] The self-employed business owner that sponsors the plan is known as the plan sponsor. Plan sponsors for one-participant plans are allowed to contribute an amount of money up to and including a fixed amount ($18,000 in 2017, plus a potential $6,000 catch-up contribution if age 50 and above) plus 25% of the business' income.[45] In 2017, the combined total of these contributions could not exceed $54,000, or $60,000 for contributors aged 50 and above.

The plan sponsor can choose from among many plan custodians. Custodians have a wide range of different administrative characteristics, such as account fees, trading fees, loan terms and availability, loan fees, hardship withdrawal terms, rules for in-service withdrawals, and administrative and tax support.[46] Payments are usually set to nominal levels, as opposed to a share of income; the latter is more typical of the large-employer 401(k) plans studied in the literature (Madrian and Shea, 2001; Butrica and Smith, 2016; Duflo and Saez, 2003; and Agnew, Balduzzi and Sunden, 2003).[47]

Plan sponsors are required to file a Form 5500 or one of its two derivative forms (the 5500-SF or 5500-EZ) if the balance exceeds a filing threshold or if the plan is terminated. The IRS requires that sponsors with accounts worth $250,000 ($100,000 before 2007) or more across all Solo 401(k) accounts file the form yearly; a number of the accounts in our sample are below this threshold. Various reporting conventions and auditing rules may make it advantageous to file the forms even if the accounts do not meet the statutory requirements for filing Form 5500.

The Department of Labor, IRS, and the Pension Benefit Guaranty Corporation developed

[44]A variety of retirement plans are required to file the Form 5500 and its derivatives; the type of plan is indicated on the form. We exclude other types of plans, such as healthcare plans and defined-benefit plans.

[45]The contribution limits as a share of income as slightly different for sponsors who own limited liability companies or are sole proprietors.

[46]Many of these features, such as loan availability, are not universal and are specific to the plan custodian. For example, one custodian offers the plan sponsor seven different conditions under which the participant can qualify for loans: Any purpose, purchasing principal residence, educational expenses, medical expenses, mortgage payments to avoid foreclosure, funeral expenses, and to cover uninsured damage to principal residence.

[47]Income and expenses can be somewhat irregular over the course of the year and, in some cases, may be timed to maximize tax efficiency. This makes it difficult and uncommon to contribute a designated share of income at regular intervals.

the Form 5500 to enable benefit plans to satisfy reporting requirements under ERISA and the Internal Revenue Code. Form 5500 is supplemented by a number of schedules used to file additional actuarial, service provider, insurance, and financial information about employer-sponsored retirement plans including the Solo 401(k).[48] The standard 5500 is the most comprehensive form and is generally required for larger plans; plans covering fewer than 100 employees are typically eligible to file the 5500-SF. In recent years, the government has required that plan sponsors file the 5500-SF electronically using the EFAST2 system.[49] The third and most parsimonious form, the 5500-EZ, was developed exclusively to satisfy the filing requirements of single-employee plans. The 5500-EZ form can only be filed as a paper form; the Internal Revenue Service encourages filers to electronically file the short form to increase speed and accuracy.

Even though they may be eligible to file the 5500-EZ, many sponsors of single-participant plans file the longer, more complicated 5500-SF and 5500 forms. Plan sponsors may substitute the more complicated forms because there was no electronic filing option for the simplest form, the 5500-EZ, prior to 2021. Thus, even though single-participants are eligible to file the shorter 5500-EZ form, the 5500 and 5500-SF filings contain as many as 20,000 single-participant plans each year.

All of the 5500 and 5500-SF filings are available from the Department of Labor.[50]

A summary of the data is presented in Table 2. The number of single-employee plan sponsors filing a 5500 or 5500-SF each year ranges from about 15,000 to 21,000. Of those, approximately 6,000 to 9,000 of filers make contributions in that year or a subsequent year, which in almost all instances, indicates that the investor is eligible to make a contribution to this account. About

[48] For more information about the forms and their requirements, see https://www.dol.gov/agencies/ebsa/employers-and-advisers/plan-administration-and-compliance/reporting-and-filing/form-5500. Instructions for each of the forms are located on the Department of Labor website. The complete 5500 plan instructions are available at https://www.dol.gov/sites/dolgov/files/EBSA/employers-and-advisers/plan-administration-and-compliance/reporting-and-filing/form-5500/2019-instructions.pdf, 5500-SF instructions at https://www.dol.gov/sites/dolgov/files/EBSA/employers-and-advisers/plan-administration-and-compliance/reporting-and-filing/form-5500/2019-sf-instructions.pdf, and 5500-EZ instructions at https://www.irs.gov/pub/irs-pdf/i5500ez.pdf.

[49] Details available at https://www.efast.dol.gov/

[50] The Department of Labor makes the forms available at https://www.dol.gov/ebsa/foia/foia-5500.html. All of 5500-EZ filings are open to public inspection, but are not compiled into an easy-to-access dataset as is done for the longer forms. The 5500-EZ also has reduced reporting requirements compared to the 5500 and 5500-SF: Distributions are not required to be listed on the 5500-EZ, although information on contributions and loans must be included with the filing.

