The Zero Bias in Target Retirement Fund Choice

AJAY KALRA
XIAO LIU
WEI ZHANG

Using a sample of individuals who hold target retirement funds (TRFs), we examine how people use arithmetic to estimate their retirement age. We find a robust "zero" bias where investors have a strong preference for TRFs that end with zero compared to TRFs that end with five. The evidence is consistent that the bias is an outcome of people using imprecise arithmetic, specifically rounding up and down in the computational estimation required to estimate their retirement year. The zero bias manifests itself in people born in years ending between eight and two. Those born in zero- through two-ending years select TRFs that imply they intend to retire at 70, whereas those born in eight- and nine-ending years choose TRFs that imply retiring at 60. The choices can significantly lower or increase wealth by altering the contribution amounts and exposing investors to risk incompatible with their age profile. The bias is particularly costly for those who are risk averse and select later TRFs but is also most beneficial to risk-averse consumers who choose early TRFs. We experimentally confirm that the contribution rates are related to the TRF choices and that the use of imprecise mathematical rounding is implicated in the bias.

Keywords: cognitive bias, computational estimation, retirement savings, behavioral finance

In many purchase decisions, consumers mentally solve numerical problems that require the use of mathematical operations. For example, estimating the cost of a vacation entails adding up the various components (airfare, hotel, meals, entertainment, and other expenses), as does determining the total cost of a wedding (catering, flowers, liquor, and other items). Similarly, converting currencies and adding taxes to determine the total price require computation. Sometimes, consumers may also have to perform subtraction—for example, the percentage off the regular price to arrive at the promoted price—or use multiplication when buying multiple units. How do consumers make these simple mental arithmetic calculations and what is the impact of the process they use?

A common decision that requires simple arithmetic is an individual's decision about when to retire. This question has to be addressed by approximately half of the American population who save for retirement using a defined contribution plan such as a 401(k) or 403(b) as part of their financial planning goals. We examine the decision using data from people selecting target retirement funds (TRFs), for which they are explicitly required to choose their likely retirement year. TRFs, named for targeting a specific year a person anticipates retiring, involve selection from a menu

Ajay Kalra (ajay.kalra@rice.edu) is Herbert S. Autrey Professor of Marketing at Jesse H. Jones Graduate School of Business, Rice University, 6100 Main Street, Houston, TX 77005-1892, USA. Xiao Liu (xliu@stern.nyu.edu) is an assistant professor of marketing at the Leonard N. Stern School of Business, New York University, Henry Kaufman Management Center, 44 West Fourth Street, New York, NY 10012, USA. Wei Zhang (wtzhang@iastate.edu) is Kingland Faculty Fellow in Business Analytics and an associate professor of marketing at Debbie and Jerry Ivy College of Business, Iowa State University, 2167 Union Drive, Ames, IA 50011, USA. Please address correspondence to Ajay Kalra. All the authors contributed equally. The authors want to thank Jiawei Li for her assistance and Utpal Dholakia, Jamie Brown, and Huifang Mao for their feedback. Supplementary materials are included in the web appendix accompanying the online version of this article.

Editor: Margaret C. Campbell

Associate editor: Gerald Häubl

Advance Access publication July 3, 2020

 • Vol. 47 • 2020
DOI: 10.1093/jcr/ucaa035

of choices with 5-year intervals (e.g., 2030, 2035, 2040). There are several possible routes to determine retirement year, including adding the desired age of retirement to birth year, adding how many more years one desires to remain in the workforce to current age, or estimating with more complex heuristics. Regardless, all involve the use of arithmetic where calculations are made mentally.

Using a large dataset from a global financial investment management firm that offers retirement plans, we identify a systematic "zero" bias in individuals' retirement investment decisions, which is a tendency to select zero-ending TRFs as compared to five-ending TRFs. A preference for zero-ending TRFs implies that some individuals intend to retire either at the age of 60 or 70, rather than 65. The zero bias is consistently evident for people born in the 1950s through the 1980s. The selection of the TRF is based on the birth year, with those born in years ending eight or nine (e.g., 1968, 1969) projecting retirement at 60, whereas those born in years ending in zero, one, or two (e.g., 1970, 1971, 1972) choosing TRFs consistent with retiring at 70. We find evidence of rounding heuristics with rounding up being more prevalent than rounding down.

We find that the zero bias affects investors in two substantial ways. First, it may lead to an investment portfolio with an incompatible level of risk. Second, the choice of the TRF appears to impact the amount people contribute toward their retirement savings. This suggests that it may perceptually alter the perceived number of earning years left before retirement. Together, these two results can significantly lower the total wealth accumulated at retirement for a segment of investors. We specifically see this with those investors who are born in years ending in eight or nine who tend to select earlier TRFs—funds with a maturing date earlier than the intended retirement year. On the other hand, the bias is beneficial to the consumers born in zero-, one- and two-ending years who are more likely to select later TRFs—funds with a maturing date later than the intended retirement year. Our simulations find that approximately 34% of people born in eight- or nine-ending years select early TRFs, and all of them end up financially worse off. In contrast, about 29% of people born in years ending 0–2 select later TRFs and end up better off except for those who are risk averse. In general, the losses for those selecting the mismatched TRFs (inconsistent with retiring at 65) are greater than the gains.

We replicate the zero bias in an experimental setting and find evidence suggesting that the choice of TRF can influence contribution rates of retirement savings. The experimental data also confirm that the use of imprecise mathematics causes the rounding bias, specifically the use of rounding heuristics. We find that the bias is attenuated when preceded by solving simple mathematical problems. We further explore demographic factors where the likelihood of observing the zero bias is stronger. We find that males, higher income, and older people are more likely to demonstrate the bias. We also observe that investors who participate in a simple 30-minute financial planning program are less likely to exhibit the zero bias tendency.

We contribute to three literature streams. First, our findings add to the literature that observes a preference for round numbers (Allen et al. 2017). In contrast to this literature, which shows round numbers as a reference or aspiration point, in our context, the zero bias is an outcome of rounding up or rounding down when using computational heuristics. We also contribute to the literature on computational estimation (Lemaire and Arnaud 2008; Lemaire and Lecacheur 2001) by examining the use of arithmetic in a substantive problem and find that people choose rounding-up heuristics more than rounding down in this class of problem. Finally, we contribute to the literature in behavioral finance by identifying a strong bias in the selection of one of the most popular retirement investment vehicles.

Our findings have direct implications for financial firms, advisors, and customers. We identify the birth years of consumers who are more prone to the bias and their specific tendencies to select earlier or later TRFs. We have also identified the combination of birth years and risk aversion levels that make specific segments the most vulnerable. When designing retirement plan menus, policymakers or fund providers should take the zero bias into consideration, clearly emphasize the implications of the choices to consumers at the point of decision, and nudge investors to make selections that maximize financial well-being.

We first review the relevant literature on retirement saving behaviors and the round number bias. Our main results about the zero bias are presented next. We then use simulations to quantify the economic impact of the zero bias. Next, we discuss the possible mechanisms of the zero bias. Then, we examine heterogeneity and explore predictors of the zero bias. Finally, we conclude and discuss the implications of our findings.

BACKGROUND AND LITERATURE REVIEW

Retirement Savings

Currently, US retirement assets total approximately $32.3 trillion (Investment Company Institute 2020). According to the Federal Reserve's Report on the Economic Well-Being of US Households (Board of Governors of the Federal Reserve System 2019), in 2018, 54% of the American population saved for retirement using a defined contribution plan such as a 401(k) or 403(b). With a 401(k), employees control how much to save, and employers typically match this contribution, often with either a 50% or a 100% matching rate up to a specific limit. In addition, employees control how the money is invested. Most plans offer a spread of mutual funds consisting of stocks, bonds, and money market investments. Employers usually hire a financial administrator such as Fidelity Investments to oversee the accounts. Based on the options made available by the administrator, employees decide on their investment portfolio and the specific allocation. As 401(k)s put much of the burden on individual choices, the quality of investment decisions plays a crucial role in people's future standard of living.

Target Retirement Funds

TRFs are funds named for a target retirement date. For example, Vanguard offers the Target Retirement 2060 Trust, BlackRock offers the LifePath 2030 Investor Fund, and Manning & Napier offers the Target 2035 R Fund. Generally, TRFs assume that employees retire at the age of 65. This is consistent with surveys identifying that approximately 80% of employees anticipate retiring at 65 (Nationwide 2017). TRFs are funds that hold many underlying stocks, bonds, and money market assets that help employees become fully diversified. For those opting to invest in TRFs, the choice of the funds is between alternatives with years ending either in zero (e.g., 2030, 2040) or in five (e.g., 2035, 2045). An important benefit accorded by TRFs is that they automatically rebalance the portfolio over time, decreasing the percentage invested in stocks and increasing the percentage invested in bonds. In other words, they follow a glide path to reallocate the percentage in each type of asset class.

For example, in a Vanguard TRF, for an investor who is 20–40 years old, almost 90% of retirement savings are invested in either international or US stocks. Then, in the next period between 40 and 65, the percentage in stocks gradually decreases while the percentage in bonds gradually increases. When the investor turns 65, only 50% of the assets remain in stocks. This ratio for stocks further decreases in the early retirement period and finally reduces to less than 30% after age 72 (see web appendix A for examples of glide paths).

Due to the "set it and forget it" approach that alleviates the pain for individuals who are not comfortable navigating financial decision-making, TRFs have become a very popular investment choice. According to a joint study by the Employee Benefit Research Institute and the Investment Company Institute (VanDerhei et al. 2018), in 2016, 72% of the 401(k) plans offered TRFs, 50% of 401(k) investors held TRFs, 21% of all 401(k) assets were invested in TRFs, and 38% of the recently hired participants' account balances were invested in target-date funds. More importantly, TRFs are proliferating. From 2008 to 2017, TRFs increased from $158 billion to $1.11 trillion in assets (Holt 2018). In addition, they are especially popular among young employees. According to Fidelity, 69% of millennials are entirely invested in this fund group (Fidelity 2020).

Round Number Bias

As previously described, individuals have a choice of selecting between zero-ending and five-ending TRFs. Prior findings suggest an affinity and preference for round-ending numbers (zeros).

First, literature across different domains has recorded the tendency to self-report using round numbers. For example, it has been observed that people use round numbers to self-report physical characteristics such as their own heights (Bopp and Faeh 2008), measurements such as beer-cask volumes or beer-bottle contents (Cunliffe 1976), and behaviors such as the number of cigarettes smoked daily (Klesges, Debon, and Ray 1995). Finance and economics literature find price clustering around round prices (zero and five) in financial markets such as stocks (Sonnemans 2006), gold (Lucey and O'Connor 2016), and bitcoins (Urquhart 2017).

