Behavioral Economics and Individual Discounting

Observed Behaviors in Deferred Retirement Option Plans

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Executive Summary

When a retirement plan offers the option to participate in a Deferred Retirement Option Plan (DROP), the expectation would be the cost of benefits would increase, assuming the option has a value. Actual experience with several retirement plans indicated some individuals make decisions related to DROP participation which is not in their best economic interest. Traditional economic principles do not explain this anomaly. Hyperbolic discounting is a behavioral economic principle which offered a possible explanation. When actual DROP participants' choices were evaluated using hyperbolic and economic discounting, the hyperbolic model failed to materially improve the predictive results. A modification to hyperbolic discounting was developed to reflect an individual's desire to have funds available for as much of their life as possible. This modification significantly improved the model of human behaviors related to DROP participants in the plans reviewed. The data was also analyzed to determine the impact of various factors on individuals' decision-making relative to DROP participation. Evidence supports the correlation between poor economic decisions and lower income. Individuals with lower compensation and benefits tend to enter DROP sooner and are more likely to return to work after DROP rather than retire when compared to individuals with higher compensation and benefits. Analysis was also performed to predict how changes in plan benefits can impact individual choices and the plan participant composition.

This paper explains the concepts of hyperbolic discounting and provides a tool for improving the modelling of individual decisions. Some individuals appear to use economically discounted cash flows in their decision-making processes, whereas others appear to incorporate some values to cash flows which are not purely economic. This paper provides some tools for improved modeling of the decision-making process for those individuals who do not rely as heavily on economic valuations. The paper also provides some tools for predicting how changes in plan design can impact the demographics of the plan participants.

Section 1: Background

1.1 PURPOSE

Our primary research goal was to determine if individuals use a form of hyperbolic discounting when presented the benefit options, specifically the option to participate in a Deferred Retirement Option Plan (DROP). We also analyzed behavioral economic and other factors that drive DROP participation to provide information useful in developing an actuarial model to include the mental discounting used by individuals, which has been described as hyperbolic discounting. Our intent was to use the data to estimate the present bias parameter (i.e., β) for individuals. We performed secondary analyses to augment professional understanding of behaviors of individuals provided the opportunity to enter DROP.

1.2 DATA USED

We obtained information from 11 public retirement plans in Louisiana which offered DROP to their members. Some plans had sub-plans with varying benefit structures. The information provided included data for the plans three years apart, either from 12/31/2018 and 12/31/2021 or from 6/30/2019 and 6/30/2022.

1.3 METHODOLOGIES

1.3.1 MORTALITY ADJUSTMENTS AND ANALYSIS

We based our expected mortality on the 2016 Social Security mortality data. Since the COVID-19 pandemic occurred during the years reviewed. We adjusted the mortality experience for calendar years 2020 and 2021 based on the results provided in "Group Life COVID-10 Mortality Survey Report". We used group experience, since we assumed it would better reflect pension plan experience than using individually underwritten policy experience. We compared mortality of active members, DROP participants, DROP participants who had returned to work, and retirees.

1.3.2 BETA DETERMINATION

To determine the present bias parameter (β) for individuals requires identification of the time when the economic value is equal to the perceived value. The parameter becomes the multiple of the hyperbolic discounted value needed to equal the value based on compound interest. If a person enters DROP as soon as they are eligible, we only know the perceived value of the cash flow from DROP participation is greater than the perceived value of working the additional years and drawing a larger retirement. If a person enters DROP a year or later after eligibility, we may assume the perceived value of DROP participation is approximately equal to the perceived value of continuing membership in the system and retiring when the person would normally exit DROP.

After modifying the hyperbolic discount formula with a life expectancy adjustment, the modified hyperbolic discount was less than the economic values. This would imply a present bias parameter greater than 1 to adjust the perceived discount to the economic discount. That is logically inconsistent, and a calibration to determine betas could not be performed with the modified hyperbolic discount. This does not present a problem in the decision analysis, since beta is a constant for the valuation of both the DROP and the non-DROP options. Other researchers (Laibson, et al 2017) have calibrated the parameter and found that $\beta = 0.5$ is generally appropriate (Laibson et al 2017).

In the literature review we found that researchers have determined that some individuals use hyperbolic discounting, and some do not. The use of hyperbolic discounting in Europe was found to vary by a group's geopolitical environment. Our study found that the level of hyperbolic discounting used by individuals varies by several factors, the most notable being level of income. In general, the lower the income level of an individual, the greater the level of hyperbolic discounting used. The factors influencing the level of use of hyperbolic discounting were addressed through statistical analysis.

1.3.3 STATISTICAL ANALYSIS

We used statistical testing to test various factors which might correlate with a member's decision to participate in DROP. These included sex, level of salary, years of service, age, benefit accrual rates, the accrued percentage of "final average compensation" (FAC) defining their benefits, and the increase in salary during the DROP participation period.

We developed a normalized quasi-hyperbolic discount function to provide continuity and smoothness over the function's domain. We added spot rates to the discount function to reflect discounting using different interest rates.

We computed the economic and perceived present values using projected mortality and average spot rates for the year. The model's perceived values were compared to economic values. Values were computed using first principles, assuming age last birthday, deaths at the end of the year, non-DROP payments were assumed to be mid-year, DROP payment at the end of the 3rd year, and all DROP participants were assumed to retire upon completion of DROP. Salary increases were assumed to be the same rate for the 3 years following DROP entry as the rate of change between the two reported salaries. If salaries of DROP participants were not available, we used the average rate of increase for active members with information available.

We used a set of High-Quality Corporate Bond spot rates reflective of the year of DROP entry or eligibility to compare the economic value of 3 years of DROP participation to the economic value of retirement benefits after 3 years of additional active participation. We then tested the differences to establish the economic value of benefits with DROP are less than the economic value of continuing active service in lieu of entering DROP. The spot rates used for an individual were the average spot rates in the year the participant entered DROP. The website of the U.S. Treasury (Corporate Bond Yield Curve Papers and Data | U.S. Department of the Treasury) provides the historical high-quality monthly corporate bond spot rates and some papers on using these rates to discount pensions.

1.3.4 PREDICTIVE ANALYSIS

In Section 3.1.1, to study who chooses to enroll in DROP plans, we use a Decision Tree, a non-parametric supervised learning algorithm. Decision trees split the data on covariates in a way to optimally classify individuals into one of three classes: continue working, retire, and enter DROP. Decision trees provide information about which covariates, and which set of values for the covariate predict working/retirement/DROP. For example, the decision tree predicts that, conditional on being eligible for retirement, individuals with less accrued service are more likely to continue working. It is difficult, however, to infer the relative importance of different variables from a decision tree.

To study the relative importance of different factors in predicting working/retirement/DROP, in Section 3.1.2 we implement a Random Forest. A Random Forest is an ensemble learning method that enhances prediction robustness and accuracy by a) introducing some randomness and b) estimating a Decision Tree on the perturbed data. By repeating this many times, a Random Forest can speak to the relative importance of variables, specifically by noting the frequency with which they were selected amongst the many trees. Moreover, a Random Forest can capture a broader range of data relationships, and provides various advantages such as robustness to overfitting, stability, and handling bias towards features with more levels.

1.3.5 CAUSAL ANALYSIS

Our descriptive and predictive analyses show that various features of the DROP plan, for example, retirement age or years of accrued service needed for eligibility, are strong predictors of individuals choices regarding working/retirement/DROP. This suggests that changes to the parameters of a DROP plan (e.g., raising the retirement age) would alter the choices of individuals. However, predictive analyses cannot justify causal statements of this form. Simply because retirement age is associated with DROP choices, does not mean changing the retirement age would change DROP choices in the way the historical relationship suggests.

To overcome this, in Section 3.3 we implement a Regression Discontinuity Design (RDD) to estimate the causal impact of a DROP plan parameter change on different outcomes, such as DROP entry. This method relies on the fact that the DROP plans participants were eligible for changed discretely depending on their date of hire (e.g., for all those hired after January 1, 2010, the retirement age rose from 60 to 62). If we assume that individuals who were hired just before and just after the cutoff are equal, but for the DROP change, then we can estimate the causal effect of the plan change by comparing the two groups. This assumption is validated through various checks, including the Covariate Balance Test, ensuring the equivalence of individuals on both sides of the cutoff.

1.4 DESCRIPTION OF THE DEFERRED RETIREMENT OPTION PLAN (DROP)

1.4.1 BACKGROUND

The Deferred Retirement Option Plan ("DROP") has been a significant feature of public pension systems in the United States since its emergence in the late 1980s and early 1990s. Initially introduced by the Texas Teachers Retirement System in 1981, these plans were designed primarily as a tool to incentivize the retention of skilled and experienced employees, providing them with attractive financial benefits while minimizing costs associated with recruitment and training new employees. Historically, an employee was compelled to retire after finishing the DROP period, providing clarity to junior employees about jobs which would be available for potential promotions. However, the rules of many DROP programs have been relaxed, and in many places, employees are allowed to continue working even after their DROP period has ended. This has somewhat offset the initial advantage of DROP plans in terms of workforce planning.

A Deferred Retirement Option Plan ("DROP") is a common retirement strategy offered by public pension systems. It allows employees who are otherwise eligible to retire, the option of continuing to work for up to 3 years, drawing their salaries; and the pension payments they would have received if they had retired accumulate in a DROP account, which is available to them upon their retirement. There are many nuances related to an employee who chooses to continue working after DROP participation, but we assume the election to participate in DROP is made with the expectation of retirement at the end of the DROP participation period; however, many employees choose to continue working after their DROP participation.

Upon entering DROP, the accrued retirement benefit is frozen: no additional benefits are accrued during DROP participation and the final average compensation does not increase during DROP participation. An employee is not required to make contributions to the pension plan during DROP participation. The DROP account does not accumulate interest during the DROP participation period.

The financial impact of a Deferred Retirement Option Plan ("DROP") on a retirement system is ambiguous, with both potential benefits and costs. One of the primary motivations of this study is to provide information to assist retirement plans and their actuaries in quantifying this impact.

1.4.2. AN ILLUSTRATIVE EXAMPLE

Suppose an individual turns 60, has 15 years of service, and is planning to retire in 3 years. They currently earn $50,000. Assume their salary will increase by 4% each year. For those three years, they can continue working or enter a DROP.

Their eventual retirement benefit will be calculated at 3% of FAC for each year of service, where FAC is the average of the last 3 years' salary. If they enter a DROP, their final pension will be frozen, and paid into an account at the beginning of the three years, earning 6% interest.

If the person continues working normally for three years:

Their salary increases by 4% each year, so their salaries over the next three years would be: $52,000, $54,080 and $56,243.20 respectively. Thus, the Final Average Compensation ("FAC") would be the average of these three years:

FAC = ($52,000 + $54,080 + $56,243.20) / 3 = $54,107.73

With 18 years of service at retirement, the retirement benefit would be:

Retirement Benefit = 3% * 18 years of service * $54,107.73 = $29,218.04.

Moreover, they continue to pay an employee contribution for these three years, which we assume is 5% per year. They pay $2,600, $2,704 and $2,812 respectively in each of the three years of work.

If the person enters DROP:

Their FAC and years of service are frozen. Thus, the current FAC is the average salary of the last three years. Since the person is currently earning $50,000 annually but with 4% growth over time, the FAC is $48,162.48.

Their retirement benefit at this point is:

Retirement Benefit = 3% * 15 years * $48,162.48 = $21,673.12.

The balance of the DROP account after three years will be:

$21,673.12 *[(1+0.06)^2.5 + (1+0.06)^1.5 + (1+0.06)^0.5] = $71,038.35.

Trade-off

Entering DROP leads to a single payment of $71,038.35 in three years' time and $2,600, $2,704, and $2,812 in reduced employee contributions during DROP with a lower final monthly benefit. These benefits to the members are in exchange for $29,218.04 - $21,673.12 = $7,544.92 less in pension benefit in every year.

Assuming mortality according to the Male RP-2000 table, we calculate the Expected Present Value ("E[PV]") of the stream of cash flow changes due to entering DROP according to one of two discount rates $\delta(t)$:

$$Exponential\ Discounting: \delta(t) = \frac{1}{(1+r)^t}$$

$$Hyperbolic\ Discounting: \delta(t) = \frac{\beta}{1+rt}$$

We set $\beta = 0.5$ as calibrated by (Laibson et al 2017). This captures the fact that individual's trade-off today versus tomorrow very differently from one week from now versus one week and one day from now. Individual's value cash flows today much more than those tomorrow, which is why a low value of β typically rationalizes choices. We included an adjustment to smoothly grade to β over 2 years, with most of the grading occurring in the early period.