3,000 filers take distributions each year. Only a small proportion of all filers' accounts —about 600 to 900 individual accounts each year—are encumbered by a loan. The number of households contributing the maximum allowed dollar contribution (for example, $54,000 in 2017 plus catch-up contributions) is around 10 percent, although the percentage is considerably lower since 2013. The median contribution—which includes both employer and employee contributions—is fairly stable around $15,000, well below any combined employer and employee contribution limit.[51]

The total contributions across these filers peaked at nearly $170 million in 2005. The empirical distribution of contributions is typically bi-modal: There is a peak in the density close to the median and then again at the statutory maximum. There is not a high density of households near the 75th percentile. Even as recently as 2005, these accounts were still growing in popularity, and contributions continued to rise very quickly for single-employee defined contribution plans. Contributions as a share of total assets grew to about 2.2 percent from 2003 to 2005 and has remained fairly steady since.

Aggregate distributions are considerably higher than contributions. These distributions consist of voluntary distributions, required-minimum distributions, and rollovers.[52] The proportion of filers taking a distribution is very stable, around 16 to 17 percent from 2000 to 2015, with the exception of 2009, the year in which the required minimum distribution was suspended. In 2009, more than a quarter of households taking a distribution from their retirement accounts suspended their distributions, demonstrating a relatively high level of financial literacy or awareness.

The rate of accounts with positive outstanding loans is very slowly trending upwards over time, and aggregate outstanding loans do not appear to respond to economic conditions. The quartiles of loan size—limited by statute to a maximum of $50,000—do not show any clear trends over the 17-year window.

Vissing-Jorgensen (2003) documents a correlation between wealth and investment decisions. We explore the relationship between contributions and returns conditioned on wealth in Figure

[51]Employer and employee contributions are typically listed separately on the contribution deposit slips even though the distinction does not matter to a huge majority of filers. Exceptions typically occur when the 5500 filer also has access to an external employer-provided 401(k) plan, in which case the filer may need to allocate the contributions to a specific category to maximize aggregate contribution limits.

[52]In the filer-level empirical analysis, we exclude accounts with rollovers that are closed. Filers who close accounts are required to file a final Form 5500 regardless of account status.

7. We split our sample into four similarly-sized groups based on the account size: The top-left panel shows the relationship between returns and contributions for households who have non-zero accounts smaller than \$30,000 to \$45,000 per year; the top-right panel for investors with accounts bigger the previous value but less than \$113,000 to \$168,000 per year on average; the bottom-left panel contains the sample of investors with more than the previous quartile but less than \$330,000 to \$480,000 per year.[53] The bottom right panel contains investors with more than \$480,000 in their accounts.

Investors in the bottom two quartiles of account size that earn top-decile returns do exhibit returns chasing; among high-wealth investors, there is no visible difference in behavior between those earning the top decile of return and all others. The effect is most marked for accounts in the bottom quartile. The 75th percentile of investors in the top-performing decile increase their contributions by as much as \$2,500 relative to other deciles. Among households in the second quartile of account size distribution, the top earners increase their contributions, on average, by about \$1,200 to \$1,500 relative to their peers. The 75th percentile in the third quartile is a few hundred dollars higher and is spread among the top two deciles. The effect is completely absent among investors in the top quartile of account wealth—typically investors with more than \$330,000 to \$500,000.

Appendix: Solution of the Model

The solution of the model closely follows Huntley and Michelangeli (2014), but with different interpolation methods applied to the value function. The stock of tax-deferred assets and the stock of taxable assets are continuous-state variables, and we use a grid with 60 points for each type of asset. The labor earnings process is discretized. The persistent component of the earning shock is discretized using a five-point grid and the transitory component is discretized using a three-point grid. The grid points and transition matrix for the persistent realization to labor earning are obtained using the approach of Tauchen (1986), and the transitory shock

[53] The quartiles can sometimes change significantly each year; an account value that is in one quartile in one year may be in another quartile in a different year.

is approximated using Gaussian quadrature. We assume that the household has no bequest motive, and thus the continuation value is zero for a household surviving to its 99th year.

To analyze the distributional effects of the shocks, we first need to approximate the ergodic distribution. We solve the household problem in Equations 4 and 5, starting at the end of its life, and solve it recursively to the youngest age. Using the policy functions obtained while solving Equation 4, we simulate 1,000 households for each annual cohort. For each age and for each income realization, a fraction of households consistent with the transition matrix is randomly selected to transition to a new labor state. The distribution over the discretized labor income is constant over time. We simulate all of the households in each cohort and take a sample consistent with the population distribution to obtain the households that will populate our simulation in period $t = 1$.

We interpolate the value function with Chebyshev interpolation. We use a slightly modified version of NPSOL, a non-linear constrained optimization package maintained by Argonne National Laboratory, to find the households' policy functions.[54] We then simulate households' choices regarding assets and consumption using bilinear interpolation for the policy functions for all T periods.

[54] Manual available at `https://wiki.mcs.anl.gov/leyffer/images/7/75/NLP-Solvers.pdf`

Tables and figures

Table 1
Occupations

Industry	Percent of Obs.
Offices of Physicians	20.34
Scientific and Technical Services (Professional)	8.35
Legal Services	7.41
Offices of Dentists	5.13
Scientific and Technical Consulting Services (Management)	3.89
Other Personal Services	3.57
Offices of Other Health Practitioners	3.54
Activities Related to Real Estate	2.91
Accounting, Tax Preparation, Bookkeeping and Payroll Services	2.61
Agencies, Brokerages and Other Insurance Related Activities	2.53
Computer Systems Design and Related Service	2.42
Offices of Real Estate Agents and Brokers	2.22
Other Financial Investment Opportunities	1.83
Architectural, Engineering and Related Services	1.68
Residential Building Construction	0.92
Independent Artists, Writers, and Performers	0.92
Lessors of Real Estate	0.9
Specialty Trade Contractors	0.85
Advertising, Public Relations, and Related Services	0.8
Services to Buildings and Dwellings	0.71
Automotive Repair and Maintenance	0.69
Other Amusement and Recreation Industries	0.66
Building Equipment Contractors	0.61
Other Miscellaneous Store Retailers	0.59
Personal Care Services	0.59
Other Miscellaneous Durable Goods Merchant Wholesalers	0.56
Business Support Services	0.56
Securities and Commodity Contracts, Intermediation and Brokerage	0.55
Home Health Care Services	0.53
Personal and Household Goods Repair	0.5

Notes: All occupations with at least a 0.5 percent share of observations in the sample are included.