People are also more likely to respond using round numbers when estimating or guessing. For example, Plug (1977) found that when asked to provide estimates of breadth-to-height ratios of geometrical figures, respondents used round numbers. It has been speculated that preferences for round numbers occur because they are likely more fluently processed than non-round numbers. In addition, round numbers occur more in the environment, for example, in texts (Coupland 2011), thereby leading to a familiarity-based effect (Zajonc 2001).

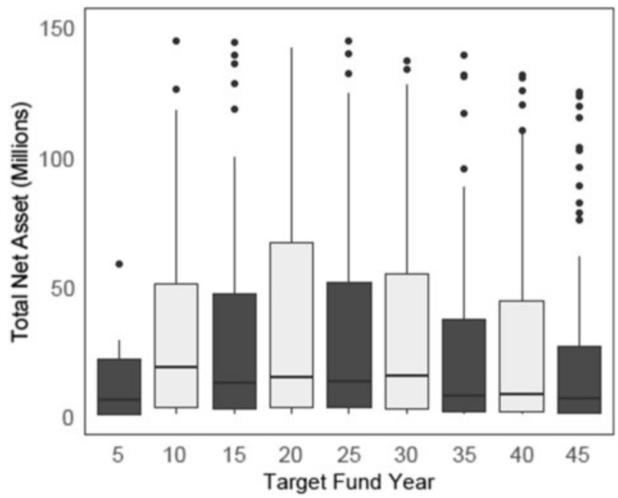
Round numbers are also utilized by people as benchmarks or reference points against which to judge their own performance. For example, SAT takers set goals at round scores like 1,300, professional baseball players aim for batting averages at numbers like 0.300 (Pope and Simonsohn 2011), and marathon runners aspire to full hours (e.g., 4 hours) as completion times (Allen et al. 2017).

In contrast to these findings where people use round numbers as goals toward which they expend effort, the zero bias in investment decisions suggests that the affinity for using a round-ending calendar year as a time to retire is a result of a rounding bias in mathematical calculations.

Findings in the computational estimation literature, defined as determining approximate answers to simple arithmetic problems, show the use of rounding-down or rounding-up strategies to arrive at solutions (Lemaire and Lecacheur 2001; Siegler and Lemaire 1997). For example, people mentally compute $146 + 59 + 48$ to be 260 by rounding up operands ($150 + 60 + 50$) or calculate 63×12 to be 600 by rounding down operands (60×10). Comparing strategies used by younger and older people, Lemaire and Arnaud (2008) found greater use of columnar retrieval by older people. For instance, in a problem of adding $12 + 46$, columnar retrieval is defined as first adding the units and then the decades ($[2 + 6] + [10 + 40]$) indicating more reliance on round numbers. The computational estimation literature finds that multiple strategies are used

FIGURE 1

DISTRIBUTION OF TOTAL NET ASSETS BY TRF YEAR



to solve different problems based on the characteristics of the problem (Campbell and Xue 2001), the situation (Trbovich and LeFevre 2003), and individual differences (Gandini, Lemaire, and Michel 2009). This literature also concludes that individuals often use multiple strategies for the same problem (Dowker 1996).

All these findings across different domains suggest that when making investment decisions, there may be a preference for zero-ending years in the choice of TRFs. To gather preliminary evidence, we collected the total net assets information of all the TRFs in the market from the Center for Research in Security Prices database. We used data from 3,289 TRFs of 443 TRF fund families and 64 providers in 2014. We define a provider to be a firm (e.g., Vanguard). A fund family denotes a particular share class of a fund. For example, "Vanguard TRF A shares" is a fund family. Within it, there are 12 funds that are divided into 5-year increment funds from 2005 to 2045. With the data from the entire universe of all TRFs, we present the distribution of total net assets by TRF year in figure 1. The *y*-axis represents the total net assets in millions of dollars. The dark gray boxplots represent the five-ending TRFs, and the light gray boxplots represent the zero-ending TRFs. Consistently, across all decades, the light gray boxes are higher than the dark gray boxes, for both the median and the third quartile, revealing that the total net assets in the zero-ending TRFs are higher than that in the five-ending ones. This plot suggests that consumers prefer the zero-ending TRFs to the five-ending TRFs.

Although the aggregate data from total assets held by the population indicate a general tendency for a preference to round-ending years, a limitation of the data is that when TRFs were first introduced, some of them offered only the zero-ending TRFs. To verify the preferences and better understand the underlying process, we obtained individual-level data of investors' choices.

DATA AND FINDINGS

Zero Bias

To study individual investors' choices among TRFs, we obtained data from a global financial investment management firm that offers retirement plans. Our 2016 proprietary data include 84,600 individual accounts from defined contribution plans of 52 employers. For confidentiality reasons, we were not provided the names of the employees or the employers. On a typical website, the TRFs' targeting retirement years are listed chronologically (e.g., 2020–2065). As the commission rates are quite similar, the focal firm has no incentive to promote any TRF of a specific year. Instead, the focal firm's main goal is to increase investment amounts in the 401(k) plans.

Nearly half of the sample (40,848 accounts) invests in TRFs. In total, our data contain 91 different TRFs from six fund providers. We observe each investor's fund choice, monthly contribution amounts, and some demographic characteristics (e.g., age, gender, marital status). Out of those who invest in TRFs, 33,876 (82.95%) invest their entire 401(k)s in only one TRF. We used only these in our analysis. Among them, 2,484 (7.33%) customers started investing before both five-ending TRFs and zero-ending TRFs became available. We deleted those observations. The final dataset consists of 31,392 customers. Table 1 provides the summary statistics of the demographics.

We first examine the choice of the TRFs. In figure 2, the solid line depicts the number of investors choosing each of the TRFs (aggregated across all providers). One easily observes that the number of investors who select any of the 2020/2030/2040/2050 ending dates is much higher than the number of investors who opt for any of the 2025/2035/2045/2055 ending dates. This confirms a zero bias in that investors choose more TRFs with years ending in zero than those ending in five.

We first conduct a robustness check to rule out that the zero bias is due to an unbalanced distribution of investor age. It is plausible that more people in our sample potentially retire around zero-ending years rather than five-ending years. To investigate this possibility, we plot the predicted number of investors choosing each TRF in figure 2, using the dashed line. To obtain the predicted number of investors choosing each TRF, we assume the typical retirement age of 65 and use each investor's birth year plus 65 to calculate their predicted retirement year and hence the associated TRF. For example, for those born in 1978, the predicted retirement year is $1978 + 65 = 2043$, leading to the 2045 fund. The dashed line in figure 2 reveals that

TABLE 1

SUMMARY STATISTICS OF DEMOGRAPHIC VARIABLES

	Sample size	Mean	Median	Std	Min	Max
Age	31,386	46.97	47.00	10.80	26.00	86.00
Female	30,174	0.50	0.00	0.50	0.00	1.00
Income	30,034	$65,495	$60,000	$29,589	$15,000	$373,000
Married	1,036	0.67	1.00	0.60	0.00	1.00
Tenure (years)	31,392	10.98	9.00	6.04	2.00	50.00
Deferral %	31,392	4.10%	3.00%	5.45%	0.01%	21.00%
Number of cities	4,356					
Number of states	50					
Number of NAICS	43					
Number of sectors	14					

FIGURE 2

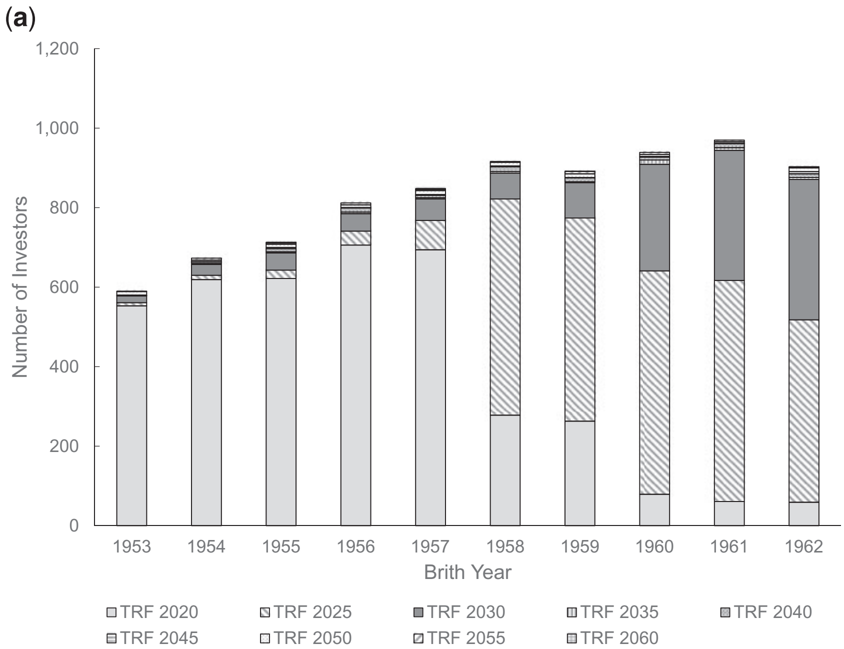
ACTUAL VERSUS PREDICTED FREQUENCY OF TRFS

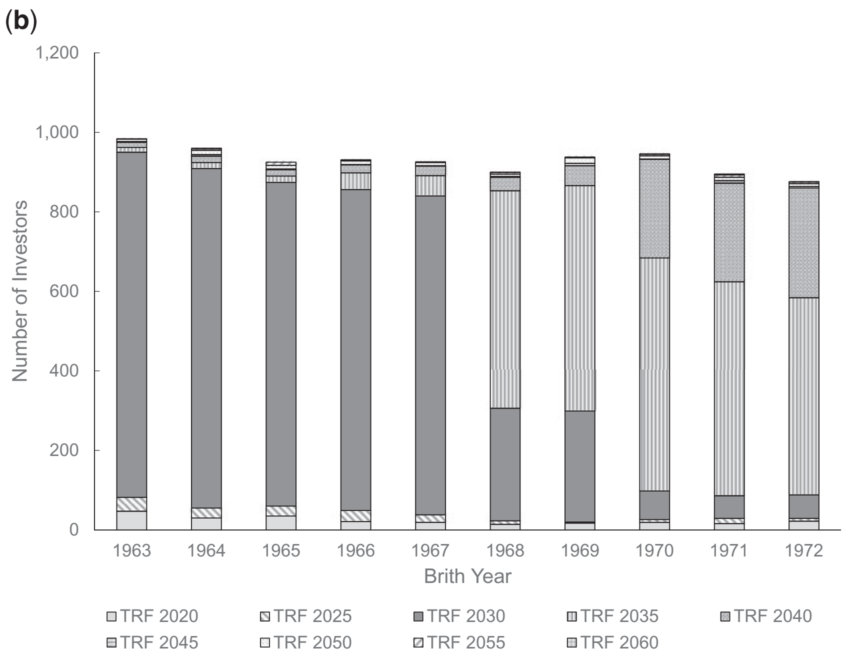
the distribution of investors' predicted target retirement years is almost uniform, ranging from 2020 to 2050. This confirms that the random sample of investors is representative. However, the observed number of investors for each fund shows a strong zigzag pattern, as displayed by the solid line.