The rate of interest r that leads to equality between the E[PV]'s according to exponential discounting and according to hyperbolic discounting is 5.09%. This was computationally solved for. Any individual with $r > 5.09\%$ would have a higher E[PV] under exponential discounting than under hyperbolic. For all individual's with $r < 5.09\%$, the E[PV] of entering DROP under hyperbolic discounting is higher than under exponential discounting. For such individuals, being hyperbolic discounters or 'present-biased' makes entering DROP more likely.

The mortality, β, hyperbolic discount formula, and interest rate in this example are for illustrative purposes and may be different than those used in the statistical analysis. However, these assumptions do reflect the approach used in the predictive analysis section.

1.5 LITERATURE REVIEW

1.5.1 HYPERBOLIC DISCOUNTING IN FINANCIAL DECISION MAKING

The literature on hyperbolic discounting in financial decision-making is extensive. A pioneering study found that hyperbolic discount functions effectively explain behavior across several contexts, including retirement savings and the exercise of retirement options (Laibson, 1997). It also pointed out how hyperbolic discounting can lead to preference reversals over time, confirming earlier findings that preferences for immediate rewards tend to dominate when decisions become imminent (Ainslie, 1975; Kirby & Herrnstein, 1995). This concept has also been shown to affect time preferences and the discounting of future outcomes. Research suggests that individuals, influenced by hyperbolic discounting, tend to struggle with self-control in saving for retirement, which often leads to under-saving (Frederick, Loewenstein, & O'Donoghue, 2002; Thaler & Shefrin, 1981, Hertwig et al 2004).

Other studies have examined how hyperbolic discounting can lead to procrastination and delay in decision-making. This delay can influence when individuals choose to retire or opt into a DROP, potentially skewing these decisions in favor of immediate rewards (O'Donoghue & Rabin, 1999; Loewenstein & Prelec, 1992). Moreover, studies have used hyperbolic discounting to model consumption behaviors, demonstrating its ability to simulate more realistic scenarios than traditional exponential discounting models (Angeletos et al., 2001).

Recent work has broadened the applications of hyperbolic discounting to include its effects under conditions of uncertainty (Epper, Fehr-Duda, & Bruhin, 2011), in real-effort tasks (Augenblick, Niederle, & Sprenger, 2015), and in the interaction of memory and procrastination (Ericson, 2015)[12]. It has also been used to distinguish between risk and time preferences, underscoring the complexity of these cognitive processes (Cheung, 2015). Another noteworthy application was in a study of how past choices can be revised, demonstrating the dynamic nature of commitment and preference that lies at the heart of hyperbolic discounting (Gine, Goldberg, Silverman, & Yang, 2018).

1.5.2 BEHAVIORAL FRICTIONS IN RETIREMENT CHOICES

The literature surrounding behavioral distortions in retirement planning is extensive, spanning multiple dimensions from saving behavior to the impact of financial literacy. For a general overview of the psychology of the retirement and decumulation decision, see (Shu and Shu, 2018).

Thaler and Benartzi (2004) studied a pioneering program called 'Save More Tomorrow', which encourages employees to pre-commit a portion of their future salary increases towards retirement savings, mitigating the influence of present bias. They further discussed the role of behavioral economics in the retirement savings crisis, highlighting the gap between optimal and observed savings behavior (Thaler & Benartzi, 2013).

In this context, Choi et al. (2004) studied how the 'path of least resistance' can impact savings for retirement, highlighting how automatic enrollment, employer match structures, and default contribution rates can significantly influence employee saving behavior. Cronqvist and Thaler (2014) expanded on this idea, examining design choices in privatized social security systems using the Swedish experience as a case study.

The issue of financial literacy and its role in retirement planning has been studied extensively. Lusardi and Mitchell (2011) demonstrated a strong correlation between financial literacy and retirement planning in the United States. Later, Lusardi, Michaud, and Mitchell (2017) highlighted that optimal financial knowledge could help reduce wealth inequality. Similarly, Kuhnen and Melzer (2017) explored how non-cognitive abilities, particularly self-efficacy, can aid in avoiding financial distress.

Studies also underscored the importance of understanding the distinction between active and passive decisions. Chetty et al. (2014) provided empirical evidence from Denmark that suggested active decisions in retirement savings accounts could crowd out passive choices. Beshears et al. (2018) also looked at how self-control and liquidity impact commitment contracts.

Framing, an essential aspect of behavioral economics, is particularly significant when planning for retirement. Brown, Kapteyn, and Mitchell (2016) provided evidence that information framing affects expected Social Security claiming behavior. Similarly, Behaghel and Blau (2012) found that behavioral responses to changes in the Full Retirement Age were affected by how the changes were framed. Maurer et al. (2018) explored people's willingness to delay claiming Social Security benefits for a lump sum, providing a perspective on the interplay between instant gratification and delayed rewards.

Pioneering work by Madrian and Shea (2001) demonstrated the power of suggestion and inertia in retirement saving behavior, a theme that finds resonance in subsequent literature. Lastly, the role of discounting functions in retirement planning is supported by studies demonstrating the prevalence of hyperbolic discounting in Europe (Eisenhauer & Ventura, 2006) and among opioid-dependent individuals (Madden, Bickel, & Jacobs, 1999), offering a unique perspective on retirement planning across different population subgroups.

Section 2: Descriptive Analysis

2.1 MORTALITY EXPERIENCE

The basic mortality table used for descriptive statistical analysis was the 2016 Social Security Mortality Table, referred to as basic mortality. After adjusting for the impact of COVID-19 for experience in 2020 and 2021, referred to as COVID-adjusted mortality, based on sex and age grouping, the mortality indicated by the data was close to the 2016 Social Security Mortality. Since most of members involved with DROP were between ages 50 and 70, we used those age limits to compare the mortality experience to the tabular mortality. Margins in most tables used for actuarial purposes distorted the actual to expected ratios and produced some unexpected results. For plans with a data start date of June 30, 2019, the mortality of the first half year was assumed to be the basic mortality followed by 2 years of COVID-adjusted mortality before mortality was assumed to revert to the basic mortality. For plans with a data start date of December 31, 2018, the mortality of the first full year was assumed to be the basic mortality followed by 2 years of COVID-adjusted mortality. When reviewing individuals who entered DROP, the mortality used included COVID-adjusted mortality for 2020 and 2021, with prior and subsequent mortality being the basic mortality.

Active employees tend to be healthier and have lower mortality than the general population, since unhealthy individuals are less likely to be actively employed than healthy individuals. Louisiana ranks 47th in mortality among the States. Public employees tend to have offsetting influences on mortality relative to the general population (e.g., better healthcare access but lower wages). The mortality of active employees was approximately 96% of the model mortality. Due to the small number of deaths of DROP participants, there was no statistically significant difference between the mortality of active employees and those participating in DROP. However, the mortality of members who returned to work after DROP participation appeared to be the highest group, the experience was statistically insignificant; however, since these individuals tend to be among those with lower compensation, the result aligns with the generally accepted idea that lower income correlates with higher mortality. The mortality for retirees was approximately 107% of the model mortality. This was considered reasonable, given that Louisiana has slightly higher than national mortality.

2.2 MODIFICATIONS TO HYPERBOLIC DISCOUNTING

We will consider the hyperbolic discount function and make several modifications to it, explaining each step, to the final function used.

2.2.1 HYPERBOLIC DISCOUNTING

Hyperbolic discounting is a key concept in behavioral economics that challenges traditional economic theories about rational decision-making. It refers to the tendency of individuals to prefer smaller, immediate rewards to larger, delayed ones. This preference intensifies the closer we get to the immediate reward, causing our effective discount rate to decrease over time. In essence, hyperbolic discounting is a reflection of human impatience and the tendency to give stronger weight to present benefits than future ones.

As an example, if given the choice of receiving $53 immediately or $54 in a week, people tend toward choosing the immediate $53; however, if the choice is between $53 in a year or $54 in a year-and-a-week, people tend toward choosing the $54 option. In both cases the return is 1.89% in one week (164% annualized). From a purely economic comparison using exponential discounting, a person would be expected to make the same decision.

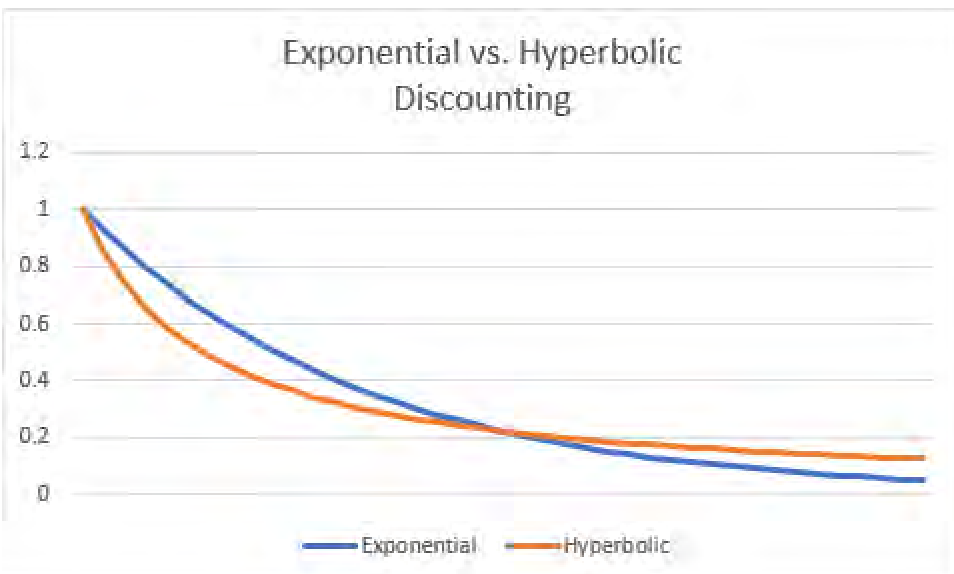
In the context of retirement economics, hyperbolic discounting can significantly influence saving behavior and retirement decisions. Individuals with a hyperbolic discounting preference often struggle to save adequately for retirement because the benefits of saving are perceived as too far in the future, while the costs (e.g., less money to spend in the present) are immediate. This behavior can lead to under-saving for retirement, inadequate pensions, and can potentially extend their working life, as individuals realize they have not accumulated enough to sustain themselves during retirement.

The decision to enter DROP is directly influenced by hyperbolic discounting. A DROP offers a near term, tangible benefit – the availability of a lump sum at retirement from the accumulation of pension benefits in a separate account while still receiving a salary. This can be particularly attractive for those employees who heavily discount far-future benefits. However, the choice to participate in a DROP can also have long-term implications that are less readily apparent due to the nature of hyperbolic discounting. For instance, by choosing to enter a DROP, employees are effectively deciding to freeze their pension benefits at the current level, which might be less than what they could have received had they stayed in active service and allowed their final average salary or years of service to increase. Employees are therefore trading-off a near-term lump sum for decreased pension in the long-term. An employee that hyperbolically discounts would find this trade substantially more attractive than, for example, an exponential discounter.

The basic formula used for hyperbolic discounting is:

$$Hyperbolic\ Discounting: \delta(t) = \frac{1}{1+\alpha t}.$$

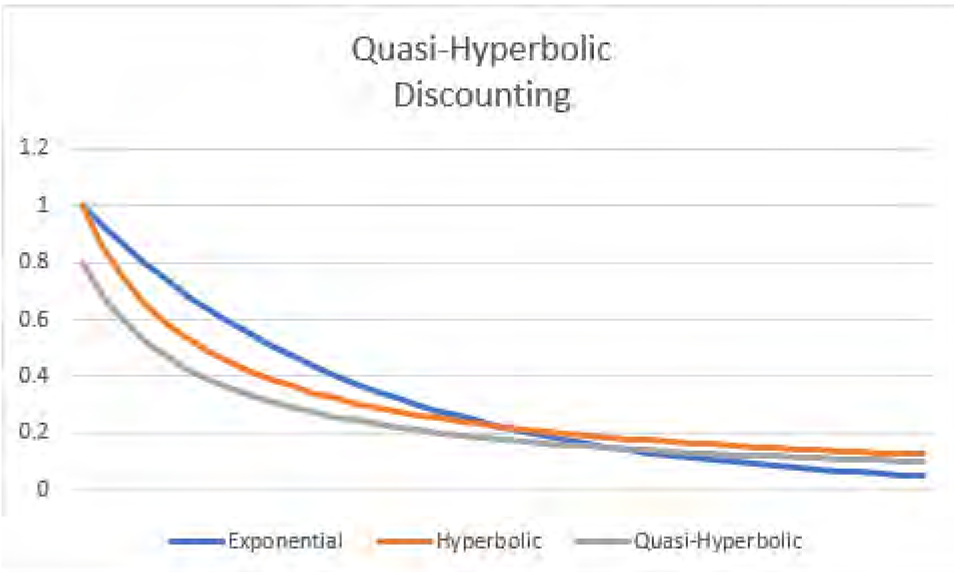
This formula bases present values on simple interest. Just as simple interest is equal to compound interest at times 1 and 0, there is a cross-over point between hyperbolic discounting and exponential discounting. The following graph reflects how exponential and hyperbolic discounting compare:



2.2.2 QUASI-HYPERBOLIC DISCOUNTING

The quasi-hyperbolic discount function accounts for the immediate drop in perceived value after the present (time=0). The discounting is multiplied by β if time is greater than 0. The factor is referred to as the present bias parameter. If β≠1, the quasi-hyperbolic function has a discontinuity at time 0. Some authors have used β × exponential discounting for time greater than 0. The use of the exponential function fails to produce a cross-over point; however, it does allow the computation of the value of a perpetuity.