Table 2

Descriptive Statistics for Contributions and Distributions

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Number of Contributions	6,974	9,930	9,951	8,752	8,039	8,018	8,255	8,551	8,505	7,515
Number of Max Contributions	463	671	495	945	1,164	1,002	1,126	1,090	1,102	851
Median Contribution ($1,000s)	9.46	9.76	10.2	11.5	12.5	14.6	15	16.1	16.5	15.5
Median Account Size ($1,000s)	68.3	99.7	95.1	88.1	85.6	109	116	115	122	103
Mean Account Size ($1,000s)	208	263	237	231	226	273	283	315	341	354
Number of Distributions	1,580	2,696	2,982	3,037	2,897	2,848	2,955	3,136	3,188	2,806
Median Distribution ($1,000s)	28.5	24	19.5	18	15	16.9	16.7	18.1	20	18.6
Median Account Size ($1,000s)	282	296	260	241	234	284	301	322	344	331
Mean Account Size ($1,000s)	623	696	624	597	543	619	709	690	748	714
Number of Loans Outstanding	556	818	736	680	660	691	720	743	751	642
Total Observations	13,997	20,747	21,228	20,749	19,054	18,152	18,502	18,918	19,407	17,675

	2009	2010	2011	2012	2013	2014	2015	2016	2017
Number of Contributions	6,515	7,390	7,427	7,591	7,854	8,021	8,182	7,835	8,011
Number of Max Contributions	665	723	724	635	581	582	598	666	529
Median Contribution ($1,000s)	13.5	12.3	13	14	14	14.2	14	14.4	15
Median Account Size ($1,000s)	109	122	116	115	109	95.9	89	74.7	68.7
Mean Account Size ($1,000s)	361	388	390	369	450	436	417	377	336
Number of Distributions	2,148	2,785	3,069	3,332	2,954	2,934	2,998	2,816	3,193
Median Distribution ($1,000s)	8.79	18	15.4	13.7	14.2	16	15.6	15.4	15.1
Median Account Size ($1,000s)	269	258	251	231	281	305	322	317	308
Mean Account Size ($1,000s)	582	587	582	593	667	684	850	821	833
Number of Loans Outstanding	620	712	792	796	874	897	919	831	900
Total Observations	15,403	19,566	19,788	20,755	20,747	21,084	21,465	20,191	22,353

Notes: The statistics in this table have been calculated from the sample of individuals making a contribution, taking a distribution, or being encumbered by an outstanding loan.

Table 3

Empirical Distribution of Changes in Contributions (USD)

Percentile	2000	2001	2002	2003	2004	2005	2006	2007	2008
5%	-8,824	-8,498	-10,671	-11,429	-11,597	-13,500	-12,950	-14,750	-17,284
15%	-3,000	-2,840	-3,600	-3,770	-3,237	-4,300	-4,467	-5,000	-6,249
25%	-1,000	-844	-1,000	-1,017	-750	-1,000	-1,076	-1,472	-2,494
35%	0	0	0	0	0	0	0	0	-306
45%	0	0	0	0	0	0	0	0	0
50%	0	0	100	0	34	0	49	58	0
55%	45	25	535	1	364	301	432	471	0
65%	680	894	2,000	1,000	1,250	1,060	1,203	1,000	600
75%	1,500	2,016	3,637	2,538	3,155	2,570	2,807	2,788	2,000
85%	3,349	4,409	6,800	5,698	7,200	6,000	6,671	6,247	5,027
95%	9,065	9,989	14,797	14,538	16,598	16,462	17,416	17,330	15,500

Percentile	2,009	2,010	2,011	2,012	2,013	2,014	2,015	2,016	2,017
5%	-15,563	-14,263	-12,892	-13,123	-13,935	-14,874	-15,000	-15,845	-13,344
15%	-5,561	-4,000	-3,750	-3,783	-3,750	-4,077	-4,376	-3,700	-3,745
25%	-1,933	-1,026	-786	-700	-741	-854	-782	-741	-774
35%	-250	0	0	0	0	0	0	0	0
45%	0	0	0	0	0	0	0	0	0
50%	0	0	0	0	27	0	126	0	0
55%	47	0	0	244	300	80	481	46	185
65%	1,000	500	658	804	800	690	1,000	720	1,000
75%	2,018	2,000	2,853	2,500	2,291	2,152	2,500	2,400	2,850
85%	5,242	5,182	6,881	6,786	6,197	6,436	6,054	6,503	7,000
95%	16,544	15,313	19,631	18,480	18,000	19,936	17,703	19,235	21,150

Notes: The statistics in this table have been calculated from the sample of “active” filers. “Active” filers are defined as those who make a contribution to their retirement accounts in the same year or a future year.