We conduct two robustness checks to verify whether the presence of a default fund drove this pattern. It is possible that some firms suggest default choices when their employees are deciding their 401(k) portfolios. One default could be the recommendation of a TRF matching the employees' retirement age of 65. Another default could be that a firm recommends a zero-ending TRF. Our data consist of 52 firms. Due to confidentiality issues, we cannot pinpoint which employers offer default funds. However, we are able to conduct analysis at the firm level to rule out these alternative explanations. If an employer offers an age-appropriate default TRF (retiring at age 65), we should observe fewer people deviating from that choice. Therefore, for each employer, we calculate the percentage of the investors that are "deviators"; that is, their choice of fund is different from the TRF that matches the employee's retirement age of 65. Seven firms have a relatively low percentage of deviators, which is <10%. We consider them as potential firms that offer an age-appropriate TRF as the default. We delete these seven firms (7,736 observations, 22.84% of the sample). Our main results still hold. There are also six firms where the zero bias is exhibited by more than 90% of the employees, suggesting that there could be a zero-ending default TRF. After removing these six firms,

FIGURE 3

(A) FUND CHOICE DISTRIBUTION FOR INVESTORS BORN BETWEEN 1953 AND 1962. (B) FUND CHOICE DISTRIBUTION FOR INVESTORS BORN BETWEEN 1963 AND 1972. (C) FUND CHOICE DISTRIBUTION FOR INVESTORS BORN BETWEEN 1973 AND 1982. (D) FUND CHOICE DISTRIBUTION FOR INVESTORS BORN BETWEEN 1983 AND 1992



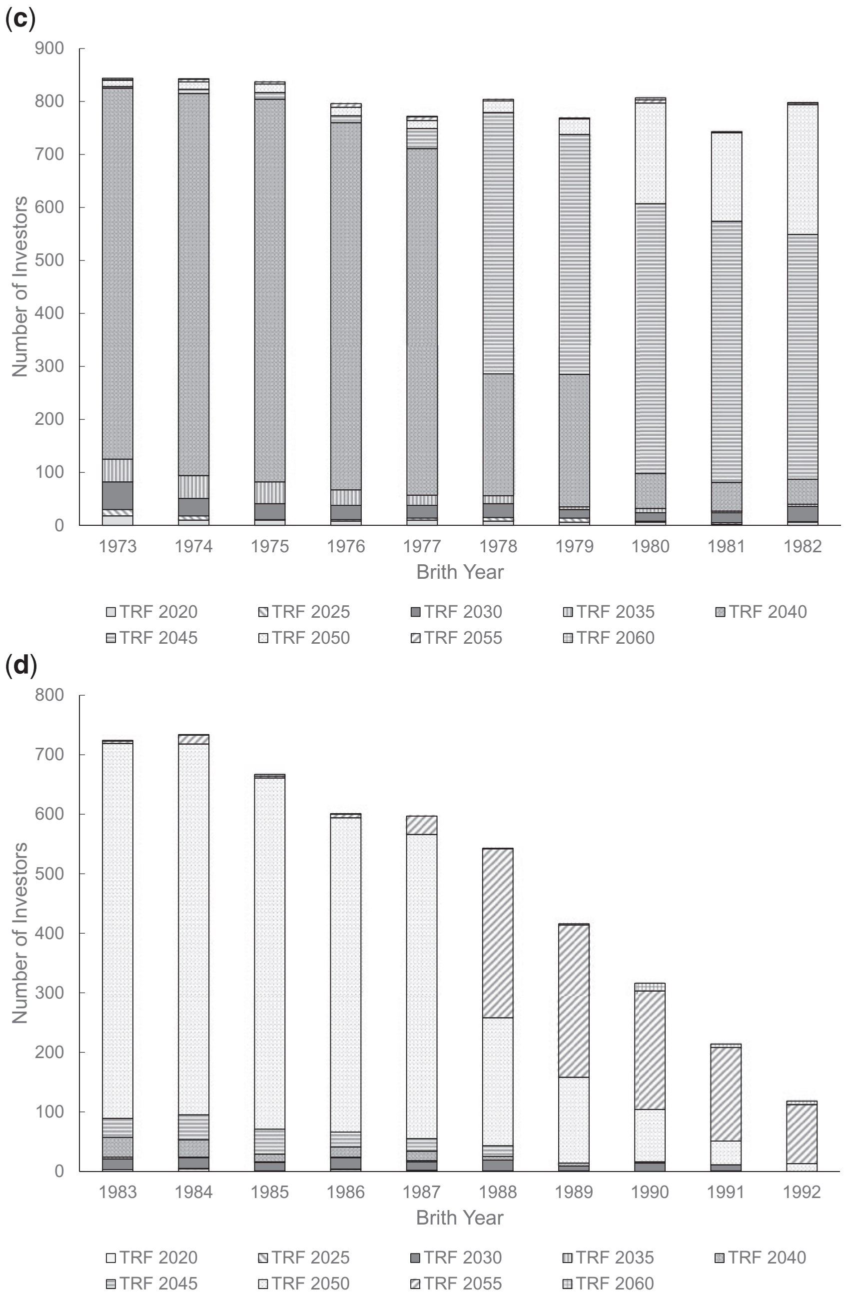


we still find a strong zero bias in the remaining data. See the detailed results in web appendix B.

To decipher the origin of the zigzag pattern in figure 2, we depict the choices made by investors of each birth year in figure 3a–d. The different patterns in figure 3a–d represent funds with different target dates, while the height of the bar represents the number of investors. For example, for those investors born in 1958, 32.11% chose 2020 (light

FIGURE 3

CONTINUED



gray), 57.01% selected 2025 (diagonal stripe), and 7.64% picked the 2030 fund (dark gray).

Figure 3a plots the fund choice for each investor born between 1953 and 1962. Consistent with data that indicate that most people retire at 65, we will refer to the fund corresponding with retirement at 65 as the matching fund from this point forward. For easy exposition, we group birth years that should lead to the selection of the same TRF. Assuming a retirement age of 65, for people born in the 1955 birth group {1953,1954,1955,1956,1957}, the 2020 fund is the matching fund, whereas for those in the 1960 birth group {1958,1959,1960,1961,1962}, the 2025 fund matches the retirement year. Given that TRFs have only zero-ending and five-ending alternatives, investors with birth years not ending with zero or five must perform computations that involve some form of rounding. For example, investors born in 1956, if planning to retire in 2021 (at age 65), should choose the 2020 TRF by rounding down ($1956 + 65 = 2021$), whereas those born in 1958 should select 2025 by rounding up ($1958 + 65 = 2023$).

We now discuss the specific patterns that emerge in the choice of TRFs. The first is that the zero bias originates primarily from investors born in the zero-ending birth groups—those who should choose the appropriate five-ending TRFs. However, instead of choosing the matching five-ending funds, they select the zero-ending ones. Figure 3a illustrates the shift in behavior for this group. Although 87.85% of the investors born in the 1955 birth group {1953,1954,1955,1956,1957} pick the matching 2020 date, only 56.97% of the investors born in the 1960 birth group {1958,1959,1960,1961,1962} choose their matching 2025 TRF. We observe similar patterns in other birth-year groups (1970, 1980, and 1990) as well, as shown in figure 3b–d. The pattern is clearly visible in all the figures. For brevity, we do not report all the numbers. Overall, the percentage of people selecting the appropriate matching fund is significantly lower in the zero-ending birth groups (59.65%) compared to the five-ending birth groups (86.91%) ($\chi^2(1) = 2{,}919.97$, $p < .0001$).

Second, the zero bias is asymmetric: investors with birth years ending with eight or nine tend to choose an earlier date (retire at 60), whereas investors with birth years ending with zero, one, or two tend to pick a later date (retire at 70). For instance (figure 3a), 56.97% (diagonal stripe) of the investors in the 1960 birth group selected the matching 2025 date, leaving the rest 43.03% as deviators. Within the deviators born in 1958 or 1959, the majority or 71.85% (29.92% of the total, shown in light gray) deviate to the earlier 2020 TRF. Also, the majority or 83.89% (36.84% of the total, shown in dark gray) of the deviators born in 1960, 1961, or 1962 deviate to the later 2030 TRF. Across all the data, within the deviators born in years ending with eight and nine, 81.61% (32.90% of the total) select the earlier fund, whereas among the deviators born in zero-, one-, and two-ending years, 77.08% (31.47%) choose the later fund. Comparing those born in eight- or nine-ending years with those born in zero-, one-, or two-ending years, we find that the pattern of choices significantly differs for these subgroups born across the four decades (all ps $<$ .0001). The systematic pattern of selecting earlier or later TRFs based on the birth year confirms some use of mental arithmetic in solving the retirement age estimation problem.

The third noteworthy effect the data show is that individuals round up more than they round down. For instance, the matching fund for people born in 1970 is the 2035 fund, as it precisely matches their retirement age. Any deviation implies a choice between rounding down to 2030 or rounding up to 2040. The data show that 72.78% (262 out of 360) of the investors who deviate round up to 2040, suggesting a strong rounding-up tendency. Similarly, for people born in 1960, 79.05% (298 out of 377) round up to 2030, and for people born in 1980, 67.11% (200 out of 298) round up to 2050. The use of the rounding-up heuristic by those born in the zero years is consistent for all age groups. If we sum over deviators born in 1960, 1970, and 1980, 73.43% round up.

To further investigate whether there are any differences in the tendency to round up or round down, we next compare only the cohort born in eight- or nine-ending years with those born in one- or two-ending years. Of the total 6,292 individuals born in eight/nine, 2,133 (33.90%) round down, whereas out of the 5,963 consumers born in one/two, 2,177 (36.51%) round up. The difference between the frequency of rounding up and rounding down is significant ($\chi^2(1) = 9.13$, $p < .01$). Together, the data indicate strong evidence for the use of rounding up relative to rounding down.

WEALTH IMPLICATIONS

We now discuss the implications of the zero bias for investors' welfare in terms of the accumulated wealth over their life cycle. The choice of the TRF can potentially serve as an anchor point to determine the number of working years left before retirement. It may, therefore, impact the rate at which the consumer saves for retirement, with people saving more if retirement looms early or saving less if retirement appears far away. We quantify the welfare impact of the zero bias and decompose the effect to the amount contributed toward retirement and exposure to risk.