A comparison of quasi-hyperbolic discounting to exponential and hyperbolic discounting is reflected in the graph below:



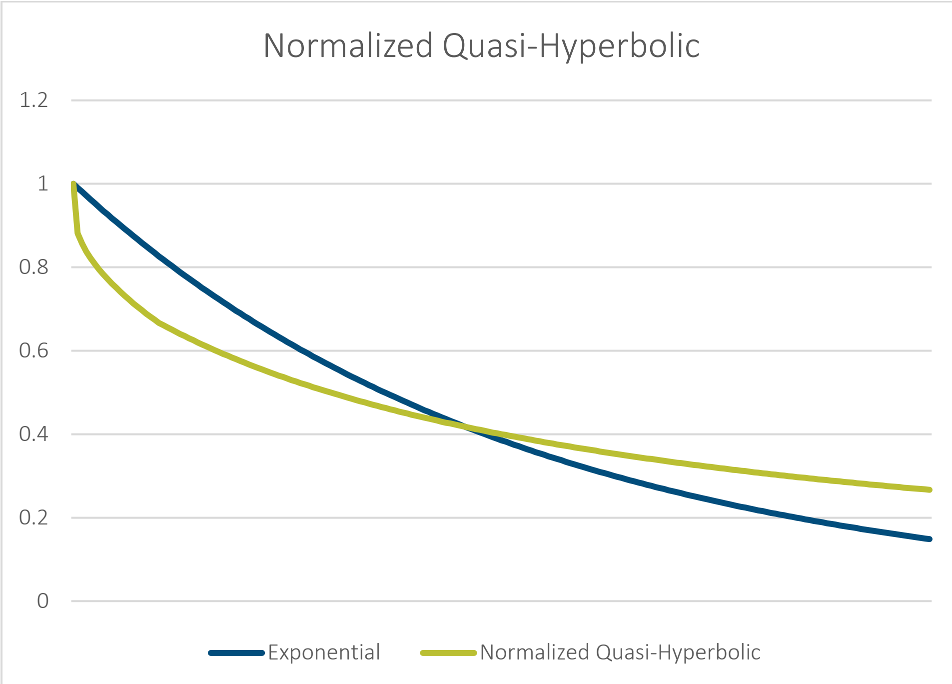
2.2.3 NORMALIZED QUASI-HYPERBOLIC DISCOUNTING

The first issue we will address with the quasi-hyperbolic discount function is the initial discontinuity. This implies the instant after the present, there is a discount of perceived value of (1- β). This is unreasonable; however, in most cases there is sufficient time between the present and the perceived value to use the function. Another alternative is to blend from the immediate value to the quasi-hyperbolic function. The blending function should be steep initially and have no slope at the point the function is equal to the hyperbolic function. One such function is the n^{th} root of the ratio of the time t to the time T when the function becomes equal to the hyperbolic function. We used the 10^{th} root and assumed 2 years fully recognized the fixed present bias, the resulting function is

$$\delta(t) = (1 - \sqrt[10]{\frac{t}{2}}) \times \frac{\beta}{1+\alpha t} + \sqrt[10]{\frac{t}{2}} for\ t\ \leq 2, and$$

$$\frac{\beta}{1+\ \alpha t}\ for\ t > 2.$$

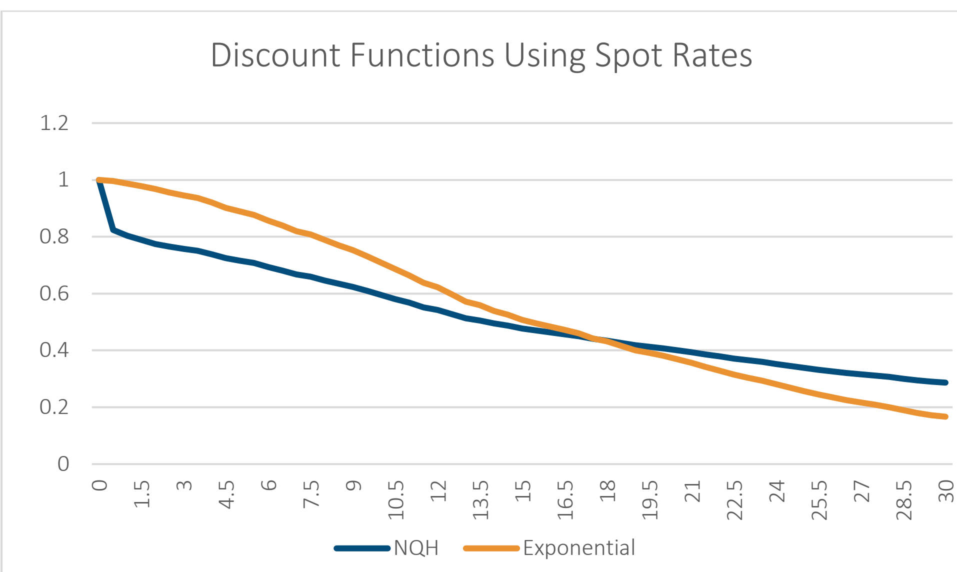
We refer to this blended function as a Normalized Quasi-Hyperbolic function ("NQH"), depicted in the graph below.



2.2.4 MODIFIED HYPERBOLIC DISCOUNTING

We modified the normalized Quasi-Hyperbolic discount function to account for two other factors: the change in interest rates based on maturity and the impact of age on an individual's discount function.

One assumption often used to simplify computations is to hold the interest rate as a constant over all maturities. If we wish our model to reflect reality, it is better to use spot rates for the interest rate at time t, denoted α(t). Including spot rates and a normal shaped yield curve produces a discount curve that more closely reflects reality but is not easily manipulated mathematically. The shapes of the curves are provided in the graph below.



The current form of the NQH has an unbounded integral and does not address limitations on an individual's use of the funds resulting from mortality. To illustrate this concept, if asked how much someone would pay for $100 payable in 100 years, most adults would not be interested in making the exchange because they do not expect to be alive in 100 years. People appear to include additional discounting based on their perceived life expectancy. Using a logical extreme, if we assume no interest and no inflation, the value to a person of an amount is proportional to their life expectancy. To modify the function to address current life expectancy and life expectancy at the time a payment is made, we will multiply the normalized hyperbolic discount function by the ratio of life expectancy at the time of payment to the current life expectancy, or

$$\frac{e_{x+t}}{e_x}.$$

The present value under this modified discount function given cash flow at time t, CF(t), for an individual age x would be

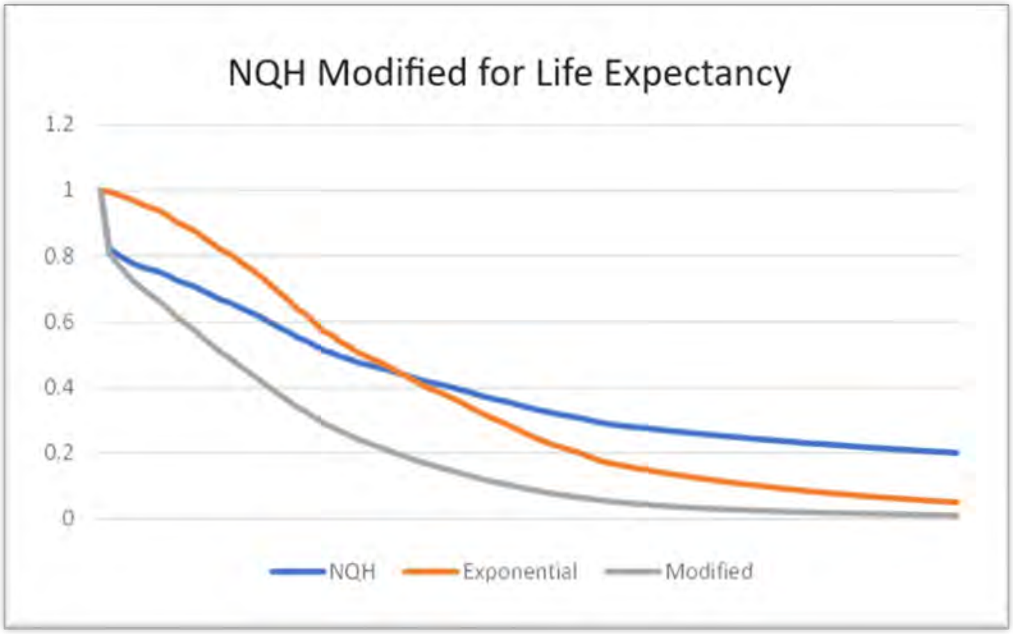
$$\int_0^{\omega-x} CF(t) \times \frac{\beta(t)}{1+\alpha(t)t} \times \frac{e_{x+t}}{e_x}\, dt \;\; or$$

$$\sum_0^{\omega-t} CF(t) \times \frac{\beta(t)}{1+\alpha(t)t} \times \frac{e_{x+t}}{e_x} \; for\ the\ discrete\ case.$$

If the cash flows occur after the grade-in period for the present value bias, we can assume β is constant. In comparing the choice between DROP or retirement, both discounts would be multiplied by β and divided by e_x, so β and e_x can be removed from both equations for comparisons, resulting in a perceived value of a cash flow proportional to

$$\sum_0^{\omega-t} CF(t) \times \frac{e_{x+t}}{1+\alpha(t)t}, where\ \alpha(t) is\ the\ spot\ rate\ at\ maturity\ t.$$

This modified hyperbolic discounting function indicates a tendency of individuals to mentally discount using simple interest while also considering how much of their remaining life the funds will be available for use.



2.3 DROP PARTICIPATION

There were 2,111 individuals on the database between the ages of 40 and 80, who were reported to enter DROP during the period of observation. 708 (33.5%) of these individuals would have had better economic benefits had they waited three years to retire. Using Normalized Hyperbolic Discounting, 916 (43.4%) of these individuals would have selected retirement over DROP. By including the life-expectancy adjustment, the number who theoretically would have selected retirement was 436 (20.7%).

The unadjusted hyperbolic discounting produced worse results than the economic discounting; however, when the hyperbolic discounting was adjusted for life expectancy, the modified hyperbolic discounting improved the projection by a statistically significant margin.

2.4 FACTORS CONSIDERED

2.4.1 MORTALITY/HEALTH

We compared the mortality of individuals who were participating in DROP to the mortality of eligible members who had elected not to participate in DROP. Although the mortality for DROP participants was slightly better than other active employees, statistical testing did not indicate a significant difference. This indicates anti-selection for entry into DROP based on health status may have a minimal impact but was not demonstrated to be material.

2.4.2 SALARY

We compared the salaries of members eligible to retire in 2018/2019 to their choices of remaining active, entering DROP, or retiring in 2021/2022. We also compared the salaries of those in DROP in 2018/2019 to their choice of retiring or returning to work. Some plans did not have salaries of DROP participants and were removed from the sample of those who started the sample period in DROP. The data are summarized in the table below:

Status	Average Salary	Standard Deviation	Number
Active to Active	$42,287.47	$24,504.12	2,710
Active to Retired	$41,204.20	$24,149.56	1,470
Active to DROP	$56,107.58	$26,424.85	1,179
DROP to Retired	$54,845.73	$23,625.29	641
DROP to Returned to Work	$50,949.02	$25,982.27	352

Statistical testing indicated the following:

Comparison	T-Statistic	Confidence of Difference
Active to Active vs. Active to Retired	1.336	81.83%
Active to Active vs. Active to DROP	15.362	>99.99%
Active to Retired vs. Active to DROP	2.305	97.88%
DROP to Retired vs. DROP to Returned to Work	2.399	98.34%

These data indicate the level of compensation is correlated to the choices of individuals eligible to retire. Members with higher compensation are more likely to enter DROP than those with lower compensation. After DROP participation, members with higher salaries are more likely to retire than to return to work compared to employees with lower compensation. The data also indicate members with higher salaries tend to continue working as non-DROP active employees or enter DROP later in their careers compared to members with lower salaries.