Table 4

Contributions Based on Solo 401(k) Returns

	Baseline	High Returns Indicator	High Returns /w Lag
2001	-808.9***	-892.7***	-895.8***
	(296.8)	(300.1)	(300.1)
2002	-607.4**	-685.7***	-673.8***
	(244.9)	(247.9)	(248.2)
2003	2,101***	2,003***	2,015***
	(309.5)	(311.8)	(312.1)
2008	958.7***	939.0***	939.9***
	(295.7)	(296.5)	(296.4)
2009	325.3	221.6	222.6
	(319.6)	(329.7)	(329.7)
2010	106.8	116.7	114.8
	(362.7)	(360.7)	(360.9)
Total Contribution (1-Year Lag)	0.943***	0.944***	0.944***
	(0.00855)	(0.00855)	(0.00855)
Investment Income	0.00782***	0.00568***	0.00605***
	(0.00113)	(0.00124)	(0.00131)
Investment Income * High Returns Indicator		0.00877***	0.00908***
		(0.00249)	(0.00250)
Investment Income * Lagged High Returns Indicator			-0.00290
			(0.00244)
Change in Emp. (Total County)	32.54*	32.31*	32.38*
	(17.74)	(17.73)	(17.73)
Change in Emp. (U.S., 2-digit NAICS)	105.6***	105.2***	105.2***
	(24.04)	(23.95)	(23.96)
Constant	1,292***	1,304***	1,299***
	(245.8)	(245.5)	(245.6)
Observations	51,829	51,829	51,829

Notes: Investment income is income earned in dollars from the Solo 401(k) accounts. The High Return Indicator equals one if yearly returns are in the top decile, and 0 otherwise. All regressions include year fixed effects and changes in employment in the different industries at a county and a national level. For brevity, we report only select coefficients the help describe investors' decisions. Standard errors are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5

Contributions Based on Solo 401(k) Returns, Account Size, and Account Age

	House Prices	Log Acc't Size	Acc't Age Continuous Indicator	High/Low Returns Indicator
Total Contribution (1-Year Lag)	0.942***	0.944***	0.944***	0.943***
	(0.00802)	(0.00860)	(0.00852)	(0.00858)
Investment Income	0.00553***	0.00578***	0.00580***	0.00746***
	(0.00140)	(0.00125)	(0.00126)	(0.00136)
Investment Income * High Returns Indicator	0.00902***	0.0759**	0.0178***	0.00740***
	(0.00316)	(0.0312)	(0.00493)	(0.00256)
Change in Median House Price	0.00522			
	(0.00399)			
Inv Income * High Returns * log Acc't Size		-0.00506**		
		(0.00235)		
Inv Income * High Returns * Acc't Age			-0.000575**	
			(0.000269)	
Investment Income * Low Returns Indicator				-0.0124***
				(0.00312)
Observations	40,393	51,811	51,604	51,829

Notes: Investment income is income earned in dollars from the Solo 401(k) accounts. The High Return Indicator equals one if yearly returns are in the top decile, and 0 otherwise. All regressions include year fixed effects and changes in employment in the different industries at a county and a national level. For brevity, we report only select coefficients the help describe investors' decisions. Standard errors are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6

Parameterization

Parameter	Variable	Value
β	Time rate of preference	0.9491
γ	Coefficient of relative risk aversion	2.0
ρ	Autoregressive parameter of the persistent income component	0.935
σ_η^2	Variance of the innovation to the persistent income component	0.061
σ_ϵ^2	Variance of the transitory income component	0.017
φ	Replacement ratio	0.6
τ^{kt}	Tax rate on taxable income	0.352
τ^{kd}	Tax rate on tax-deferred income	0.134
τ^l	Tax rate on labor income	0.30
τ^c	Tax rate on consumption	0.05
a	Curvature of approximation function	200
ξ^{65-}	Ordinary tax rate to withdrawals/deferrals before age 66	0.285
ξ^{66+}	Ordinary tax rate to withdrawals after age 66	0.178
ξ^p	Penalty on withdrawals before age 59.5	0.100

Notes: The table reports the values of model parameters.