First, we find that individuals are more likely to contribute less if they select a later-date fund compared to selecting the matching TRF. Figure 4 shows the average contribution, measured as percentage of income, by the birth year of the individual. The three lines—dotted, solid, and dashed—represent the average contribution when investors choose an earlier date, the matching TRF that reflects the retirement age of 65, and a later fund, respectively. For example, for investors born in 1970, the fund that matches the retirement age of 65 is the 2035 TRF. Within these investors, those who choose the 2035 fund, on average, contributed 4.38% of their income toward their retirement. In contrast, those who choose the earlier 2030 fund, on average contributed 4.57%, which is significantly higher than that of investors who choose the 2035 fund ($t(656) = 13.82$, $p < .001$). On the other hand, those who select the later 2040 fund on average contributed 4.21%, which is significantly lower than that of investors who choose the 2035 fund ($t(832) = 11.26$, $p < .001$). The downward trend in figure 4 simply indicates that older

FIGURE 4

AVERAGE CONTRIBUTION AS A PERCENTAGE OF INCOME BY BIRTH YEAR

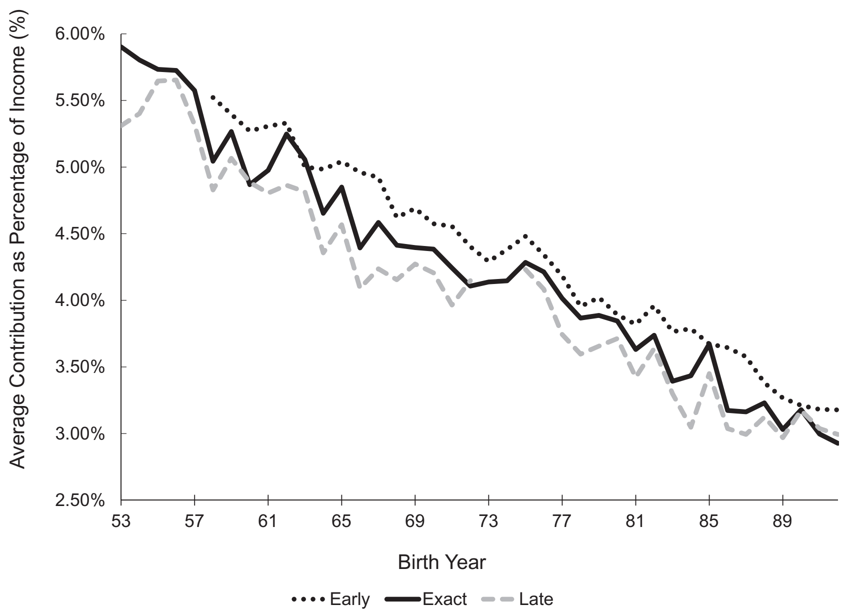


TABLE 2

REGRESSION OF PERCENTAGE CONTRIBUTED

Independent variables	Estimate	Standard error
Intercept	1.105467488***	0.06096842
Birth year	−0.000537638***	0.00003091
Income	0.000000129***	0.00000001
Female	−0.002430144***	0.00065761
Late TRF	−0.006961999***	0.00099075
Early TRF	0.007825348***	0.00099088
$N = 31{,}392$	$R^2 = 0.026$	

Note.—*** indicates .01 significance level.

people contribute a higher percentage. Summarizing over all age groups, we find that people who select a later retirement date contribute 4.63% less than those who pick the matching fund.

To verify the intuition in figure 4, we regressed the percentage contributed on age, income, gender, and choice of TRF. The results are provided in table 2. The analysis shows that those who select late (early) TRFs are more likely to contribute a lower (higher) percentage as compared to those who select the appropriate TRFs. We also find that older and richer individuals contribute more of their income. Interestingly, women contribute a lower percentage than men.

In addition to contributions, the zero bias exposes investors to different risk-return trade-offs: choice of a later date generally implies a higher risk than that of the TRF matching a retirement age of 65. To understand the impact of risk preferences on consumers' welfare, we follow the approach in Poterba et al. (2009) to simulate the retirement wealth.

The notion behind the simulation is to construct the path of contributions over an investor's life before retirement and combine these contributions with information on asset returns. For each investor, we simulated future retirement wealth using data from past monthly contributions and past returns. We extrapolate the data to obtain the yearly contributions until the age of 65 for each investor using these contribution trajectories, regardless of the chosen TRF.

For each investor i, let $C_i(a)$ be her contribution at age a, $R_i(a)$ be the return of TRF chosen by investor i at age a, and S_i be the age when investor i starts to invest for retirement. The retirement wealth at age 65 is therefore given by

$$W_i(65) = \sum_{t=0}^{65-S_i} \{\prod_{j=0}^{t} [1 + R_i(65 - j)]\} C_i(65 - t). \quad \textbf{(1)}$$

This equation implies that retirement wealth is the sum of the cumulative returns from each contribution throughout the working life. Because $R_i(a)$ is the return of a TRF whose mix of stocks and bonds varies with time, we collected data on the glide paths for each TRF in our sample. The glide paths inform us of the weights of stock and bond holdings. To simulate the returns, we chose a well-

TABLE 3

CONSUMER TRF CHOICE BY BIRTH YEAR GROUP

Birth year	No deviation (%)	Early TRF (%)	Late TRF (%)
8/9	59.4	33.9	6.7
0/1/2	61.5	9.9	28.6
3–7	86.6	7.0	6.5

established index to represent each asset class. For domestic stocks, domestic bonds, and international stocks, we used the S&P index, Bloomberg Barclays US Aggregate Bond Index and MSCI World Index, respectively. For the annual returns of each asset class, we made random draws from a distribution with mean and standard deviation based on historical returns. We collected 30 years (1988–2017) of historical return for the three indexes and calculate mean and standard deviations. During that period, the mean of S&P index was 12.14% and the standard deviation was 17.25%; the mean of Bloomberg Barclays US Aggregate Bond Index was 6.47% with the standard deviation of 4.91%; and the mean of MSCI World Index was 18.34% with standard deviation of 7.89%. We calculated the returns of the TRFs by varying portfolio weights over time according to the glide paths. Note that TRFs continue to accept monthly contributions and invest in various asset classes even after maturity. For the ease of comparison, we simulated retirement wealth only up until the age of 65.

Since any TRF consists of stocks and bonds where returns are uncertain, we simulate a consumer's retirement wealth using the following algorithm: for each specific investor i at age a, we generate a sequence of (65 - a)returns of stock and bond using random draws from the empirical return distribution of the assets in the TRF that the investor owns. Then, the sequence of returns of the entire TRF span is calculated by applying the weights obtained from the glide path of the TRF. Next, we use equation (1) to calculate the cumulative wealth at age 65. For each investor, we simulate the retirement wealth 20,000 times. To assess the impact of asset returns on consumers' well-being, we calculate consumers' expected utility associated with the distribution of these simulated terminal wealth values.

Because we do not observe individual risk aversion values, we follow Poterba et al. (2009) and compare the results at four different risk aversion values, $\alpha \in \{0,\ 1, 2, 4\}$, with higher values indicating stronger risk aversion.

Following Poterba et al. (2009), we use the utility function with a constant relative risk aversion parameter. As a result, the utility of investor i for the return history h (one iteration in the simulation) is given by

$$U_{ih}(W_{ih}) = \frac{W_{ih}^{1-\alpha}}{1-\alpha}. \tag{2}$$

We then obtain the expected utility as the probability-weighted average of these utility outcomes. Given that the expected utility is a function of consumers' risk tolerance, we construct a certainty equivalent measure, the total certain wealth that can provide utility at the same level as the expected utility. Specifically, the certainty equivalent of the accumulated wealth is

$$Z_i = E[U_{ih}(W_{ih}) \times (1-\alpha)]^{\frac{1}{1-\alpha}}. \tag{3}$$

The notion of a certainty equivalent suggests that an investor with a higher level of risk aversion has a lower expected utility for a later TRF because the later TRF puts investors in portfolios with higher variance. However, an investor with a low level of risk aversion will have a higher expected utility for the later TRF as a result of better expected returns.

We use equations (1)–(3) to simulate the retirement wealth (certainty equivalent) for all investors in our sample. We use each investor's TRF choice observed in the data to find the corresponding glide path. To make comparison easier, we assume that all the investors save between ages 25 and 65.

In tables 3 and 4, we present the wealth impact of the zero bias by birth year and the risk aversion levels. Risk aversion is particularly important to consider because a large percentage of the population can be characterized as highly risk averse (Barsky et al. 1997). For example, according to the 2014 Wells Fargo/Gallup Investor and Retirement Optimism survey (Saad 2014), majority of the working professionals and retirees prefer their investments to be secure, even if the growth potential is low. Furthermore, young workers who have more time to weather bear markets also favor security over high growth, indicating that they are risk averse.

Please note that when the relative risk aversion coefficient equals zero ($\alpha = 0$), the certainty equivalent of wealth and the actual wealth are the same. We classify the birth groups into three categories: those born in years ending {3,4,5,6,7}, {0,1,2}, and {8,9}. Table 3 shows the percentage of all people in the birth years who select either the early or later TRFs. Table 4 shows how investors fare due to the bias, accounting for the finding that the bias impacts retirement contribution rates. The results of wealth impact without contribution adjustment are included in web appendix C.

The first column in table 3 shows the percentage of consumers who are not impacted by the bias—those who select the matching TRFs. As can be seen, the {3,4,5,6,7} group is not much affected, with 86.6% selecting the matching choice, whereas the {8,9} group is most heavily impacted, with only 59.4% choosing the matching TRFs. We now discuss only the {8,9} and {0,1,2} birth years.

Consider the {8,9} group in the risk-neutral scenario in table 4. It shows that 33.9% of people born in {8,9} are

TABLE 4

DISTRIBUTION OF CONSUMERS' WEALTH CHANGES BASED ON TRF CHOICES (WITH CONTRIBUTION ADJUSTMENT)

		Deviation							
		Risk neutral ($\alpha = 0$)		Risk averse ($\alpha = 1$)		Risk averse ($\alpha = 2$)		Risk averse ($\alpha = 4$)	
Birth year	No deviation (%)	Worse off (%)	Better off (%)	Worse off (%)	Better off (%)	Worse off (%)	Better off (%)	Worse off (%)	Better off (%)
8/9	59.4	33.9	6.7	31.3	9.4	27.0	13.7	7.9	32.8
0/1/2	61.5	9.9	28.6	10.5	28.0	23.4	15.1	28.9	9.6
3–7	86.6	7.0	6.5	6.7	6.7	8.5	4.9	6.7	6.7

TABLE 5

WEALTH IMPLICATION (WITH CONTRIBUTION ADJUSTMENT)

Case	Birth year	Risk aversion	Gain/loss of early TRF relative to matching TRF (%)	Gain/loss of late TRF relative to matching TRF (%)
1	Nine ending	0	−14.77	1.35
2	Nine ending	1	−7.76	−0.95
3	Nine ending	2	−2.33	−3.74
4	Nine ending	4	4.39	−10.74
5	Zero ending	0	−20.67	2.03
6	Zero ending	1	−12.47	−0.51
7	Zero ending	2	−5.25	−3.50
8	Zero ending	4	5.15	−10.48

worse off, while only 6.7% are better off. These numbers indicate that all people (from table 3) born in the years {8,9} who deviate to the earlier TRFs end up worse off than if they had chosen the matching TRF. The reason that such a high percentage of investors are worse off is that an early TRF, consisting of a higher proportion of less risky portfolio, provides lower returns. Looking across the row, as risk aversion increases, the percentage of investors worse off in this group declines and the percentage of those better off increases. This is consistent with risk-averse people's preferences for low variability in returns.