2.4.3 SALARY INCREASES

We limited the salary increase reviews to sub-plans with DROP participants. We removed one plan because the salary increases did not appear reasonable. (e.g., The salary changes over 3 years ranged from a 71% decrease to a 263% increase, and approximately 4% had increases of over 100% and 4% had decreases of at least 50%; so the salary data for the plan was considered unreliable.) We also removed one plan which did not provide salaries for members in DROP. The table below summarizes the data used related to salary increases.

Group	Count	Average 3-Year Salary Increase	Standard Deviation of Salary Increases
Active to Active (newly eligible)	1,351	13.42%	21.27%
Active to DROP (newly eligible)	500	11.99%	11.55%
Active to Active (previously eligible)	1,287	10.83%	12.51%
Active to DROP (previously eligible)	669	12.19%	13.92%

Data suggest when a person is first eligible for DROP, they are less likely to enter DROP if their salary will have a greater increase over the next 3 years than those who do enter DROP as soon as eligible. These members appear to have some sense of their future salary increases and behave accordingly with respect to DROP participation. However, DROP participants who enter DROP at least a year after eligibility tend to experience slightly greater than average salary increases. The confidence levels from statistical testing for these two comparisons were 96.7% and 98.3%, respectively.

2.4.4 YEARS OF SERVICE

We compared the years of eligible service of members eligible to retire in 2018/2019 to their choices of remaining active, entering DROP, or retiring in 2021/2022. We also compared the eligible service of those in DROP in 2018/2019 to their choice of retiring or returning to work. The data are summarized in the table below:

Status	Average Service	Standard Deviation	Number
Active to Active	18.75	6.57	2,710
Active to Retired	19.26	6.51	1,470
Active to DROP	23.94	4.33	1,179
DROP to Retired	23.09	5.68	641
DROP to Returned to Work	20.35	6.36	352

Statistical testing indicated the following:

Comparison	T-Statistic	Confidence of Difference
Active to Active vs. Active to Retired	2.422	98.45%
Active to Active vs. Active to DROP	28.849	>99.99%
Active to Retired vs. Active to DROP	21.171	>99.99%
DROP to Retired vs. DROP to Returned to Work	28.033	>99.99%

These data indicate individuals who enter DROP tend to have more service than those who chose to retire or continue working if their years of eligible service are higher. After DROP participation those with more years of service are more likely to retire than to return to work.

2.4.5 BENEFIT ACCRUAL RATE

The plans had various benefit accrual rates: 2.00%, 2.50%, 3.00% and 3.33 %. Eligible members in plans with 2.00% or 2.50% benefit accrual rates were compared to those in plans with 3.00% or 3.33% benefit accrual rates.

	Lower Accrual Rates (2.00%-2.50%)	Higher Accrual Rates (3.00%-3.33%)
Number Eligible	2,406	4,624
Number Entering DROP	350	1,123
Percent	14.55%	24.29%
Number in DROP	743	1,776
Number Returned to Work	337	581
Percent	43.36%	32.71%

Statistical testing indicates the probability of entering DROP for the eligible employees with higher accrual rates is greater than the probability for eligible employees with lower accrual rates. Furthermore, employees with lower accrual rates are more likely to return to work after their DROP participation period. Both tests had confidence levels greater than 99.99%.

2.4.6 SEX

Of 3,019 males eligible to retire at the start of the observed period (2018/2019), 731 were in DROP at the end of the observed period (2021/2022). Of 2,340 females eligible to retire at the start of the observed period, 448 were in DROP at the end of the observed period. The DROP participation rate over the three years for males and females was 24.2% and 19.1% respectively. Statistical testing produced a T-factor of 4.45, indicating a confidence of more than 99.99% that males are more likely to enter DROP than females.

2.4.7 AGE

We considered the impact of age on an individual's time of DROP election; however, the age distribution tended to cluster at the ages when retirement eligibility is reached, such as 55, 60, and 65. Since age at DROP entry appears to be primarily influenced by eligibility to retire, we did not pursue age further.

2.4.8 RETIREMENT ELIGIBILITY

Although different plans have different requirements for retirement and DROP eligibility, we looked at when people enter DROP relative to the number of years they are past eligibility. There was significant variation between plans. Despite similar benefits, one plan had as few as 20% and another had more than 96% of DROP participants electing to enter DROP in the first year of eligibility. The results provided in the table below indicate most people who elect to enter DROP do so within their first year of eligibility.

Year Beyond Eligibility	Count	Percent Entering DROP	95% Confidence Range Floor	Ceiling
0	1,180	55.24%	53.13%	57.36%
1	160	7.49%	6.37%	8.61%
2	179	8.38%	7.20%	9.56%
3	125	5.85%	4.85%	6.85%
4	101	4.73%	3.82%	5.63%
5	171	8.01%	6.85%	9.16%
6	69	3.23%	2.48%	3.99%
7	56	2.62%	1.94%	3.30%
8	40	1.87%	1.29%	2.45%
9	23	1.08%	0.63%	1.52%
10	15	0.70%	0.34%	1.06%
11	3	0.14%	0.00%	0.30%
12	6	0.28%	0.05%	0.51%
13	3	0.14%	0.00%	0.30%
14	3	0.14%	0.00%	0.30%
15	0	0.00%	0.00%	0.13%
16	1	0.04%	0.00%	0.13%
17	1	0.04%	0.00%	0.13%

Section 3: Predictive Analyses

3.1 UNDERSTANDING DROP ELECTION

The descriptive analyses provide evidence as to the importance of different factors in individuals choice to retire, continue working, or enter DROP. We analyzed one variable at a time. This ignores the interaction and correlation between variables. These interactions and correlations that inhibit firm interpretations of the descriptive statistics. For example, those with higher benefit accrual rates entered DROP at a higher rate. Was this because of the benefit accrual rate, or because benefit accrual rates correlate with employer and the type of job, and the latter is the true driver of DROP choice. To disentangle which of these correlated variables are truly driving individual choices, we perform predictive analyses that analyze them all at once.

3.1.1. DECISION TREE

A decision tree is a non-parametric supervised learning algorithm used for classification and regression tasks. Decision trees partition the input space into regions, each of which is associated with a class. In our case there are three classes an individual can fall into:

1. Continue working
2. Retire
3. Enter DROP

A decision tree works as follows:

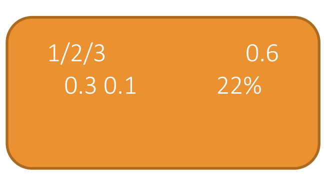
1. Feature Selection: At each node of the tree, the algorithm selects a feature and a threshold that minimizes an impurity measure. In our case, we use the change in entropy as the measure of information gain. The algorithm searches over all features and all possible thresholds for each feature to find the best split. Entropy is defined as

$$E = \sum_{terminal\ nodes} \sum_{i=1}^{3} -p_i \log p_i.$$

Where p_i is the proportion of type $i = 1\ (continue\ working), 2\ (retire), 3\ (enter\ DROP)$ at a given terminal node.

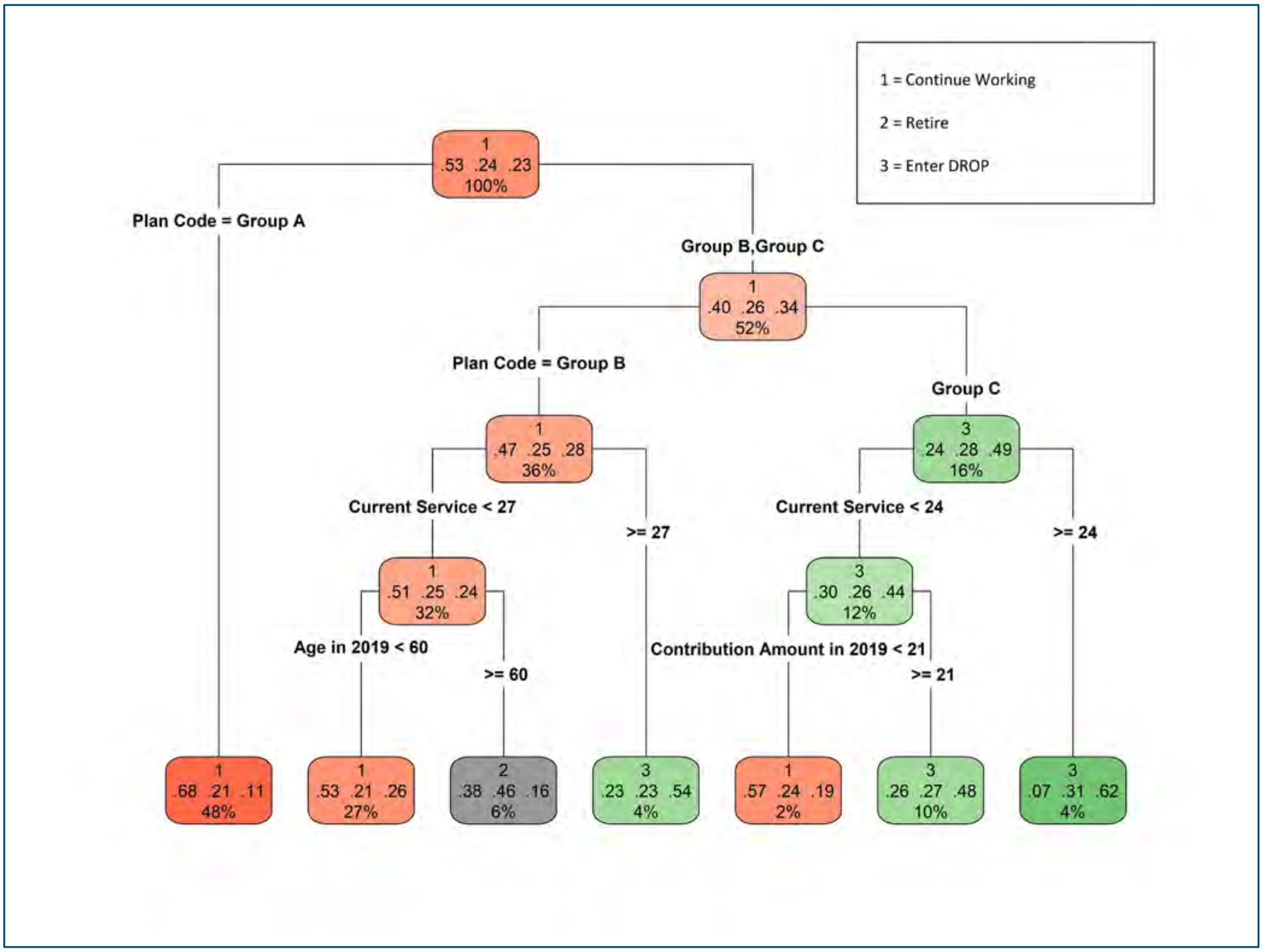
2. Splitting: The data is split into subsets based on the best feature-threshold pair. Each subset forms a branch of the tree emanating from the node.
3. Tree Growing: The process of feature selection and splitting is recursively applied to each subset of the data. This creates a binary tree of decisions, with each leaf of the tree representing a prediction.
4. Pruning: To prevent overfitting, the tree is pruned back to an optimal size. Pruning typically involves collapsing some nodes of the tree back into their parent node, converting it into a leaf. The complexity parameter controls the size of the decision tree and prevents the model from overfitting to the training data. We choose a complexity parameter of 0.005, which means splits that achieve an information gain of less than 0.005 are pruned and dropped.

The fitted tree is in Figure 1 - Work/Retire/DROP Decision Tree. Each node (the colored rectangle) is interpreted as follows:



The number at the top (1 or 2 or 3) of the node is the majority class at that node. The color of the rectangle also represents this. The middle row lists the proportions of each class at that node. The number in the bottom row is the percent of the total population in that node.

Figure 1
WORK/RETIRE/DROP DECISION TREE



This tree provides insight into which variables are important in predicting whether an employee continues working, retires, or joins a DROP.

Plan Code: which employer and therefore which DROP plan is available has significant discriminatory power for the outcome classes. In other words, Plan Code appears to be a major factor in determining the work outcomes for the employees. This suggests that some employers or agencies typically continue working beyond minimum retirement age.

Current Service: how much service an employee had accumulated in 2019 is an important predictor. Those with less service typically continue working, conditional on being eligible for retirement. Those with more service typically enter DROP, perhaps because the extra years of creditable service foregone by entering DROP are less important for those who already have lots of accumulated creditable service.

Age in 2019: within the set of retirement-eligibles with less than 27 years of service, participants who were older than 60 are more likely to retire upon eligibility, whereas those younger than 60 are more likely to continue working.

Contribution Amount in 2019: the size of the participants mandatory contribution in 2019, which is highly correlated with annual salary in 2019, was an important predictor of DROP entrance. Those with high contribution amounts often entered DROP. When entering DROP mandatory contributions no longer need to be paid. This explains why those with a high contribution amount were more likely to enter DROP.