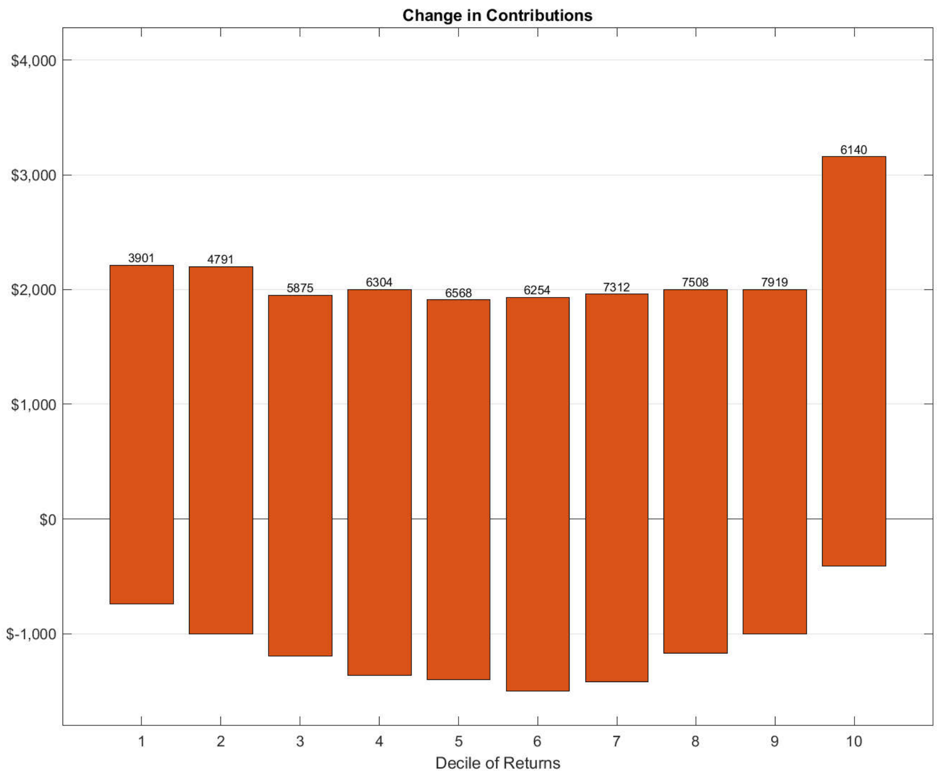

Figure 1 **Changes in Contributions By Decile of Returns.**

The dollar change in contributions conditional on Solo 401(k) returns. The x-axis is the decile of the annual percent return. The number above each bar is the number of observations in that decile; each bar shows the middle two quartiles (25th–75th percentile) of the empirical distribution of those observed changes in contributions. Our calculations are based on Form 5500 data for single-employee businesses.

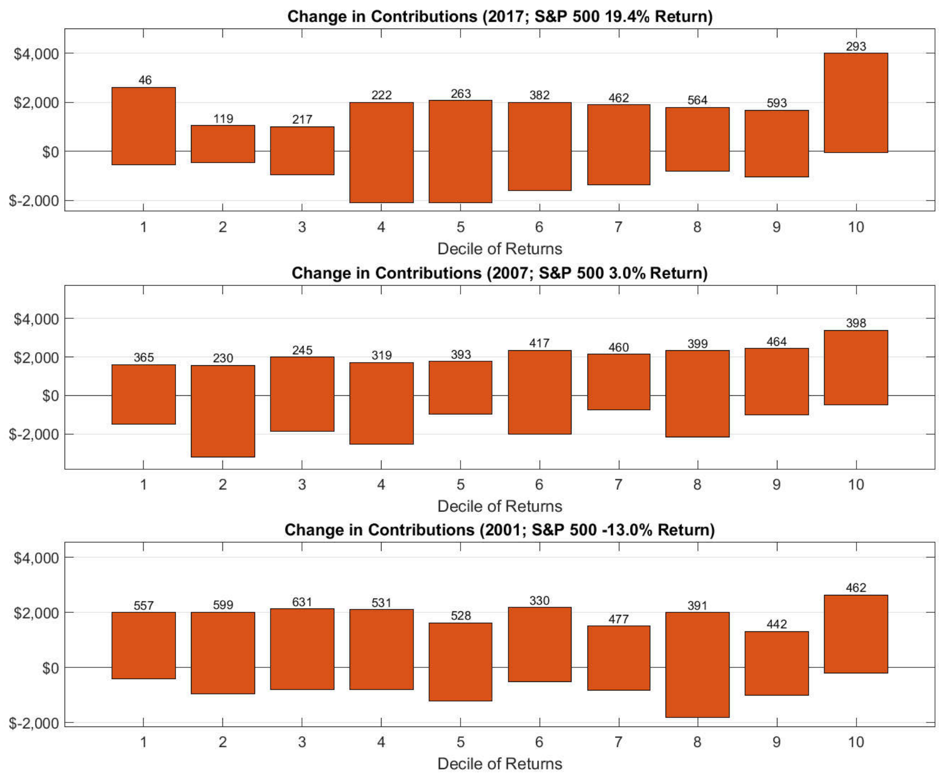

Figure 2 **Changes in Contributions by Return and Year.**

Each panel represents the dollar change in contributions in three illustrative years. The x-axis is the decile of the annual percent return. The number above each bar is the number of observations in that decile; each bar shows the middle two quartiles (25th–75th percentile) of the empirical distribution of those observed changes in contributions. The top panel shows investors' behavior in 2014 (the lower bound of the top decile is 13 percent), the middle panel in 2005 (the top decile is bounded below by 14 percent), and the lower panel in 2001 (the lower bound of the top decile is six percent). Our calculations are based on Form 5500 data for single-employee businesses.