In comparison, those born in {0,1,2} show the opposite pattern. Examining the risk-neutral consumers shows that 28.6% are better off whereas only 9.9% are worse off. More people born in these years buy later TRFs because of the zero bias, and end up with greater accumulated wealth as their portfolios have a higher percentage of stocks that provides greater returns. However, as risk aversion increases, their certainty equivalent declines as the portfolio is subject to excess risk.

We now turn to the magnitude of the impact for an individual consumer who selects early/late TRF versus matching TRF. We run the simulation for a consumer who was born in a either nine-ending or zero-ending year. Table 5 presents the wealth implications considering that consumers may adjust how much they contribute, with a lower contribution when buying a later TRF and a higher contribution when selecting an earlier TRF.

As can be seen, regardless of risk aversion, a consumer who chooses early TRFs, with the exception of very risk-averse investors, always ends up worse compared with a consumer who chooses the matching TRF. The magnitude of the losses from buying an early TRF is much larger for those born in the zero-ending year. Even though there is only a 1-year difference in time, the difference in losses is substantial. This difference occurs because the TRFs have a fixed schedule with the composition of the portfolio shifting in three phases from being stocks dominant to a "mixed" composition and finally to being bond heavy before the retirement year. During the mixed phase, the allocation of stocks and bonds changes to a more bond-heavy allocation. Compared to a person born in a zero-ending year, a person born in a nine-ending year has one less year on the stock-dominant portfolio. This 1 year decrease in the stock-heavy portfolio has a large effect as the investor misses out on the stock market return of the large accumulated portfolio balance.

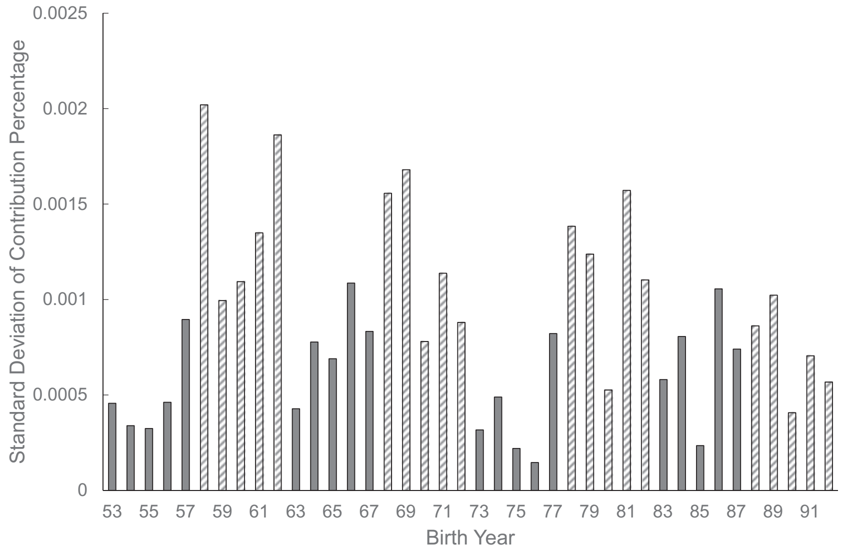
On the other hand, the well-being of a consumer who chooses a later TRF differs based on their individual level of risk aversion, with the return declining as risk aversion increases. When consumers are risk averse, they end up worse off by selecting any nonmatching TRF.

Finally, table 5 highlights the large difference the birth year makes to wealth. People born in a nine-ending year mostly deviate by selecting early TRFs and therefore end up worse. However, those born in a year later in a zero-ending year deviate mainly by choosing later TRFs and serendipitously are less impacted.

To summarize, selecting a nonmatching TRF exposes consumers to a portfolio with risk that may be

FIGURE 5

STANDARD DEVIATION OF CONTRIBUTION PERCENTAGE BY BIRTH YEAR



incompatible with their stage of life. The impact on consumers is particularly large if there is a huge volatility in the market during their intended year of retirement. For example, for consumers who were planning to retire in 2008 (financial crisis) or in 2020 (Coronavirus outbreak), the wealth impact of selecting a nonmatching TRF that is heavy on stocks is particularly pernicious. We now turn to examine the relationship between the choice of TRF and saving rates.

CHOICE OF TRF AND CONTRIBUTIONS TO RETIREMENT

The patterns in figure 4 that show an association between TRF choice and contribution rates as a percentage of income can be rationalized by two alternative explanations. First, if an investor can afford to save at a high rate now, she can choose to retire early, whereas another investor who cannot save adequately for retirement has to retire later. In other words, a consumer may first decide how much to save and then choose the retirement age and TRF accordingly. Second, there may be some other factor that drives both retirement age and contribution rate. In contrast, we suggest and provide evidence that it is likely that consumers first choose the expected retirement age and the associated TRF and then plan contributions accordingly. We do so using the real-world data supplemented with an experiment.

The data cast doubt on the two alternative explanations. Our intuition is that if it is true that consumers make the contribution decision before the TRF choice, then the contribution percentage should not be connected to the zero bias. That is, the contribution percentage choice should not be associated with whether her birth year is around zero or around five. Similarly, if factors other than the birth year are driving the contributions, we have no reason to believe that the distribution of contribution for each segment differs by birth year. Therefore, we should observe a similar distribution of contribution percentage for those birth years around zero and birth years around five.

In figure 5, we plot the standard deviation of contribution percentage for each birth year. As can be easily observed, the standard deviation of contribution percentage is much larger for birth years around zero (8–2). This pattern occurs because when an individual's birth year is around zero, she is more likely to deviate to nonmatching TRFs, leading to a higher standard deviation of the contribution percentage. However, a consumer whose birth year is around five (3–7) is less likely to deviate by selecting the matching TRF, resulting in a small standard deviation of the contribution percentage. In particular, there are interesting changes in standard deviations in specific years: they sharply increase from birth year ending in seven to birth year ending in eight and then sharply decrease from birth year ending in two to birth year ending in three. Please note that the standard deviations are similar for the two groups born after 1983—here, the sample sizes are very small compared to the other groups.

TABLE 6

TRF CHOICE OF RESPONDENTS IN THE NO-DEFAULT/DEFAULT CONDITION (PERCENTAGE OF RESPONDENTS)

		Actual choice			
		No-default condition		Default condition	
		Zero-ending fund (%)	Five-ending fund (%)	Zero-ending fund (%)	Five-ending fund (%)
Matching choice	Zero-ending fund	75	25	85	15
	Five-ending fund	47	53	16	84
	Overall	60	40	49	51

The contrasting contribution percentage distribution patterns for birth years around zero versus around five suggest that the contribution choice likely stems from the choice of the TRF.

It is possible that there may be systematic differences between the segments of those who belong to different birth years. The two observed variables that are very likely to influence contribution rates are gender and income. To further investigate whether the choices and contribution rates are driven by factors other than birth year, we run the Kolmogorov–Smirnov test on gender and income to determine whether the distribution of these two variables is different by birth year group. We find no significant differences. However, we find the difference in the distribution of the contribution rates across these groups to be significantly different. Detailed results are provided in the web appendix D. We next describe an experiment that provides additional evidence that the TRF choices may impact retirement contribution rates.

EXPERIMENT 1

This experiment serves two purposes. First, our goal is to examine whether the zero bias replicates in an experimental setting. Second, we want to obtain insights into whether the distribution of the retirement contribution rates changes after people are nudged to the default TRF. If the distribution of contribution rates shifts after the nudge, it provides additional evidence that the choice of the TRF can impact contribution rates.

Two hundred twenty-five participants were recruited from CINT, a web-based research firm. They were paid \$1.10 for participating. Thirteen participants were excluded from the analysis as they either did not pass the attention check or were less than 21 years old, resulting in a sample size of 212. The average age was 39.44 years (range 21–65). They all held retirement savings. The household income distribution was as follows: \$25,000–\$49,999 (10.38%), \$50,000–\$79,999 (33.02%), \$80,000–\$99,999 (20.28%), \$100,000–\$149,999 (24.53%), \$150,000–\$199,999 (7.55%), and \$200,000 or more (4.25%). There were two conditions in the experiment where the participants were either given a default TRF or not (no default vs. default). In the no-default condition ($n = 103$), we first asked participants their birth year. They were then asked to imagine that they were investing entirely in a TRF for their retirement. They were provided a description of a TRF, including an example of a glide-path. We then asked them to choose from a set of TRFs ranging from 2015 to 2070, given vertically in that specific order. Next, each participant was asked to provide their savings contribution rate as a percentage of income on a sliding scale anchored between 0% and 15%. Finally, other demographics were elicited. In the default condition ($n = 109$), like the no-default condition, after reporting their birth year, participants read the descriptions of the TRFs. Next, they were asked to select from the same menu of TRFs and told what their matching TRF was, i.e., "Based on your age, 20XX is the TRF fund that matches your retirement age of 65." Following the choice of the TRF, participants indicated their retirement contribution rate finally followed by demographic information.

Table 6 provides the results of the TRF choice. For the number of respondents, see tables in web appendix E. First, the results of the no-default condition show that the zero bias replicates in an experimental setting, with 60% of the participants selecting a zero-ending TRF. Figure 6a shows the identical zigzag pattern observed in the real-world choices. Next, table 6 and figure 6b show that providing the default matching TRF has a strong impact on choices, with only 49% of the participants selecting the zero-ending TRF. Approximately 84% of the participants in the default condition selected the matching TRF as compared to 63% in the no-default condition. Further examination of the data shows that, in the no-default condition, 68% of the participants who did not chose matching TRF deviates in the direction of zero-ending funds (see web appendix E for the calculations). From the TRF choices we impute that, on average, participants want to retire at 63.72 (no-default condition) and 65.28 (default condition).