While decision trees are simple to understand and interpret, they do have several limitations:

1. Instability: Decision trees are highly sensitive to the data they are trained on. Small changes in the training data can result in vastly different trees. If the data changes, the decisions made by the tree can also change dramatically.
2. Overfitting: Decision trees can easily overfit the training data. This is because the trees can grow complex enough to approach perfect classification. This makes them perform poorly on unseen data.
3. Bias towards features with more levels: Decision trees are biased towards variables that have more levels or categories. These variables can create more splits and therefore seem more important than they really are.

To overcome these limitations, we use ensemble methods like Random Forests. Random Forests construct a multitude of decision trees at training time and output the class that is the mode (for classification) or mean (for regression) prediction of the individual trees.

3.1.2. RANDOM FOREST

A Random Forest is an ensemble learning method that combines multiple decision trees to create a robust and accurate model. It works as follows:

1. Random Sampling: Random Forest starts by randomly sampling the training data with replacement (bootstrapping). This creates multiple bootstrap subsamples of the data.
2. Random Feature Selection: For each decision tree in the Random Forest, a random subset of features is selected from the total set of features. This helps to introduce diversity among the trees and prevents dominant features from overpowering the model.
3. Tree Construction: Each decision tree in the Random Forest is built using the bootstrap sample and the randomly selected features. The trees are grown by recursively splitting the data as described in the prior section.
4. Voting for Prediction: Once all the trees are constructed, predictions are made by aggregating the results from individual trees. For classification, the mode (most frequent class) of the predicted classes is taken as the final prediction.
5. Ensemble Prediction: The final prediction of the Random Forest is determined by combining the predictions of all the trees. This ensemble approach helps to reduce overfitting, increase accuracy, and improve the model's generalization ability.

The randomness introduced through random sampling and random feature selection in Random Forests helps to de-correlate the trees and reduce overfitting. It also allows the model to capture a wide range of relationships present in the data.

Advantages of Random Forests:

1. Robustness to overfitting: Because each tree in the forest is trained on a different subset of the data, and at each node, a random subset of features is considered for splitting, the variance of the model decreases, making the model more robust to overfitting.
2. Stability: Due to the averaging procedure, Random Forests are much less sensitive to changes in the training data, thus providing a more stable and robust model.
3. Handling bias towards features with more levels: Random forests help mitigate the decision tree's bias towards features with more levels. By using a subset of features at each split, it gives a chance for variables with fewer levels to be selected as well.

We fit the random forest and predict a classification based on the modal predicted class of all the trees. The following table summarizes the out-of-sample accuracy of the random forest.

Predicted Class	Actual Actives	Actual Retirees	Actual DROP	Class Error
Active	2,142	271	288	21%
Retired	688	233	268	80%
DROP	516	149	494	57%

The random forest is quite good at classifying those that end up continuing to work: 80% are predicted to be in this class. However, the random forest is very bad at predicting those who will retire. While those who are predicted to enter DROP end up entering DROP or working – suggesting that the margin of work or work with DROP versus retirement is somewhat predictable – perfectly distinguishing who will enter DROP is difficult. Overall, of the 5,049 participants, we correctly classify 2,849, a rate of 57%.

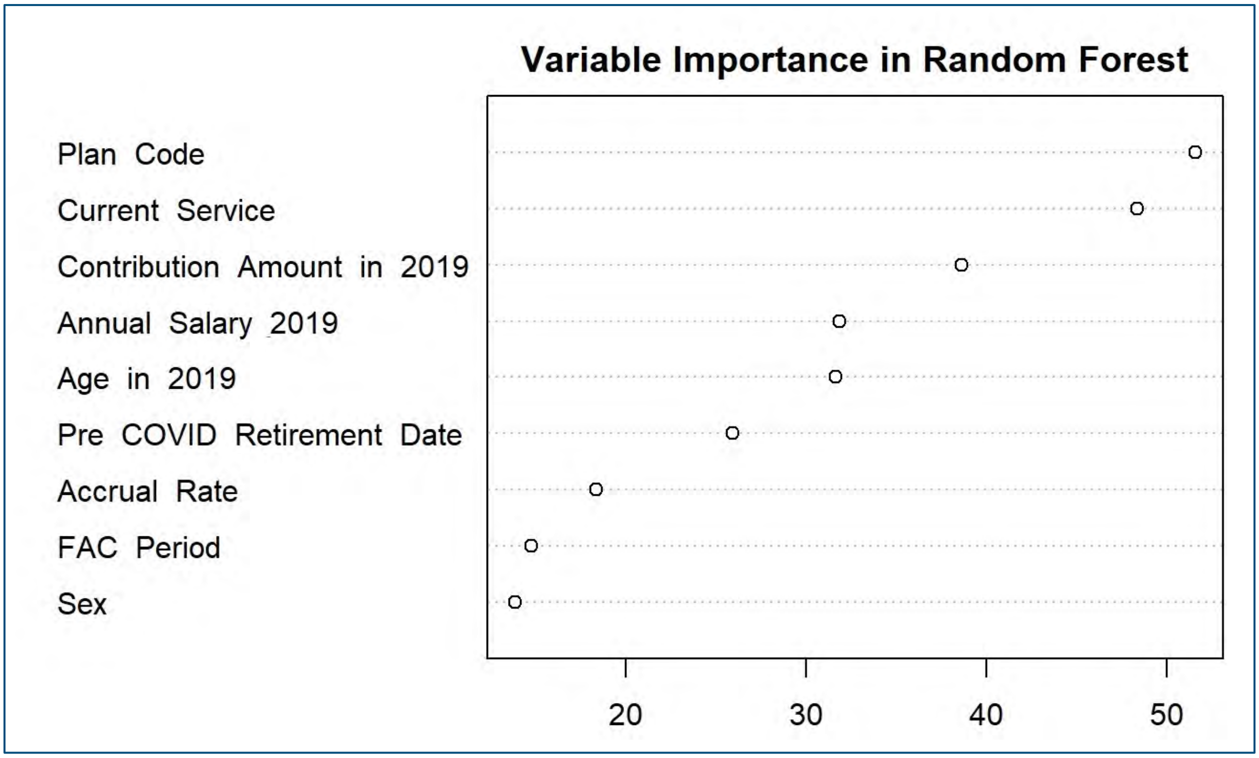
Finally, to measure the relative importance of different variables, we perform the following process:

For each variable:

1. Randomly permute data for that variable.
2. Recompute predictions for each of the estimated trees.
3. Recompute the predicted class based on the modal prediction of the trees.
4. Compute how many additional incorrect classifications are made relative to the original forest.

The results are in Figure 2 - Ranking of Variable Importance in the Random Forest below.

Figure 2
RANKING OF VARIABLE IMPORTANCE IN THE RANDOM FOREST



We see that, consistent with the decision tree above, plan code, current service, age, and contribution amount in 2019 are the most important predictors. Leaving any of them out unilaterally would add 30-50 further incorrect classifications, or about 1-2% relative to the base rate of incorrect classification. Many of these variables are correlated. For example, annual salary and contribution amount in 2019. For that reason, leaving just one of these variables out doesn't impact accuracy that much, since the remaining variable contains most of the information lost. However, for this reason leaving both out would likely do much more damage than the sum of leaving each out.

3.2 PREDICTIVE/CORRELATIONAL VS. CAUSAL ANALYSIS

Consider the scenario where a pension fund is contemplating a change in their retirement plan structure. For example, they may be considering changing the retirement condition to 10 years of service at 60 years of age instead of 62. The fund's objective is clear: optimize the retirement plan structure to best serve both the interests of its beneficiaries and the long-term health of the fund itself.

In order to make the most informed decision, the fund needs to understand the potential impact of such changes on retirement behaviors and the overall sustainability of the pension fund. Two commonly employed approaches to this kind of impact analysis are predictive (or correlational) modelling and causal analysis. While both are valuable, they provide different kinds of insights and should not be confused with one another.

For concreteness, let's consider two plans: plan A requires 10 years of service at age 60 to retire, plan B requires 10 years of service at age 62. Predictive modelling, such as the tree and forest analysis above, may reveal that employees in a plan A enter DROP at a higher rate than B. Specifically, plan B might have a DROP take-up rate of 30%, compared to plan A's rate of 40%.

Does this mean that if a pension fund that is considering raising the retirement age from 60 to 62 should expect a 10% decline the rate of DROP take-up? No! Predictive or correlational analyses typically say nothing about causal effects of, for example, plan changes. The individuals in the data from which the 40% and 30% were estimated for plans A and B respectively might differ in many ways, observed and unobserved. They might work in a different industry, different region, level of physically strenuous work, have a different workplace culture regarding retirement, and a multitude of other unobservable factors. The 10% difference might be due to other correlates of plan A in the data, not plan A versus B itself.

To give a valid causal estimate of what would happen if a change was made to a retirement condition, such as if a plan raised their retirement age by 2 years, we need to move beyond predictive or correlational analysis. The ideal methodology – and how this is done in a laboratory – is to run a random experiment. One would randomly assign some employees to plan A, and others to plan B, and compare their choices. The key is that because of the random assignment, those in plan B would be ~~an~~ identical on average – in terms of observable and unobservable factors - to those in plan A, *but for the plan*. As a result, any difference in DROP choices between these two experimental groups could be attributed – causally – to the difference in plan.

Actual experimentation is often impossible in real life. However, we can do almost as well by finding 'quasi-experimental' variation such that those in plan A and those in plan B are as good as randomly assigned.

In this setting, we exploit the fact that the retirement plan in which employees are enrolled can change discontinuously depending on their date of hire. For example, those hired on December 31st, 2010, might be in plan A, whereas those hired on January 1st, 2011, in plan B. If we believe that it is pure chance (for example, who got the paperwork in first) as to who was hired a day earlier or later, then we can use those hired just before the plan change cutoff as a valid control group for those hired just after. This generates quasi-random variation: those hired on either side of the cutoff should not differ from each other, but for the change in plan. In such a setting, we can use a statistical technique called a Regression Discontinuity Design to infer a causal effect of the plan.

3.3 REGRESSION DISCONTINUITY DESIGN (RDD) TO ESTIMATE THE EFFECT OF A PLAN CHANGE

Suppose our aim is to estimate the causal impact of changing plans on the actual age of retirement, or whether an individual entered DROP, or similar. We set up and explain the RDD procedure.

The 'running variable' that determines plan assignment is in our case the Date of Entry into the plan ("DOE"), which is typically the date at which employment commences. We have a cutoff date c at which plan assignment changes, which might typically be December 31st or June 30th. We are interested in multiple outcomes, labeled Y, such as average retirement age, average service at DROP entry and so on.

First, we flexibly estimate (for example, with a high order polynomial) the conditional mean function separately for the data above and below the cutoff:

$$f(x) = E[Y \mid x < c],$$

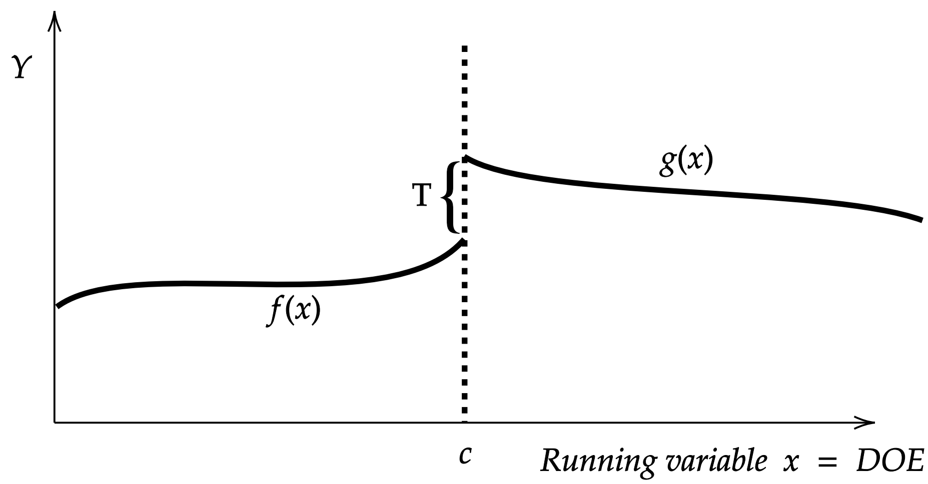
$$g(x) = E[Y \mid x > c].$$

Then the causal effect T of being in the new plan (i.e., if $x > c$) relative to the old plan (i.e., if $x < c$) is given by the difference in conditional means functions, evaluated at the cutoff:

$$T = f(c) - g(c).$$

This procedure is intuitively illustrated in Figure 3 - RDD Illustration. A full econometric explanation and results for valid standard errors and confidence intervals can be found in Calonico, Cattaneo and Titiunik (2014).