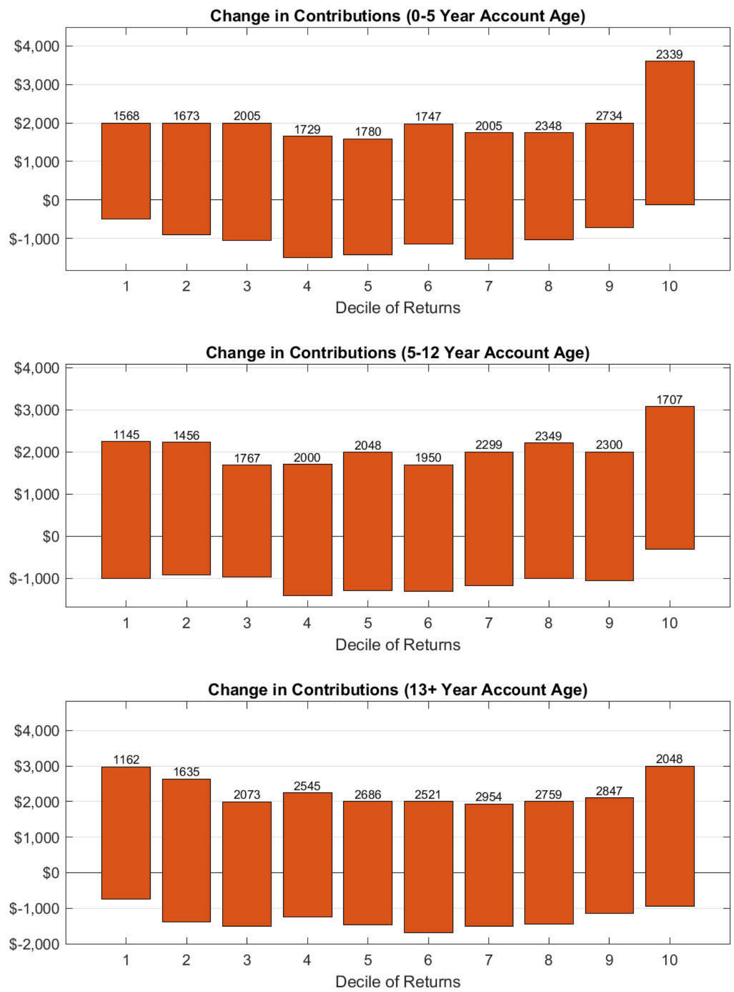

Figure 3 **Changes in Contributions by Account Age.**

The dollar change in contributions conditional on account age. The x-axis is the decile of the annual percent return. The number above each bar is the number of observations in that decile; each bar shows the middle two quartiles (25th–75th percentile) of the empirical distribution of those observed changes in contributions. Top panel: The dollar change in contributions conditional on having the account open for one to four years. Middle panel: The dollar change in contributions conditional on having the account open for five to 12 years. Bottom panel: The dollar change in contributions conditional on having the account open for more than 12 years. Our calculations are based on Form 5500 data for single-employee businesses.

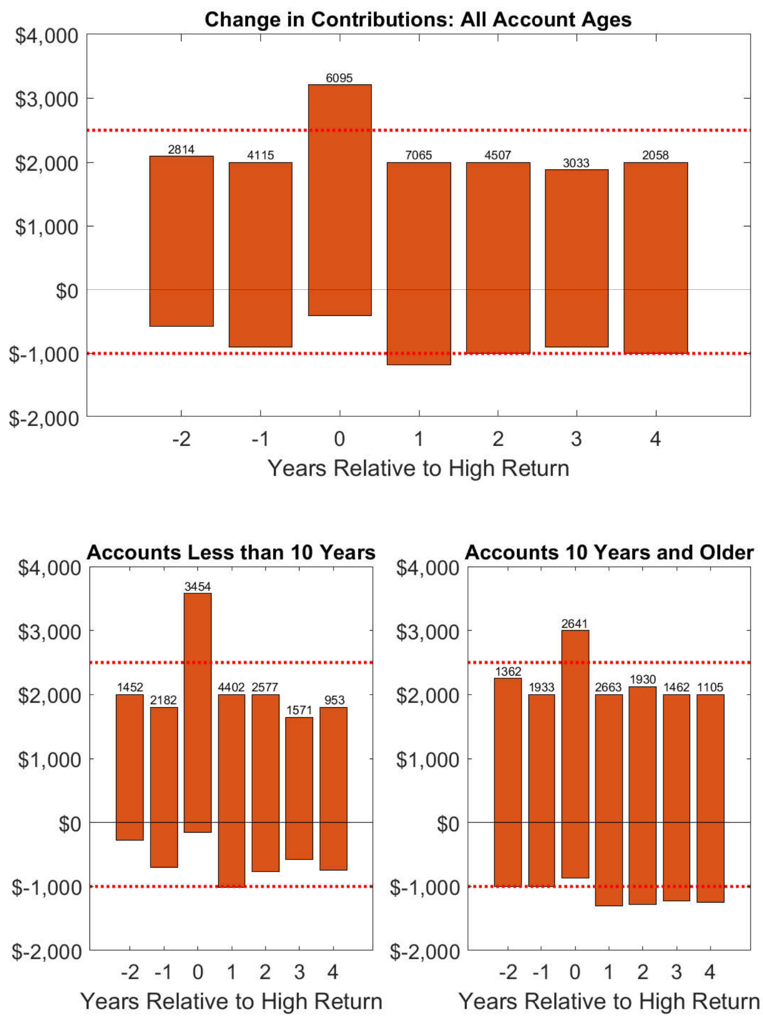

Figure 4 **Changes in Contributions over Time.**

he bars display the range of the middle two quartiles (25th–75th percentile) of the empirical distribution of changes relative to the year in which the investor earned 401(k) returns in the top decile ($t = 0$). The horizontal lines are the middle two quartiles for the entire sample of changes in contributions. Top panel: The dollar change in contributions for the entire sample. Bottom left panel: The dollar change in contributions for accounts open fewer than 10 years. Bottom right panel: The dollar change in contributions for accounts open 10 or more years. Our calculations based on Form 5500 data for single-employee businesses.