Table 7 provides mean and standard deviation of the contribution rate (as a percentage of income) for each condition. In the no-default condition, the average contribution rate of the zero-birth groups is 5.25% while it is 4.58% for the five-birth groups. The difference is not statistically significant ($t(97) = 1.63$, $p = .11$). In the default condition,

FIGURE 6

(A) FUND CHOICE DISTRIBUTION IN THE NO-DEFAULT CONDITION OF EXPERIMENT 1. (B) FUND CHOICE DISTRIBUTION IN THE DEFAULT CONDITION OF EXPERIMENT 1

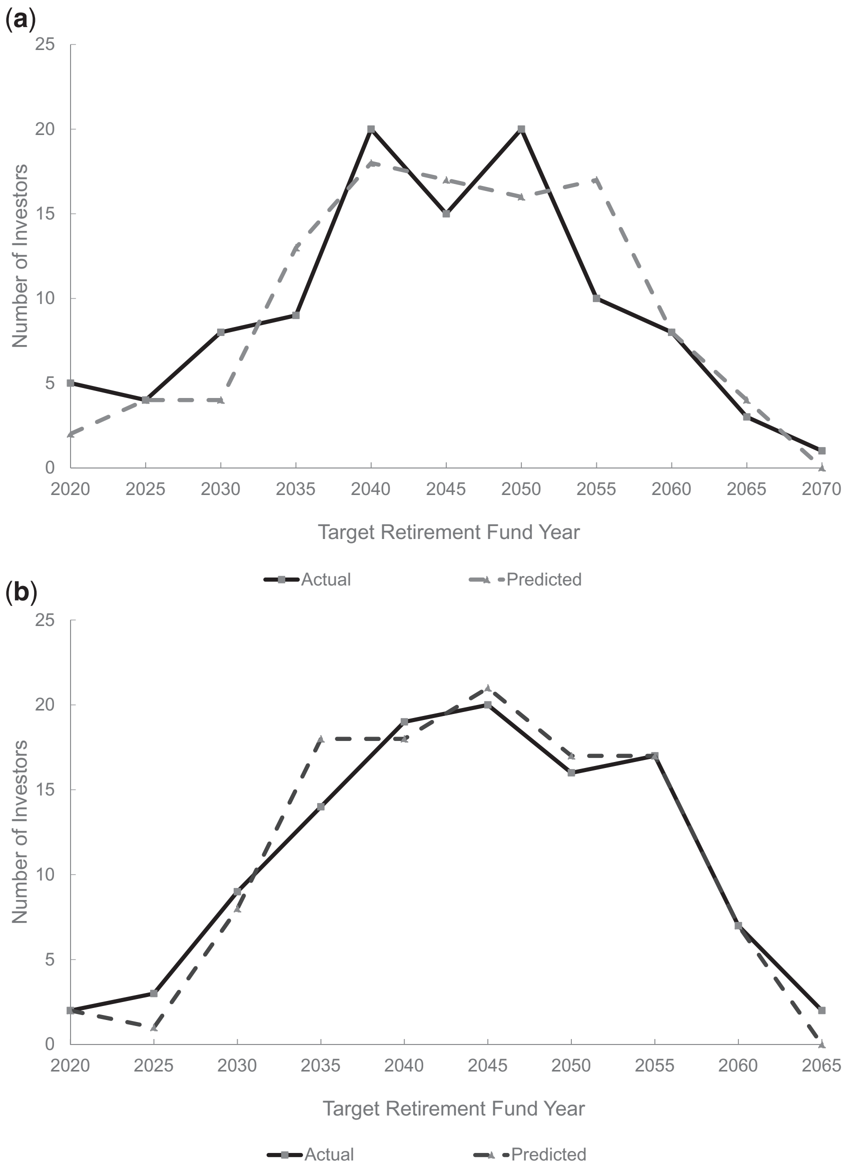


TABLE 7

CONTRIBUTION RATES (%) IN EXPERIMENT 1

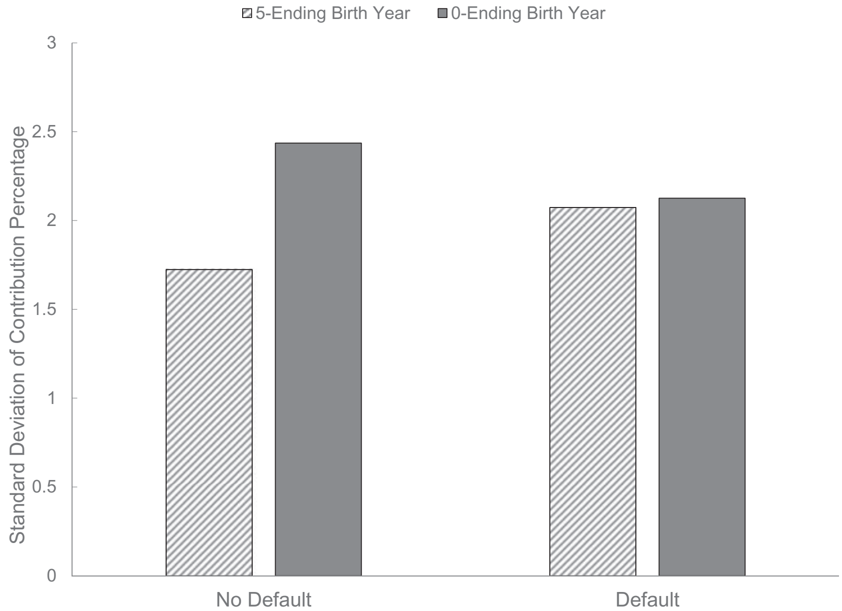
		Condition			
		No default		Default	
		Mean	SD	Mean	SD
Birth year group	Five ending	4.58	1.72	5.23	2.07
	Zero ending	5.25	2.44	4.74	2.13

the average contribution rate of the zero-birth groups is 4.74% as compared to 5.23% for that of the five-birth groups ($t(107) = -1.23$, $p = .22$).

Next, we turn our attention to the standard deviation of the contribution rates. We plot the standard deviations of the saving rates in figure 7. The results of the no-default condition mimic the standard deviations observed in the real-world: the standard deviation of the contribution rates is significantly higher ($F(54, 47) = 2.00$, $p = .02$) in the

FIGURE 7

STANDARD DEVIATIONS OF CONTRIBUTION RATES IN EXPERIMENT 1



zero-birth groups as compared to the five-birth groups. Importantly, in the default condition, where participants were nudged to the matching TRF, the standard deviation of the savings contributions for the zero-birth group shrink from 2.44 to 2.13, leaving the difference of standard deviations in the two groups insignificant ($F(56, 51) = 1.05$, $p = .86$). This provides additional evidence that the choice of the TRF impacts the savings contributions rates.

EXPERIMENT 2

Our next goal is to better understand the mechanism behind the zero bias. To do so, we conduct two additional experiments. Our main proposition is that the zero bias is rooted in the imprecise mathematics used in the estimation process, specifically the use of rounding up and rounding down. People are uncertain of their retirement year and the use of the imprecise mathematics leads them to generate a biased estimate. Furthermore, the choice set when selecting TRFs is constrained in that consumers have to select between zero- and five-ending alternatives, necessitating that the retirement year be approximated between these options.

Experiment 2 comprises two separate instruments: an unconstrained version where participants wrote their intended retirement year and a constrained version where participants chose between a zero- and five-ending TRF.

Two hundred twenty-six participants were recruited from CINT and paid $1.10 for participating. Three participants were excluded from the analysis as they either did not pass the attention check or were less than 21 years old. Two participants were excluded because they did not answer the key question. The final data have a sample size of 221. The average age was 43.42 years (range 23–66). All participants held retirement savings. The household income distribution was as follows: $25,000–$49,999 (27.60%), $50,000–$79,999 (31.22%), $80,000–$99,999 (15.84%), $100,000–$149,999 (16.29%), $150,000–$199,999 (5.43%), and $200,000 or more (3.62%).

In the constrained condition, we explained how TRFs work and then asked participants to select a specific TRF and, finally, asked their birth year. The responses are provided in table 8. In the data from the constrained version, 44% of participants whose matching TRF is five-ending selected zero-ending TRFs.

In the unconstrained version ($n = 110$), we asked participants to write down the year they plan to retire and then provide their birth year. Figure 8a presents the results of the end-digits for the intended retirement year. As can be seen, a large portion of consumers naturally chose either a zero-ending year (30.91%) or five-ending year (20.00%) as their intended retirement year.

Those who did not select a zero-ending year also exhibited a tendency to use round numbers in the calculations. For example, the most common heuristic was to begin with

TABLE 8

PARTICIPANTS' TRF CHOICE (CONSTRAINED CONDITION).

		Actual choice	
		Zero-ending fund (%)	Five-ending fund (%)
Matching choice	Zero-ending fund	82	18
	Five-ending fund	44	56
	Overall	63	37

birth year and add a round number such as $1981 + 70 = 2051$ (18 participants) or begin with the current year and add a round number $2019 + 30 = 2049$ (13 participants). The use of multiple origination points and other strategies to perform addition is not surprising and well chronicled in computation estimation literature (Lemaire and Arnaud 2008; Lemaire, Arnaud, and Lecacheur 2004; Uittenhove et al. 2013; Uittenhove and Lemaire 2013). As we conjectured, the utilization of rounding heuristics or round numbers to estimate the retirement year is pervasive.

Figure 8b presents the inferred retirement age base on participants' intended retirement year and their birth year. The average expected retirement age was 64.48, with a standard deviation of 8.33.

The distribution of these estimates is relatively inconsistent with the actual retirement ages that we observe from the focal firm's data. During the data period, we have a subsample of 453 investors (1.4%) out of total 31,392 sample who started withdrawing money from their 401(k)s. We use the inception time of withdrawal as the indicator for retirement time. We can differentiate regular retirement withdrawal from hardship withdrawal as these withdrawals require going to different webpages. Figure 9a and b shows the distribution of retirement age for the two subsets of investors, investors choosing the zero-ending TRF and investors choosing the five-ending TRF, respectively. As easily seen, most of the investors retire at 65. Comparing figure 8a with figure 9a and b confirms that people generate a biased estimate of their retirement year.

Finally, we compare the key numbers from both versions to delineate the effect of the natural rounding to zero versus the artifact of only zero- and five-ending funds available. We estimate that approximately 46% of the zero bias occurs due to a natural tendency to round to zero, and remaining 54% occurs due to the constrained choice between zero and five offered by TRFs. The detailed calculations are available in web appendix F.