Figure 3
RDD ILLUSTRATION



For this T to be a valid estimate of the causal effect of moving from the old plan to the new, we need the individuals on either side of the cutoff to be, on average, identical except for the plan change. We can assess this in multiple ways:

Covariate Balance Test – We will check whether the individuals on either side of the cutoff are equal on dimensions such as salary, age of hire, sex etc. If not, this would bias our causal estimates, as the effect we see might be due to the imbalanced covariate as opposed to the plan change.

Density Test – To check that there is no manipulation of the running variable (e.g., individuals are not strategically bringing forward or back their hire date to take advantage of the change in retirement plan) we look for continuity in the density function of the forcing variable.

Placebo Tests – We run our RDD analysis at placebo's other than the true cutoff c. We expect to find no effect at other cutoffs. If we did find an effect, it would suggest the results are spurious.

3.4 RDD EVALUATION OF A PLAN CHANGE

We study a real reform in one of the Louisiana public pension plans in which the retirement conditions changed. Under the old plan, a member could retire with 7 years of service at 65, or 10 years of service at 60, or 25 years of service at 55. Under the new plan, to retire, a member was required to have 7 years at 67, 10 years at 62, or 30 years at 55. Since the first two conditions are most common for actual retirement eligibility, this change had the primary effect of increasing retirement age by 2 years. Additionally, the FAC period increased from 36 months to 60 months.

Members hired before December 31st of a particular year were in the old retirement plan. Members hired from January 1st onward of the next year were in the new retirement plan. Hence, our running variable is date of hire, and our cutoff is January 1st.

We begin with some tests of the validity of the RDD. First, we check whether members on either side of the cutoff differ in their non-plan related characteristics, such as salary or sex. This functions as a test of whether individuals were strategically starting their jobs just before the cut-off to benefit from the more favorable conditions. Not all the predictors used in, for example, the random forest analysis, are relevant to this kind of check. Some predictors, such as age at retirement, are explicitly affected by the plan change. These are analyzed later, after we have established validity of the RDD by checking that non-plan predictors are comparable before and after the cutoff.

Figure 4

EFFECT OF PLAN CHANGE ON THE MIX OF THE SEX OF MEMBERS

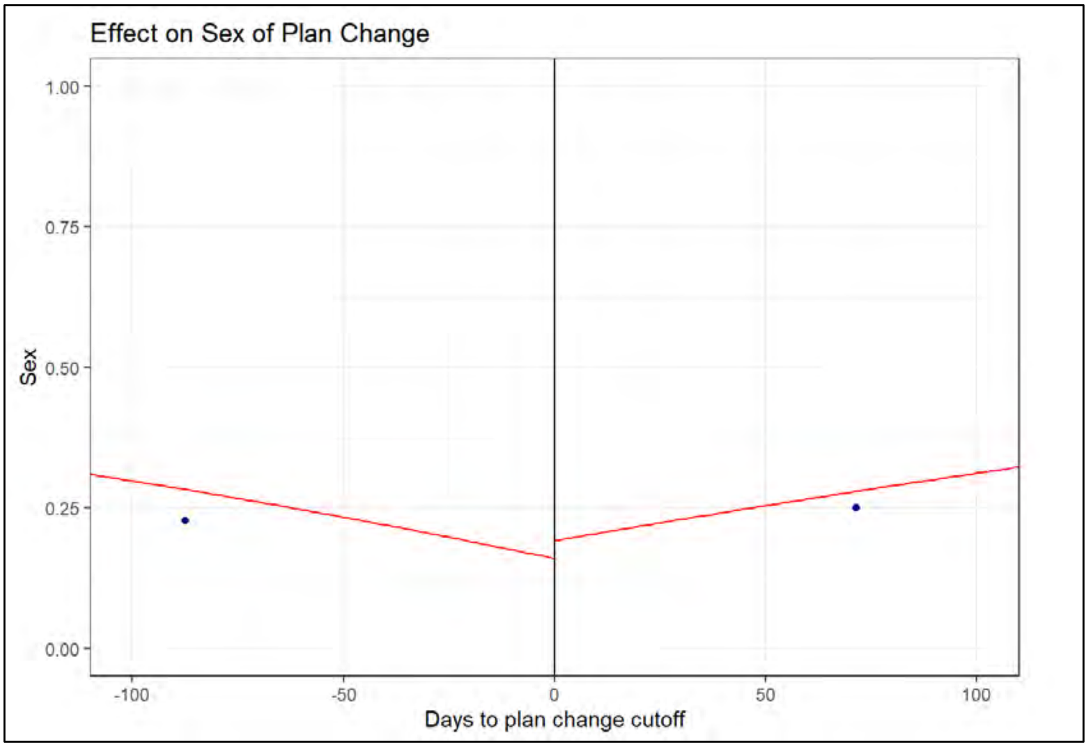
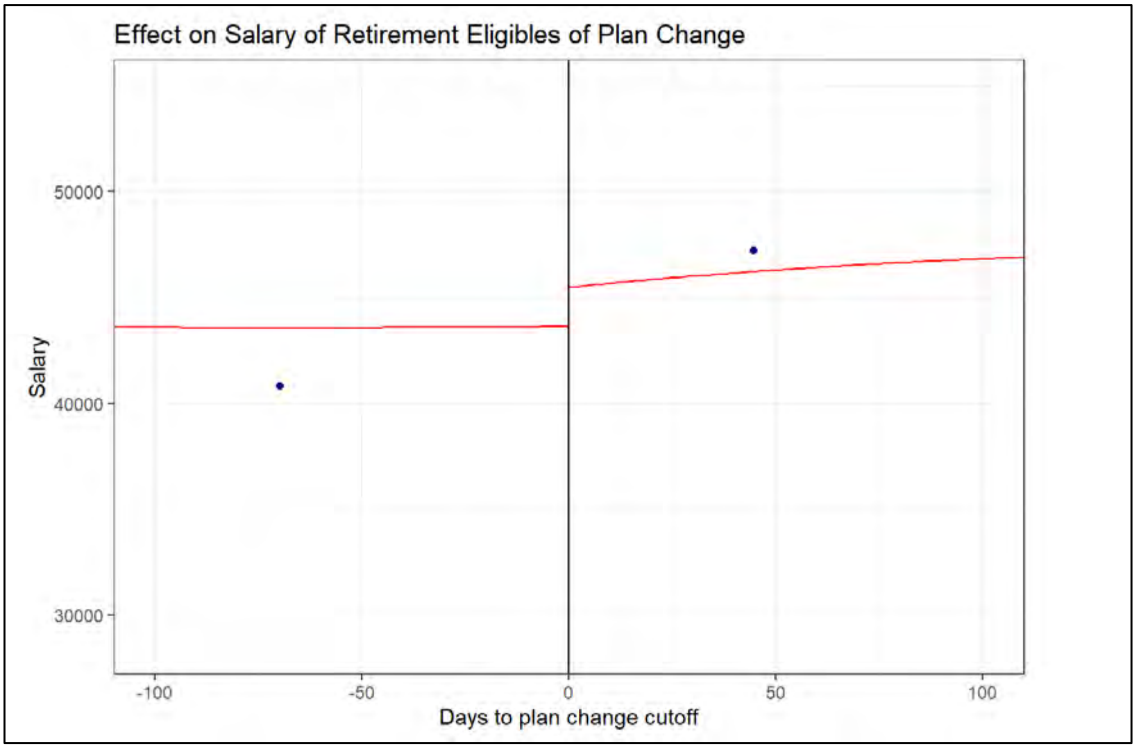


Figure 5
EFFECT OF PLAN CHANGE ON THE AVERAGE MEMBER SALARY IN 2019



As the two figures above show, there is no marked difference on sex or salary of those hired just before or just after the cutoff. The standard errors for the estimates of T are 0.2 (sex) and $8,000 (salary). Hence there is no statistically significant difference on sex or salary before or after the cutoff. Note that our small sample size (approximately $n = 200$ people) is reducing the precision of the estimates. Nevertheless, it is reassuring that on these two covariates there does not seem to be any difference around the cutoff, increasing our confidence in quasi-random assignment.

Next, we study the effect the plan change had on its intended target: retirement age.

Figure 6
EFFECT OF PLAN CHANGE ON THE AGE OF ELIGIBLE RETIREES

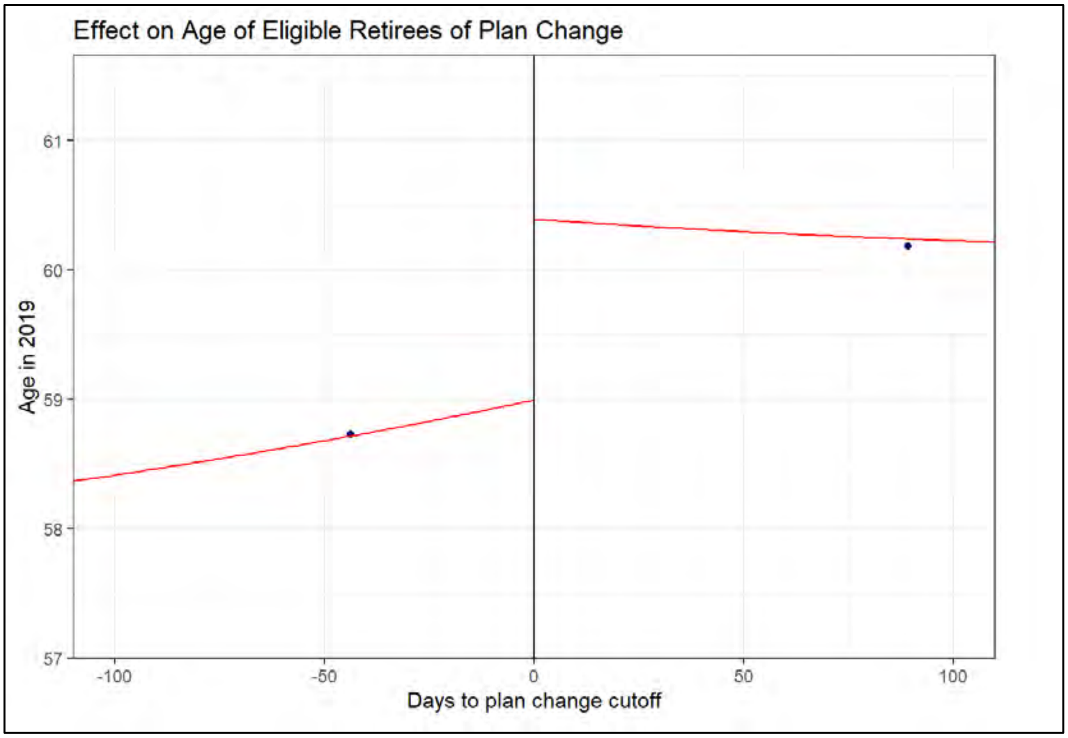
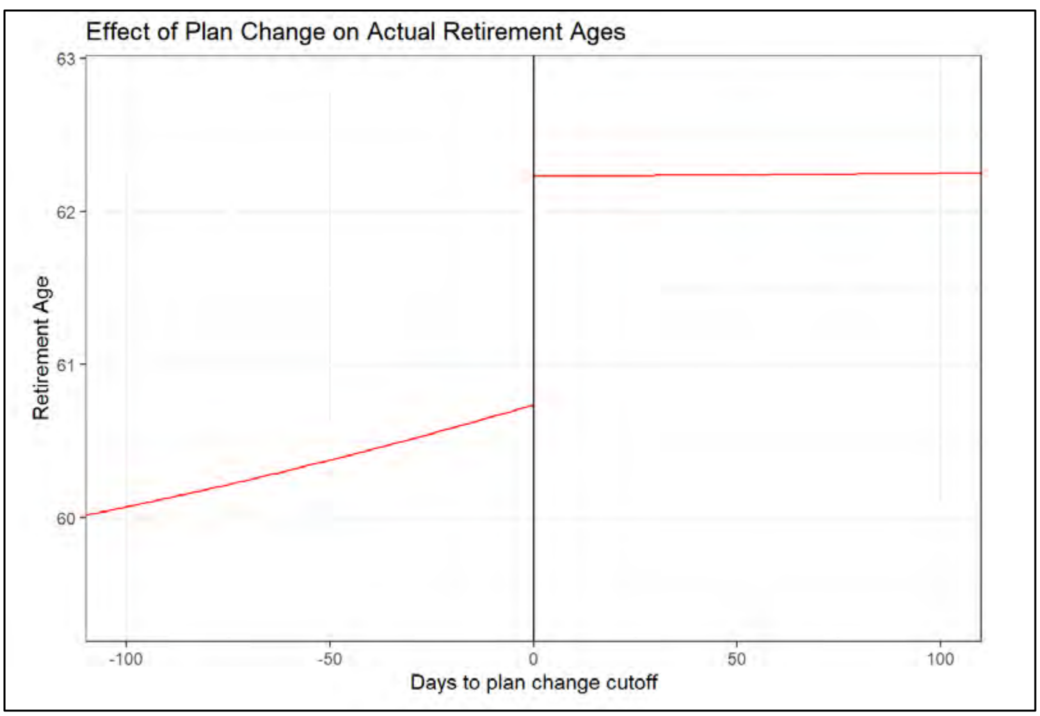


Figure 7
EFFECT OF PLAN CHANGE ON ACTUAL RETIREMENT AGES



The two figures above show that the plan change had its intended effect. The age of eligibility for retirement mechanically increased from, on average 59 to 61 (with a standard error of 0.47 years) and this led to an increase in actual retirement age from just under 61 to just over 62 (with a standard error of 0.48 years).