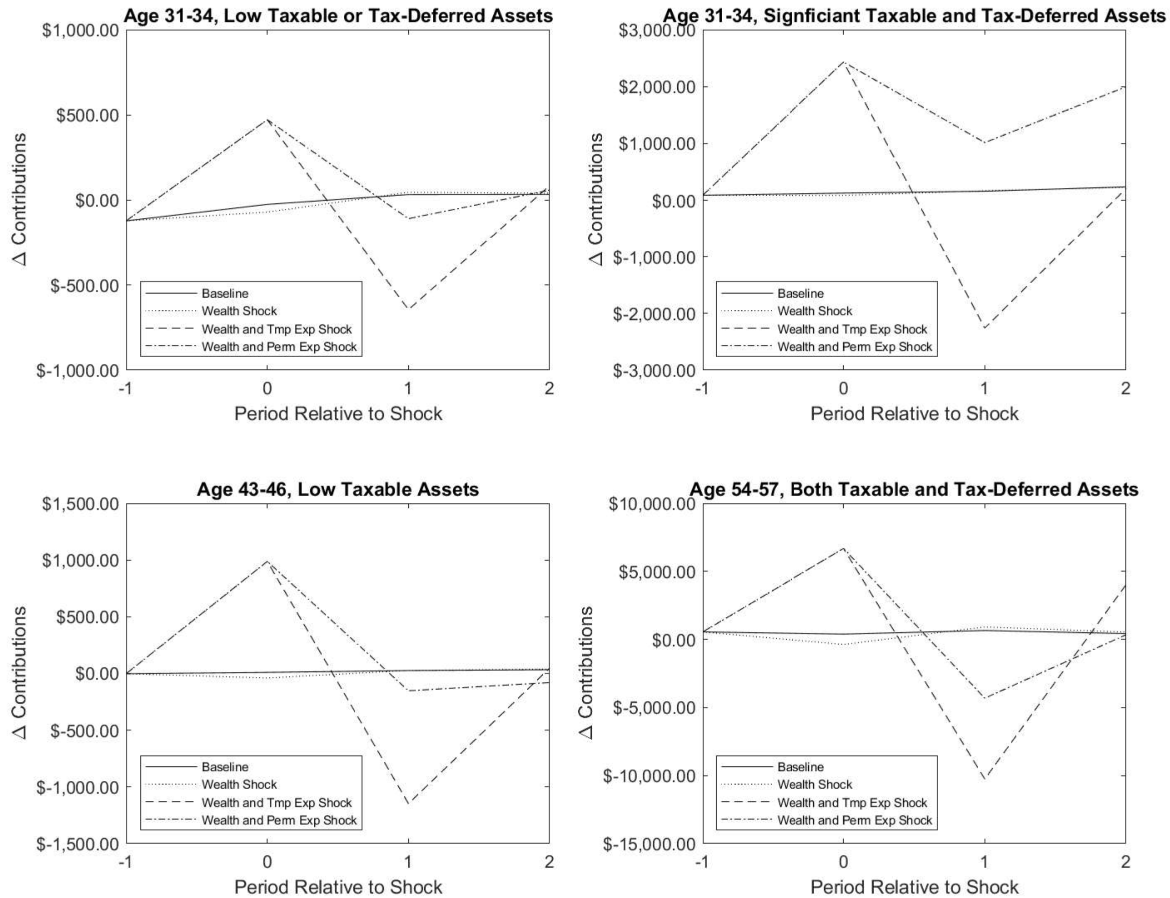

Figure 5 **Changes in Investment in Tax-Deferred Accounts for Select Individuals.**

Selected simulated individuals, chosen for having constant labor productivity realizations over four periods. The solid line (Baseline) shows the baseline change in investment in the tax-deferred account. The dotted line (Wealth Shock) shows the change in investment in the tax-deferred account when the individual earns an additional 15 percent in period $t = 0$. The dashed line (Wealth and Tmp Exp Shock) shows the change in investment in tax-deferred account for an individual earning an additional 15 percent and expecting in period $t = 0$ that all future returns would increase by one percent. The dotted and dashed line (Wealth and Perm Exp Shock) shows the same, except that in all periods $t \geq 0$, the individual expects returns to increase by one percent in all future periods.