EXPERIMENT 3

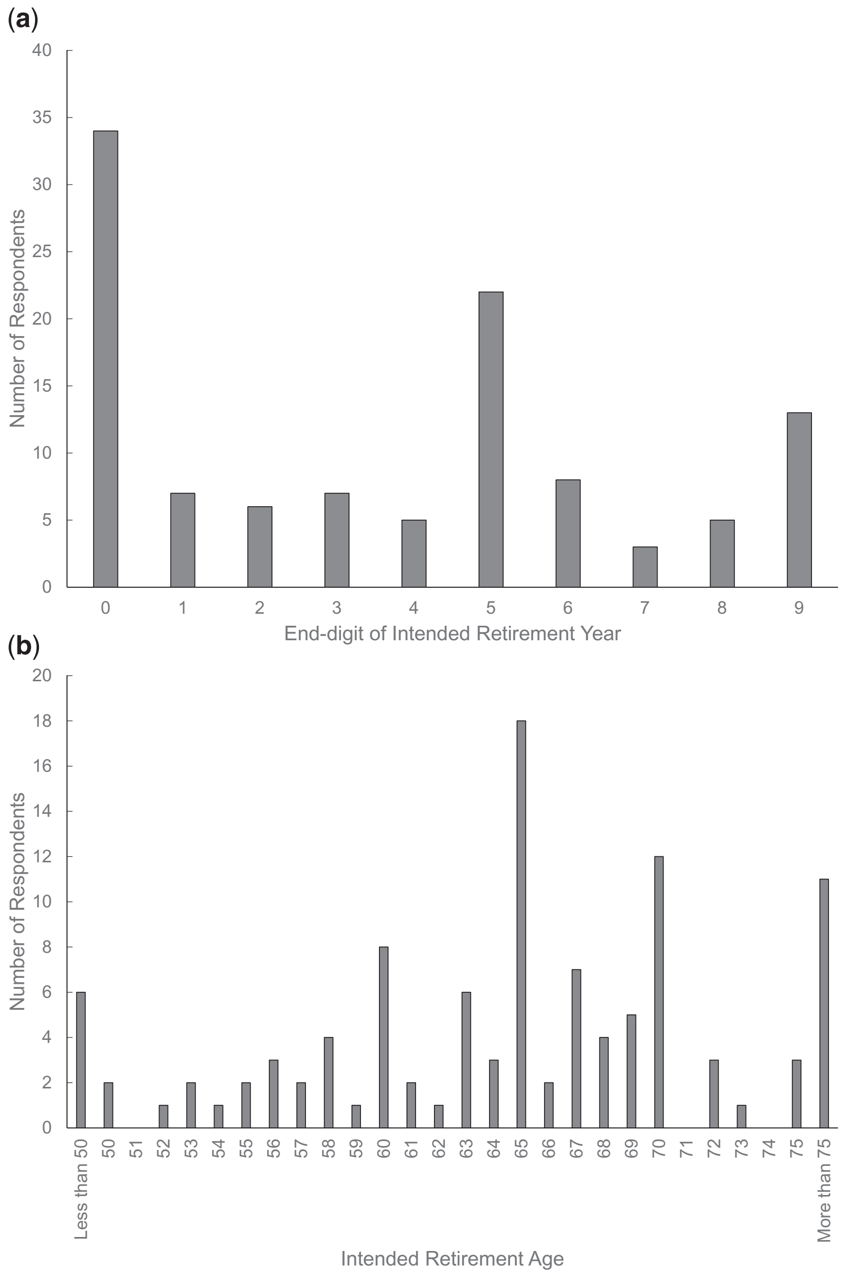
The results of Experiment 2 provide evidence that the use of imprecise mathematics accounts for the zero bias. Our goal in this experiment is to validate the process of imprecise mathematics. We do so by creating a calculative mindset, which is a predilection to solve problems mathematically (Fiske 1992; Wang, Zhong, and Keith Murnighan 2014). If the zero bias is attenuated by encouraging consumers to arrive at more accurate answers to mathematical problems, we can establish that the bias is embedded in the heuristics used in the calculations.

We conducted an experiment where we manipulate the mindset prior to participants making the TRF choice. We employed a single factor between-subjects design (mindset) with three levels (calculative-mindset, feeling, control). Three hundred sixteen respondents were recruited from CINT for a payment of \$1.11. Following the same criteria as in experiment 1, 14 participants were eliminated as a result of failing either the attention check or the age requirement, yielding 302 participants. All participants held a retirement savings account. The average age of participants was 43.75 (range 23–64). The household income distribution was as follows: \$25,000–\$49,999 (27.81%), \$50,000–\$79,999 (31.79%), \$80,000–\$99,999 (14.24%), \$100,000–\$149,999 (17.88%), \$150,000–\$199,999 (4.97%), and \$200,000 or more (3.31%). We first informed the participants that the experiment consisted of two independent parts where in the first task they would respond to five questions. The stimuli are adapted from Hsee and Rottenstreich (2004) and are provided in web appendix G. In the calculative-mindset condition ($n = 106$), participants were told "We are now going to ask you to solve a few mathematics equations. Please try your best." They were given five mathematics questions and 30 seconds to solve each problem. For instance, one question asked "If an object travels at five feet per minute, then by your calculations how many feet will it travel in 360 seconds?" In the feeling condition ($n = 102$), participants were asked five questions that required them to report their feelings. For example, "When you hear the word 'baby', what do you feel? Please use one word to describe your predominant feeling." As in the calculative-mindset condition, participants were given 30 seconds to provide the answer. In the control condition ($n = 94$), respondents were immediately taken to the TRF choice task.

These questions were selected based on a pretest with the same participant pool ($n = 214$). No participants were excluded. After answering the questions, participants were

FIGURE 8

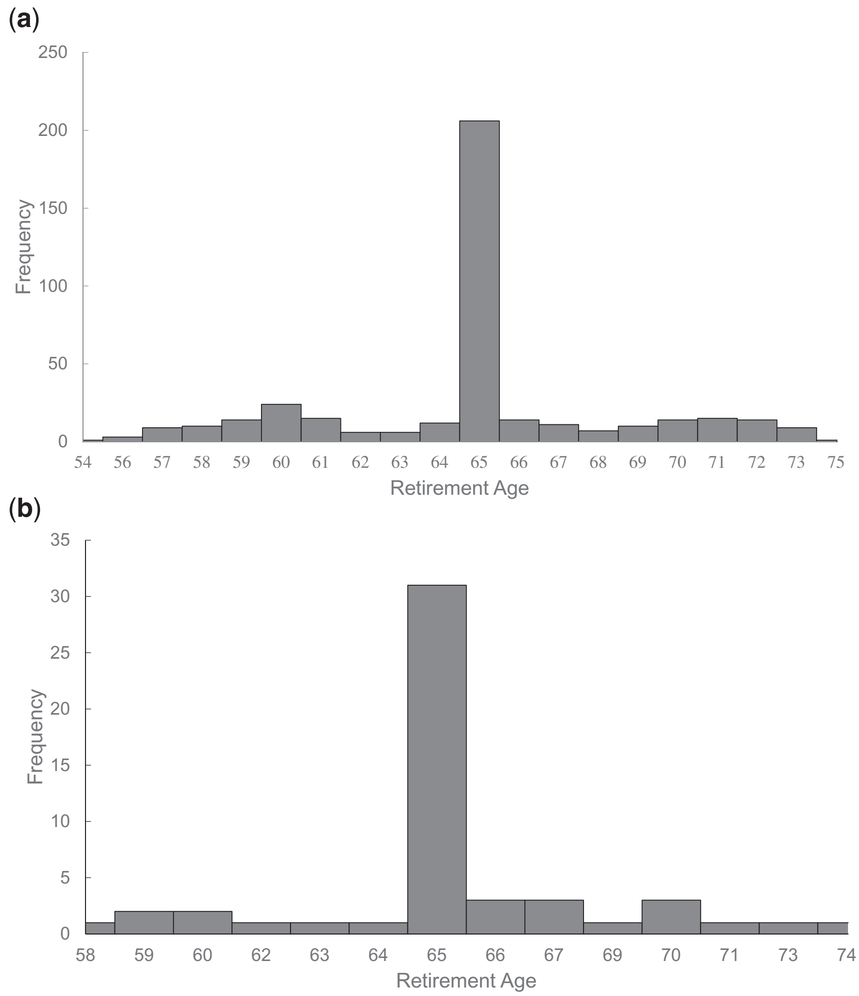
(A) FREQUENCY OF THE END-DIGITS FOR PARTICIPANTS' INTENDED RETIREMENT YEAR (UNCONSTRATINED CONDITION). (B) HISTOGRAM OF PARTICIPANTS' INTENDED RETIREMENT AGE (UNCONSTRAINED CONDITION)



asked to rate the task on six criteria by answering the question "To what extent do you find the calculation/feeling question" on a 5-point scale (1 = strongly disagree, 5 = strongly agree): (i) difficult; (ii) fun; (iii) enjoyable; (iv) tiring; (v) challenging; and (vi) time consuming. As a manipulation check, participants were asked to rate how much the task made them think verbally and numerically on a 5-point scale. Table 9 provides the results of the pretest. These results show that the manipulation was successful and that the tasks are equivalent, with the exception that participants perceived the feeling task to be marginally more tiring.

FIGURE 9

(A) HISTOGRAM OF RETIREMENT AGE FOR ZERO-ENDING TRF INVESTORS. (B) HISTOGRAM OF RETIREMENT AGE FOR FIVE-ENDING INVESTORS



In the next phase, in all conditions, similar to experiment 1, we explained the main idea behind TRFs and then asked participants to choose a TRF from a menu with options ranging from the 2015 TRF to the 2070 TRF. The results are presented in table 10. For the number of respondents, see tables in web appendix H.

As compared to the feeling condition where 67% of the participants selected the zero-ending TRF, as anticipated, the proportion in the calculative-mindset condition significantly decreases to 52% ($\chi^2(1) = 4.70$, $p = .03$). Similarly, fewer participants in the calculative-mindset condition selected the zero-ending TRFs as compared to 69% in the control condition ($\chi^2(1) = 6.19$, $p = .01$). More convincingly, in the calculative-mindset condition, 80% of participants select the matching five-ending TRFs, which are significantly higher than 55% in the feeling condition ($\chi^2(1) = 7.05$, $p < .01$) and 48% in the control condition ($\chi^2(1) = 10.73$, $p < .01$). The results confirm that imprecise mathematics causes the zero bias. When consumers are in a calculative mindset and cognitively addressing problems more mathematically, the zero bias effect is attenuated. We now turn back to the data from the focal firm to examine if there are any demographic markers associated with the zero bias.

HETEROGENEITY IN THE ZERO BIAS

We now explore some factors that can explain heterogeneity in the zero bias. Specifically, we examine whether any demographic variables are predictive of the zero bias.

TABLE 9

PERCEPTIONS OF TASK IN PRETEST

	Calculative-mindset	Feeling	*t*-statistics	Degree of freedom	*p*-Value
Difficult	2.11	2.33	−1.39	212	0.17
Fun	3.18	2.94	1.43	203	0.15
Enjoyable	3.07	2.99	0.49	212	0.62
Tiring	2.30	2.58	−1.67	200	0.10
Challenging	2.56	2.83	−1.60	212	0.11
Time consuming	2.50	2.34	1.04	212	0.30
Verbal thinking	2.71	3.08	−2.23	212	0.03
Numerical thinking	4.25	2.25	15.06	194	<0.01

TABLE 10

TRF CHOICE OF RESPONDENTS IN EXPERIMENT 3 (PERCENTAGE OF RESPONDENTS).