The plan change functioned as if to randomly increase the age of retirement eligibility on either side of the cutoff. Thus, we can consider the change in plan as a quasi-random increase in retirement eligibility age and study its effects on DROP enrollment.

Figure 8
EFFECT OF PLAN CHANGE ON DROP MEMBERS

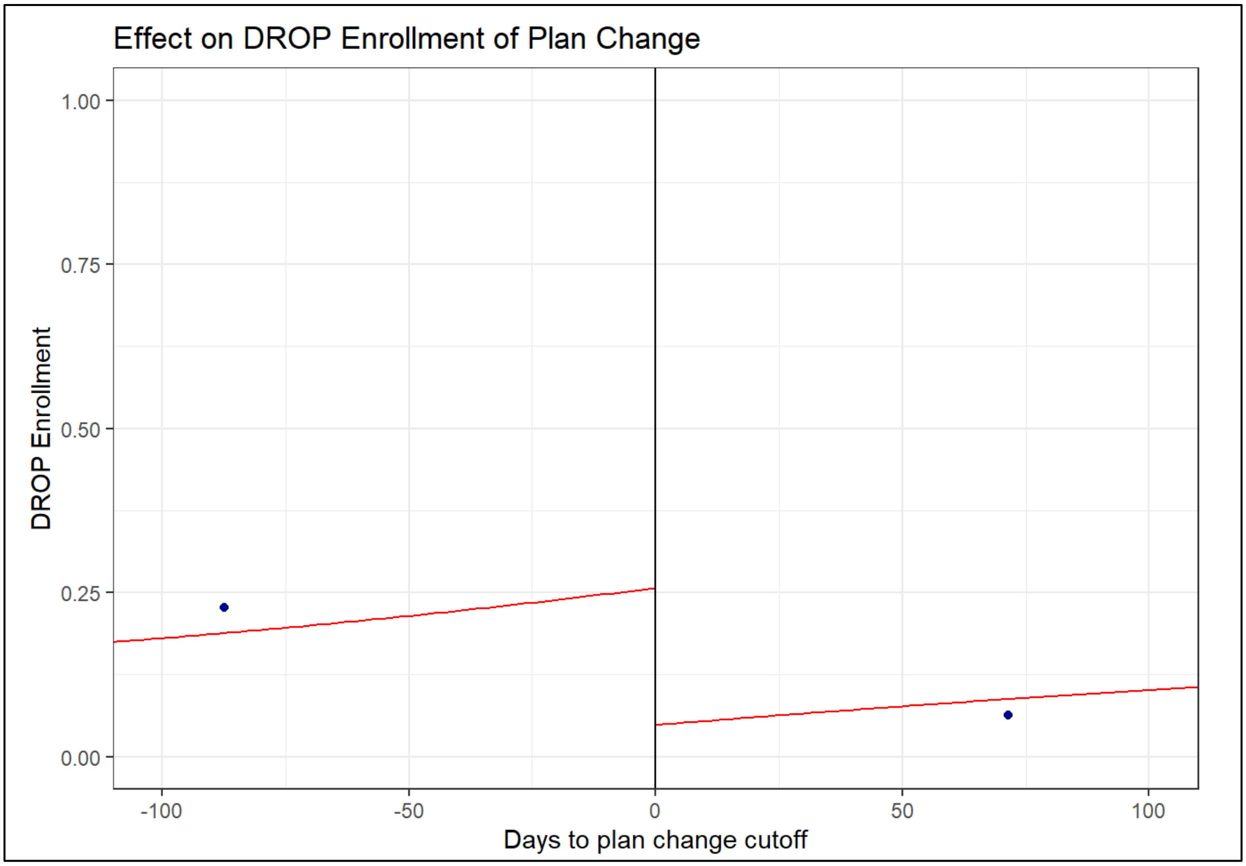


Figure 8 above demonstrates that DROP enrollment falls by approximately 25% (with standard error of 0.15) following the introduction of the plan change. This (imprecisely estimated) causal effect confirms the correlation we found in the tree and forest analysis: the older a member is when they first become eligible for retirement, the lower the chance of entering DROP.

This section is primarily about introducing and explaining RDD and applying it to DROP plans. Owing to very limited data size, most of our estimates are quite noisy. Nevertheless, these techniques can be applied in a wide variety of insurance settings in which there is a discontinuous change in plan parameter and causal effects wish to be estimated.

Section 4: Study Conclusions and Limitations

4.1 CONCLUSIONS

Although hyperbolic discounting partially addresses the immediate discount of perceived values, the model fails to improve the predictive value of DROP participation in the plans tested.

Modifying hyperbolic discounting by multiplying the future cash flows by the relative life expectancy materially improves the decision-making model for election of DROP participation.

The data supports the concept that individuals who have relatively lower compensation and benefits are less likely to make optimal economic decisions.

4.2 LIMITATIONS

No model is perfect, and simplifying assumptions are usually necessary. The study is based on data from 11 public retirement systems in one state, so some of the behaviors could be attributed to public employment and to regional or other cultural considerations; therefore, the findings may not be applicable for all DROP plans. Some key considerations not included in our model are identified and discussed below.

4.2.1. DATA QUALITY

Although we reviewed the data and determined it appeared reasonable, errors in the data reported could distort the results of the study. We identified a few anomalies, but they were rare and not material to the study. We either omitted records with missing data or used reasonable assumptions to construct the missing data, such as missing salaries for some DROP participants.

4.2.2. SALARY PAYMENTS DURING DROP PARTICIPATION

We compared DROP participation to continuing employment through the DROP participation period. This avoided the impact of differing salary payments beyond the employee contributions to the plan; however, this approach does not provide a comparison of DROP entry to immediate retirement, which could be part of a member’s consideration when making a decision about DROP participation.

4.2.3. IMPACT OF SOCIAL SECURITY AND OTHER PENSION BENEFITS

One significant issue we were unable to address was the interplay between Social Security Benefits and pension benefits. Since most public pension plans and railroad retirement is separate from Social Security and the members do not generally participate in Social Security while in these plans, either the participants are not eligible for Social Security benefits, or their Social Security benefits are reduced for the retirement benefits paid for service not subjected to Social Security contributions. The Social Security considerations vary by individual, and the impact on an individual’s Social Security benefit could not be considered in this study.

4.2.4. IMPACT OF TAXES

Another consideration, which could be significant, is the impact of taxes on an individual’s choices. This is also an individual consideration.

4.2.5. CHANGES IN INTEREST RATES

The interest rate curve used did not always reflect the interest rate curve at the time individuals chose to enter DROP. We did not consider the impact of changing interest rates or inflation. We believe it is unlikely that most individuals perform an actual present value calculation using current rates; however, it is reasonable to assume individuals have a general idea of interest rate levels.

4.2.6. BENEFIT OPTIONS

Pension plans usually offer several retirement options in exchange for a reduction in benefits. These include having benefits payable to the spouse, or other designated individual if permitted, upon the member's death of up to 100% of the reduced member's benefit or a guarantee of the minimum payout to be at least as great as the member's contributions. We assumed the DROP benefits and subsequent retirement benefits are the accrued benefit without consideration of the impact of the selection of a different payment option. The economic value of various payment options may not be actuarially equivalent. This is due to both anti-selection and the consequences of the Norris decision, which has resulted in gender neutral option factors. Although some benefits may be payable upon death of the member, these were not considered in the computations.

4.2.7. REDUCED EARLY RETIREMENT BENEFITS

Some plans allow early retirement with reduced benefits. We assumed all retirements and DROP participation occurred without consideration of any early retirement benefit options.

4.2.8. COST OF LIVING ADJUSTMENTS

Some of the plans have historically granted cost of living adjustments (COLAs) to retirement benefits. These are usually funded from excess earnings. The treatment of the DROP accrual amount and an actual retiree pension payment may not be treated the same with respect to any COLAs granted by the plan. These COLAs are not guaranteed benefits and were not taken into consideration in our analysis. Similarly, inflation or anticipated inflation can influence perceived value, but this issue is not addressed here.

4.2.9. CORRELATIONS AND CAUSATIONS

We considered the variables independently and did not investigate any correlations or possible causations between them.

4.2.10. BIAS RESULTING FROM CLUSTERED AGES OF ELIGIBILITY

There was insufficient data and too much age-at-first-eligibility bias to perform an age study with significant granularity.

4.2.11. RECIPROCAL SERVICE RECOGNITION

Some members have service in more than one plan. The service in the other plan may be counted towards eligibility to retire; however, the inter-plan reciprocal recognition of service was not included in this study.

4.2.12. IMPACT OF COVID-19

The period under study included two years significantly impacted by the COVID-19 pandemic, 2020 and 2021. Although we adjusted mortality for COVID-19 in those two years, we could not access the impact the pandemic may have had on member's choices.

4.2.13. VALUES LIMITED TO LIFE OF INDIVIDUALS

The integral of the hyperbolic function, including modifications herein without the life-expectation adjustment, is unbounded. This indicates there is no defined perceived present value of a stream of payments; therefore, the hyperbolic discounting does not fully reflect reality and the model is only useful for a limited time, after which some form of exponential discounting may be applied. No adjustments to the model formula were made since the time periods in question are limited to the remaining lifetimes of the members.

4.2.14. ANTI-SELECTION

Individuals may have specific information, such as expectations of promotions or their health conditions, which could impact their decision-making related to DROP participation. Although some of this was explored in the study of various factors, the impact of beneficial or adverse selection could not be directly measured from the data available.

Section 5: Acknowledgments

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Appendix A: Social Security 2016 Mortality Tables

Exact age	Male			Female		
	Death	Number of	Life expectancy	Death	Number of	Life expectancy
2016 SSA Mortality Table						
0	0.005837	100,000	74.12	0.004907	100,000	79.78
1	0.00041	99,416	73.55	0.000316	99,509	79.17
2	0.000254	99,376	72.58	0.000196	99,478	78.19
3	0.000207	99,350	71.6	0.00016	99,458	77.21
4	0.000167	99,330	70.62	0.000129	99,442	76.22
5	0.000141	99,313	69.63	0.000109	99,430	75.23
6	0.000123	99,299	68.64	0.0001	99,419	74.24
7	0.000113	99,287	67.65	0.000096	99,409	73.25
8	0.000108	99,276	66.65	0.000092	99,399	72.25
9	0.000114	99,265	65.66	0.000089	99,390	71.26
10	0.000127	99,254	64.67	0.000092	99,381	70.27
11	0.000146	99,241	63.68	0.000104	99,372	69.27
12	0.000174	99,227	62.69	0.000123	99,362	68.28
13	0.000228	99,209	61.7	0.000145	99,349	67.29
14	0.000312	99,187	60.71	0.000173	99,335	66.3
15	0.000435	99,156	59.73	0.00021	99,318	65.31
16	0.000604	99,113	58.76	0.000257	99,297	64.32
17	0.000814	99,053	57.79	0.000314	99,271	63.34
18	0.001051	98,972	56.84	0.000384	99,240	62.36
19	0.00125	98,868	55.9	0.00044	99,202	61.38
20	0.001398	98,745	54.97	0.000485	99,159	60.41
21	0.001524	98,607	54.04	0.000533	99,111	59.44
22	0.001612	98,456	53.12	0.000574	99,058	58.47
23	0.001682	98,298	52.21	0.000617	99,001	57.5
24	0.001747	98,132	51.3	0.000655	98,940	56.54
25	0.001812	97,961	50.39	0.0007	98,875	55.58
26	0.001884	97,783	49.48	0.000743	98,806	54.61
27	0.001974	97,599	48.57	0.000796	98,732	53.66
28	0.00207	97,406	47.66	0.000851	98,654	52.7
29	0.002172	97,205	46.76	0.000914	98,570	51.74
30	0.002275	96,994	45.86	0.000976	98,480	50.79
31	0.002368	96,773	44.97	0.001041	98,383	49.84
32	0.002441	96,544	44.07	0.001118	98,281	48.89
33	0.002517	96,308	43.18	0.001186	98,171	47.94
34	0.00259	96,066	42.29	0.001241	98,055	47
35	0.002673	95,817	41.39	0.001306	97,933	46.06
36	0.002791	95,561	40.5	0.001386	97,805	45.12
37	0.002923	95,294	39.62	0.001472	97,670	44.18
38	0.003054	95,016	38.73	0.001549	97,526	43.24
39	0.003207	94,725	37.85	0.001637	97,375	42.31
40	0.003333	94,422	36.97	0.001735	97,215	41.38
41	0.003464	94,107	36.09	0.00185	97,047	40.45
42	0.003587	93,781	35.21	0.00195	96,867	39.52
43	0.003735	93,445	34.34	0.002072	96,678	38.6
44	0.003911	93,096	33.46	0.002217	96,478	37.68
45	0.004137	92,732	32.59	0.002383	96,264	36.76
46	0.004452	92,348	31.73	0.002573	96,035	35.85
47	0.004823	91,937	30.87	0.002777	95,788	34.94
48	0.005214	91,493	30.01	0.002984	95,522	34.04
49	0.005594	91,016	29.17	0.00321	95,237	33.14
50	0.005998	90,507	28.33	0.003476	94,931	32.24
51	0.0065	89,964	27.5	0.003793	94,601	31.35
52	0.007081	89,380	26.67	0.004136	94,242	30.47
53	0.007711	88,747	25.86	0.004495	93,852	29.59
54	0.008394	88,062	25.06	0.00487	93,430	28.72
55	0.009109	87,323	24.27	0.005261	92,975	27.86
56	0.009881	86,528	23.48	0.005714	92,486	27.01
57	0.010687	85,673	22.71	0.006227	91,958	26.16
58	0.011566	84,757	21.95	0.006752	91,385	25.32
59	0.012497	83,777	21.21	0.007327	90,768	24.49