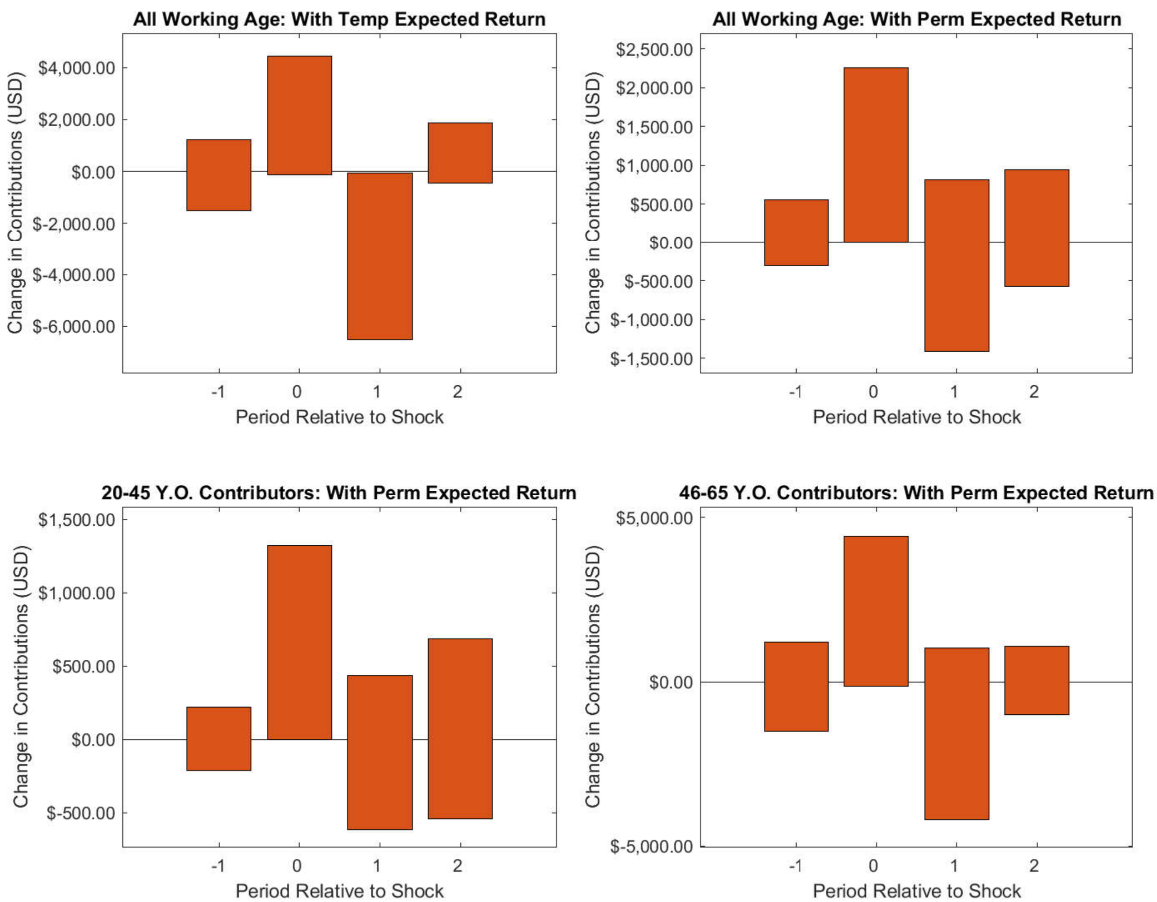

Figure 6 **Changes in Contributions for All Individuals.**

The bars display the range of the middle two quartiles (25th–75th percentile) for the dollar change in contributions relative to the year in which the agent has a wealth and expectations shock (period $t = 0$). Top left panel: All individuals making positive contributions to their tax-deferred accounts. Top right panel: All individuals making positive contributions to their tax-deferred accounts. Bottom left panel: All 45-year-old and younger individuals making positive contributions to their tax-deferred accounts. Bottom right panel: All individuals between 45 and 65 years old making positive contributions to their tax-deferred accounts.

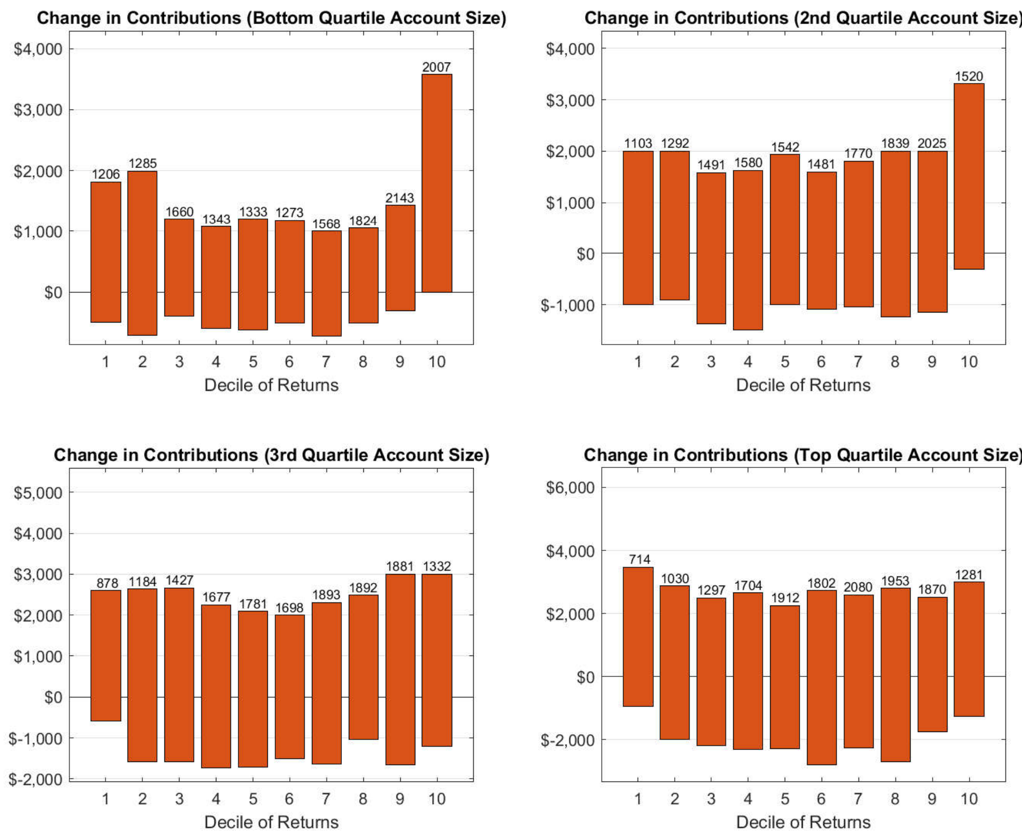

Figure 7 **Changes in Contributions by Account Size Quartile.**

The dollar change in contributions conditional on Solo 401(k) returns by account size. The x-axis is the decile of the annual percent return. The number above each bar is the number of observations in that decile; each bar shows the middle two quartiles (25th–75th percentile) of the empirical distribution of those observed changes in contributions.

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