		Actual choice					
		Calculative-mindset condition		Feeling condition		Control condition	
		Zero-ending fund (%)	Five-ending fund (%)	Zero-ending fund (%)	Five-ending fund (%)	Zero-ending fund (%)	Five-ending fund (%)
Matching choice	Zero-ending fund	85	15	83	17	83	17
	Five-ending fund	20	80	45	55	52	48
	Overall	52	48	67	33	69	31

Table 1 presents the summary statistics of the demographic variables. The average age of the investors is 46.97, with the share of females at 50.00%. Married consumers comprise 67% of the sample, and the mean income is $65,495. The average tenure with the company is 10.98 years. The average contribution percentage is 4.10%. The investors are geographically diverse, with the sample containing individuals from each of the 50 states in the United States. Employment also spans a wide range of industries or sectors.

We ran a logistic regression where the dependent variable is the presence of the zero bias. Table 11 presents the results. We controlled for geographical location and employment sector (denoted as yes) using a random-effects model. We find that older individuals, males, those who have longer tenure with the firm, and those who earn higher income are predictors of the zero bias.

Please note the underlying assumption of this analysis is that the choices of all nonmatching TRFs are due to the rounding bias. It is possible that some nonmatching choices are made because consumers intend to retire before or after the 65 years target we consider in the analysis. Next, we describe a natural experiment conducted by the focal firm that examines how to mitigate the zero bias.

REDUCING THE BIAS—A NATURAL EXPERIMENT

We consider whether it is possible to assuage the zero bias problem using a one-on-one planning program. We therefore leverage a natural experiment. Unlike the experimental approach, the natural experiment provides an investigation of the specific segments that are more likely to be influenced by financial education. During the sample period, the firm offered a planning/financial education program that was a 30-minute, one-on-one meeting in which retirement professionals helped investors identify their personal goal and needs. The natural experiment is similar to a randomized encouragement design where participants are randomly assigned to a condition but are given the option of whether to receive the manipulation (Frangakis, Rubin, and Zhou 2002). In the meeting, employees were asked to think and answer questions such as "What are your goals," "When do you intend to retire," "Are you saving enough," and "What has been your investment strategy so far." To gauge effectiveness, the meetings were offered only to a select sample of investors at the initial stage. A total of 13,036 investors participated in the program. The participation rates in each firm varied from 32.50% to 75% of

TABLE 11

EFFECTS OF DEMOGRAPHICS ON ZERO BIAS (LOGISTIC REGRESSIONS).

Variables	Estimate	SD
Age	0.00833***	0.00262
Female	−0.0467*	0.0262
Tenure	0.0457***	0.00447
Income	1.619E−6**	9.446E−7
Location	Yes	
Employment	Yes	
AIC	11,191.45	
Pseudo R^2	0.33	
$N = 12,480$		

Note.—*, **, and *** indicate .10, .05, and .01 significance levels, respectively.

employees in a specific firm, with an average overall participation rate of 38.61%. We compared the characteristics of participating employees with the characteristics of those who did not. There was no significant difference between the employees who participated versus those who did not in age ($p = .39$), gender ($p = .65$), tenure with the focal firm ($p = .45$), or savings rates ($p = .11$). However, those who participated had higher incomes ($65,929.84 vs. $65,227.40, $p = .05$). Despite the high participation rates, there is an issue of self-selection. We use the local average treatment effect methodology to address this issue (see web appendix I). We find that investors who receive the financial education/planning service are significantly less likely to have the zero bias than those without the service ($M_{\text{Bias}} = 45.63\%$, $M_{\text{NoBias}} = 27.97\%$; $\chi^2(1) = 457.94$, $p < .0001$). This analysis is far from conclusive, because we are not privy to the precise content discussed in these meetings. However, it appears that the financial planning helps soften the zero bias.

We observe that the lapse of time between the service date and the TRF decision date was on average 3 days, with a range of 0–35 days. Interestingly, we find that the effect of this program is not homogeneous. To see how the treatment effect varies for different investors, we use the (instrumental) causal forest model in Athey and Wager (2018) to quantify the heterogeneous treatment effect. The model builds on a regression tree model (Armstrong and Andress 1970; Breiman et al. 1984; Homburg, Steiner, and Totzek 2009) and allows us to partition the entire sample of consumers into subgroups that differ in the magnitude of their treatment effect of receiving the financial planning service. Please note that the regression tree model recursively partitions data according to a relationship between the X and Y values, creating a tree of partitions. It finds a set of cuts or groupings of X values that best predicts a continuously distributed Y value. It does this by exhaustively searching all possible cuts or groupings. These splits (or partitions) of the data are done recursively, forming a tree of decision rules until the desired fit is reached. This is a powerful platform, because it chooses the optimum splits from a large number of possible splits. For a more complete description of the regression tree model, see Breiman et al. (1984). Here, we consider demographic heterogeneity. The final output for the causal tree is fairly complex. Simply put, we find that the program is more effective for female investors ($M_{\text{treatment}} = -0.151$, $p < .001$) than for males ($M_{\text{treatment}} = -0.129$, $p < .007$). This intervention heterogeneity is consistent with the notion that women prefer lower levels of investment risk and that an intervention is helpful in informing them that they are taking on more risk by investing in a farther dated fund. In contrast, the male investors may have a preference for the greater risk associated with the long-dated fund in the first place and so may not need correcting. The program is also more effective for lower-income (less than $47,000) investors ($M_{\text{treatment}} = -0.138$, $p < .001$) than for higher-income investors (greater than $47,000).

CONCLUSION

We document that investors (specifically those born in years ending eight, nine, zero, one, and two) are subject to the zero bias in their choice of TRFs, where they are more likely to choose zero-ending TRFs than five-ending TRFs. Those born in years ending in zero, one, or two select TRFs that imply that their goal is to retire at 70, whereas those born in years ending in eight and nine select TRFs that suggest that they plan to retire at 60.

The bias has far-reaching implications for the total wealth accumulated at the time of retirement. First, an incorrect choice in TRFs can expose investors to risk that is incompatible with their profile. Second, the results show that the saving rates are associated with the choice of TRF year, with people selecting later (earlier) TRFs contributing less (more) to their savings than those who select the matching TRFs. Overall, our simulations find that the birth year matters: consumers born in eight- or nine-ending years tend to select early TRFs, and most of them who do so are worse off financially at the time of retirement unless they are extremely risk averse. People born in the years ending 0–2 are fortuitously impacted by the bias as they choose later TRFs that provide higher expected returns but are also subject to more risk. Highly risk-averse consumers in this birth-year group also tend to be worse off by not selecting a matching TRF. The extent of losses incurred by not choosing a matching TRF can be quite large depending on the birth year, with those born in the years ending eight or nine being the worst off.

The evidence we gathered suggests that the choice of the year for the TRF potentially serves as an anchor against which people estimate the number of working years left. People (born in zero- through two-ending years) who buy later TRFs save at a significantly lower rate than those who buy the matching TRFs. Fortunately, people born in years ending in eight and nine self-correct by contributing more. However, those born in years ending in zero, one, and two suffer a double whammy by contributing less and potentially bearing unnecessary risk.

Our findings have substantive policy implications for firms in identifying and minimizing the bias if necessary. First, we provide insights into targeting for intervention. Since those born in eight- or nine-ending years tend to buy early TRFs, they can be specifically informed that their choices imply a low-risk low-return portfolio. Those investors born in 0–2 ending years can be informed that they might be taking risks incompatible with their preferences. Our findings give the financial advisors concrete information about the tendencies of customers simply based on their birth years. Second, our analysis shows that the level of impact of the bias also rests on the customers' risk aversion. Together, this will help identify those most vulnerable to the zero bias.

The paradigm in the computational estimation literature examines how people solve problems using simple mathematical problems. In contrast to this paradigm, we examine how people make estimates using mental arithmetic. The estimations for retirement year conceptually differ from standard problems, as multiple starting points are available (birth year, current year, age). In addition, rather than arriving at one solution, consumers must determine the best fit among the alternatives. We therefore add to the computational estimation literature by investigating a different class of problems. We also add to the literature in computational estimation by examining the use of rounding in the real world and observe more evidence of the heuristic of rounding up than of rounding down. Since the choice of TRFs is constrained by alternatives ending in either zero or five, we are also able to parcel out the portion of consumers' zero bias due to their natural affinity to zero versus the forced decision of fitting retirement year into one of the few alternatives. Finally, we provide process evidence of the use of rounding heuristics by creating a calculative mindset. Gaining insight into the mechanism may help policymakers to develop better tools to navigate consumers into selecting an appropriate TRF.

Our analysis has some limitations. We observe only the investments in the focal firm and therefore do not capture the entire portfolio. We do not believe this to be a significant issue. While we do not have a window to people's entire portfolios, a majority of investors have only one 401(k) account and a considerable amount of them invest a bulk of their savings in TRFs (Fidelity 2019). A question that we cannot completely address with the empirical data is the precise nature of the computational estimation used in the choice process. The experimental evidence indicates that people use several starting points to perform calculations to estimate their retirement year. The starting points include birth year, current year, or current age. This finding is consistent with the literature on computation estimation that finds different strategies are used for the same problem depending on perceived difficulty and heterogeneity in working memory (DeStefano and LeFevre 2004) that also impede the accuracy of arriving at an approximately correct answer. Regardless of how individuals calculate their retirement year,

the empirical data suggest that use rounding up or down yielding imprecise answers. As most people select TRFs that project them to retire when they are between 60 and 70 years old, they are clearly using computational heuristics that include rounding. What is unclear is how and why the starting point (date of birth, current age, or current year) is selected. The experimental data also demonstrate that when prompted to provide precise answers to simple mathematical problems, the bias is mitigated. We have proposed that the bias occurs due to the imprecise mathematics in estimating the retirement year, specifically rounding up and rounding down. There could also be other mechanisms that account for this effect. For instance, a more conservative segment who engages in less wishful thinking rounds down. However, the evidence for rounding is quite strong. Within the deviators born in years ending with eight and nine, 83.5% select the earlier fund, whereas among the deviators born in zero-, one-, and two-ending years, 74.3% select the later funds.

The strong effectiveness of the financial intervention employed by the focal firm stands in contrast to the generalized finding that financial education interventions are less efficacious than improving financial literacy (Fernandes, Lynch, and Netemeyer 2014). We speculate three reasons for the contrast. First, this intervention comes "just-in-time," precisely at the point of decision-making. Second, unlike other approaches, the intervention does not aim at improving financial literacy, which is generally an important antecedent to financial behaviors. It instead enables an investor to temporarily use cognitive resources that facilitate their estimations to be more precise. Third, the impact of the intervention is "one-shot" in that it changes only one specific action as compared to financial behaviors such as savings that require a change in actions that need to occur on a continuous basis.

Identification of the zero bias effect has clear and actionable implications for consumers and fund providers. The designers of 401(k) plan menus should take this bias into consideration, educate investors on the long-term consequences of the choices made at the point of decision, and nudge investors into making selections that increase their financial well-being.

DATA COLLECTION INFORMATION

All the experimental and survey data were collected by the second author from CINT from 2019 to 2020. The proprietary data were obtained by the third author. The experiments were jointly designed and analyzed by all the authors. OSF link to data and materials: https://osf.io/6mkps/.

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