Appendix B: Average of Monthly High Quality Market Corporate Bond Spot Rates

Maturity	2018	2019	2020	2021	2022
0.5	2.51	2.32	0.76	0.18	2.78
1.0	2.70	2.37	0.85	0.30	3.10
1.5	2.87	2.41	0.93	0.42	3.36
2.0	3.00	2.44	0.98	0.54	3.55
2.5	3.10	2.46	1.03	0.65	3.67
3.0	3.18	2.48	1.06	0.77	3.73
3.5	3.25	2.49	1.10	0.89	3.77
4.0	3.32	2.52	1.15	1.02	3.80
4.5	3.38	2.56	1.22	1.15	3.84
5.0	3.44	2.61	1.30	1.28	3.88
5.5	3.51	2.68	1.39	1.42	3.93
6.0	3.57	2.75	1.49	1.56	3.99
6.5	3.64	2.83	1.60	1.70	4.06
7.0	3.71	2.91	1.72	1.83	4.13
7.5	3.77	2.99	1.84	1.96	4.20
8.0	3.84	3.08	1.96	2.09	4.28
8.5	3.90	3.16	2.07	2.21	4.35
9.0	3.96	3.23	2.18	2.32	4.41
9.5	4.01	3.31	2.28	2.42	4.48
10.0	4.06	3.38	2.37	2.52	4.53
10.5	4.10	3.44	2.46	2.60	4.58
11.0	4.15	3.50	2.54	2.68	4.63
11.5	4.18	3.55	2.61	2.75	4.66
12.0	4.22	3.60	2.68	2.81	4.70
12.5	4.25	3.64	2.74	2.86	4.72
13.0	4.27	3.68	2.79	2.91	4.74
13.5	4.30	3.71	2.84	2.95	4.76
14.0	4.32	3.74	2.88	2.99	4.77
14.5	4.34	3.77	2.91	3.02	4.78
15.0	4.35	3.79	2.94	3.05	4.78
15.5	4.37	3.81	2.97	3.07	4.78
16.0	4.38	3.83	2.99	3.09	4.78
16.5	4.39	3.84	3.01	3.10	4.78
17.0	4.40	3.86	3.03	3.12	4.77
17.5	4.41	3.87	3.05	3.13	4.77
18.0	4.42	3.88	3.06	3.14	4.76
18.5	4.42	3.89	3.07	3.15	4.76
19.0	4.43	3.90	3.08	3.16	4.74
19.5	4.43	3.90	3.09	3.16	4.74
20.0	4.44	3.91	3.10	3.17	4.73
20.5	4.44	3.92	3.11	3.17	4.72
21.0	4.45	3.92	3.12	3.18	4.71
21.5	4.45	3.93	3.13	3.18	4.71
22.0	4.45	3.94	3.13	3.18	4.70

22.5	4.46	3.94	3.14	3.19	4.69
23.0	4.46	3.94	3.14	3.19	4.68
23.5	4.46	3.95	3.15	3.19	4.67
24.0	4.46	3.95	3.16	3.20	4.67
24.5	4.47	3.96	3.16	3.20	4.66
25.0	4.47	3.96	3.17	3.20	4.66
25.5	4.47	3.97	3.17	3.21	4.65
26.0	4.48	3.97	3.18	3.21	4.65
26.5	4.48	3.97	3.18	3.21	4.64
27.0	4.48	3.98	3.19	3.21	4.64
27.5	4.48	3.98	3.19	3.22	4.63
28.0	4.49	3.98	3.20	3.22	4.63
28.5	4.49	3.99	3.20	3.22	4.63
29.0	4.49	3.99	3.21	3.23	4.62
29.5	4.49	3.99	3.21	3.23	4.62
30.0	4.50	4.00	3.22	3.23	4.62
30.5	4.50	4.00	3.22	3.24	4.61
31.0	4.50	4.01	3.22	3.24	4.61
31.5	4.50	4.01	3.23	3.24	4.61
32.0	4.51	4.01	3.23	3.25	4.61
32.5	4.51	4.01	3.24	3.25	4.60
33.0	4.51	4.02	3.24	3.25	4.60
33.5	4.51	4.02	3.24	3.25	4.60
34.0	4.51	4.02	3.25	3.26	4.60
34.5	4.52	4.03	3.25	3.26	4.59
35.0	4.52	4.03	3.26	3.26	4.59
35.5	4.52	4.03	3.26	3.26	4.59
36.0	4.52	4.03	3.26	3.27	4.59
36.5	4.52	4.04	3.26	3.27	4.59
37.0	4.52	4.04	3.27	3.27	4.59
37.5	4.53	4.04	3.27	3.27	4.58
38.0	4.53	4.04	3.27	3.27	4.58
38.5	4.53	4.04	3.28	3.28	4.58
39.0	4.53	4.05	3.28	3.28	4.58
39.5	4.53	4.05	3.28	3.28	4.58
40.0	4.53	4.05	3.28	3.28	4.58
40.5	4.53	4.05	3.29	3.28	4.57
41.0	4.54	4.05	3.29	3.29	4.57
41.5	4.54	4.06	3.29	3.29	4.57
42.0	4.54	4.06	3.29	3.29	4.57
42.5	4.54	4.06	3.30	3.29	4.57
43.0	4.54	4.06	3.30	3.29	4.57
43.5	4.54	4.06	3.30	3.29	4.56
44.0	4.54	4.06	3.30	3.30	4.56
44.5	4.54	4.07	3.31	3.30	4.56
45.0	4.54	4.07	3.31	3.30	4.56
45.5	4.55	4.07	3.31	3.30	4.56
46.0	4.55	4.07	3.31	3.30	4.56
46.5	4.55	4.07	3.31	3.30	4.56
47.0	4.55	4.07	3.31	3.30	4.56

47.5	4.55	4.08	3.32	3.31	4.56
48.0	4.55	4.08	3.32	3.31	4.55
48.5	4.55	4.08	3.32	3.31	4.55
49.0	4.55	4.08	3.32	3.31	4.55
49.5	4.55	4.08	3.32	3.31	4.55
50.0	4.55	4.08	3.33	3.31	4.55
50.5	4.56	4.08	3.33	3.31	4.55
51.0	4.56	4.08	3.33	3.31	4.55
51.5	4.56	4.08	3.33	3.31	4.55
52.0	4.56	4.09	3.33	3.32	4.55
52.5	4.56	4.09	3.33	3.32	4.55
53.0	4.56	4.09	3.34	3.32	4.54
53.5	4.56	4.09	3.34	3.32	4.54
54.0	4.56	4.09	3.34	3.32	4.54
54.5	4.56	4.09	3.34	3.32	4.54
55.0	4.56	4.09	3.34	3.32	4.54
55.5	4.56	4.09	3.34	3.32	4.54
56.0	4.56	4.09	3.34	3.32	4.54
56.5	4.57	4.10	3.35	3.32	4.54
57.0	4.57	4.10	3.35	3.32	4.54
57.5	4.57	4.10	3.35	3.32	4.54
58.0	4.57	4.10	3.35	3.33	4.54
58.5	4.57	4.10	3.35	3.33	4.54
59.0	4.57	4.10	3.35	3.33	4.54
59.5	4.57	4.10	3.35	3.33	4.54
60.0	4.57	4.10	3.35	3.33	4.53
60.5	4.57	4.10	3.36	3.33	4.53
61.0	4.57	4.10	3.36	3.33	4.53
61.5	4.57	4.10	3.36	3.33	4.53
62.0	4.57	4.11	3.36	3.33	4.53
62.5	4.57	4.11	3.36	3.33	4.53
63.0	4.57	4.11	3.36	3.33	4.53
63.5	4.57	4.11	3.36	3.33	4.53
64.0	4.57	4.11	3.36	3.33	4.53
64.5	4.57	4.11	3.36	3.34	4.53
65.0	4.57	4.11	3.37	3.34	4.53
65.5	4.57	4.11	3.37	3.34	4.53
66.0	4.58	4.11	3.37	3.34	4.53
66.5	4.58	4.11	3.37	3.34	4.53
67.0	4.58	4.11	3.37	3.34	4.53
67.5	4.58	4.11	3.37	3.34	4.53
68.0	4.58	4.11	3.37	3.34	4.53
68.5	4.58	4.11	3.37	3.34	4.52
69.0	4.58	4.11	3.37	3.34	4.52
69.5	4.58	4.12	3.37	3.34	4.52
70.0	4.58	4.12	3.37	3.34	4.52
70.5	4.58	4.12	3.37	3.34	4.52
71.0	4.58	4.12	3.38	3.34	4.52
71.5	4.58	4.12	3.38	3.34	4.52
72.0	4.58	4.12	3.38	3.34	4.52

72.5	4.58	4.12	3.38	3.34	4.52
73.0	4.58	4.12	3.38	3.34	4.52
73.5	4.58	4.12	3.38	3.35	4.52
74.0	4.58	4.12	3.38	3.35	4.52
74.5	4.58	4.12	3.38	3.35	4.52
75.0	4.58	4.12	3.38	3.35	4.52
75.5	4.58	4.12	3.38	3.35	4.52
76.0	4.58	4.12	3.38	3.35	4.52
76.5	4.58	4.13	3.38	3.35	4.52
77.0	4.58	4.13	3.38	3.35	4.52
77.5	4.58	4.13	3.38	3.35	4.52
78.0	4.59	4.13	3.39	3.35	4.52
78.5	4.59	4.13	3.39	3.35	4.51
79.0	4.59	4.13	3.39	3.35	4.51
79.5	4.59	4.13	3.39	3.35	4.51
80.0	4.59	4.13	3.39	3.35	4.51
80.5	4.59	4.13	3.39	3.35	4.51

Endnotes/References

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Serving as the research arm of the Society of Actuaries (SOA), the SOA Research Institute provides objective, data-driven research bringing together tried and true practices and future-focused approaches to address societal challenges and your business needs. The Institute provides trusted knowledge, extensive experience and new technologies to help effectively identify, predict and manage risks.

Representing the thousands of actuaries who help conduct critical research, the SOA Research Institute provides clarity and solutions on risks and societal challenges. The Institute connects actuaries, academics, employers, the insurance industry, regulators, research partners, foundations and research institutions, sponsors and non-governmental organizations, building an effective network which provides support, knowledge and expertise regarding the management of risk to benefit the industry and the public.

Managed by experienced actuaries and research experts from a broad range of industries, the SOA Research Institute creates, funds, develops and distributes research to elevate actuaries as leaders in measuring and managing risk. These efforts include studies, essay collections, webcasts, research papers, survey reports, and original research on topics impacting society.

Harnessing its peer-reviewed research, leading-edge technologies, new data tools and innovative practices, the Institute seeks to understand the underlying causes of risk and the possible outcomes. The Institute develops objective research spanning a variety of topics with its strategic research programs: aging and retirement; actuarial innovation and technology; mortality and longevity; diversity, equity and inclusion; health care cost trends; and catastrophe and climate risk. The Institute has a large volume of topical research available, including an expanding collection of international and market-specific research, experience studies, models and timely research.

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